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Estimating Global Demand for Coniferous Sawnwood Taking Uncertain Variables into Account

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PREFACE

This Master's Thesis concludes my studies in Forest Sciences at the Norwegian University of Life Sciences (NMBU). The studies have been intellectually and socially rewarding in delightful companionship with my fellow students. The coffee, our conversations and the distinct smell of two-stroke engines and sawdust will be affectionally remembered.

I want to thank my supervisors, Maarit Kallio, Birger Solberg and Olvar Bergland for their much-needed help and attention. I am grateful and humble for this experience.

I take the full responsibility for the contents of this thesis.

Svein Harald Frøberg Skjerstad

Ås, May 13, 2019

ABSTRACT

This thesis aims at providing new estimates regarding the global demand for coniferous sawnwood. Individual and representative elasticities of demand for the sample of 92 countries that represented 97 % of the global coniferous sawnwood demand in 2015 were estimated using econometric methods. Both the availability and the quality of data impose challenges with obtaining reliable results. The estimates from the panel data regressions seem more reliable than those from the country-individual regressions. These can be used as proxies for country-specific price and income elasticities of demand and add updated estimates to the limited amount of literature on the subject.

According to a conventional demand model applied on the currently available data, elasticities of demand vary greatly among countries and within regions. The results are thoroughly evaluated with regards to data quality and stationarity. Compared to the results found in the previous literature, the absolute value of the elasticities of demand from this study in general are higher.

The obtained elasticities were applied to project future demand for coniferous sawnwood assuming constant sawnwood prices using the recently developed Shared Socioeconomic Pathways scenarios from the Intergovernmental Panel on Climate Change. The future rate of the global economic growth will have significant impacts on the demand for sawnwood.

SAMMENDRAG

Denne oppgaven har som mål å gi nye estimater angående etterspørselen etter trelast av bartrær. Individuelle og representative elastisiteter for etterspørsel for hvert av utvalgets 92 land, som utgjorde 97% av etterspurt volum i 2015, ble estimert med økonometriske metoder. Kvaliteten og tilgjengeligheten av data gjør det utfordrende å oppnå troverdige resultater. Estimatene fra de longitudinelle regresjonene virker mer troverdige enn de individuelle tidsserieregresjonene. Disse kan brukes som representative pris- og inntektselastisiteter for etterspørsel for de ulike landene og bidra med en oppdatering av estimatene i foreliggende litteratur om temaet.

Basert på en konvensjonell etterspørselsfunksjon og tilgjengelig data varierer elastisitetene for etterspørsel mellom land og innen regioner bestående av flere land. Resultatene ble grundig evaluert med hensyn til datakvalitet og hvorvidt de stammer fra stasjonære prosesser. Sammenlignet med foreliggende litteratur er de absolutte verdiene av elastisitetene for etterspørsel generelt høyere.

Fremtidig global etterspørsel med priser holdt konstant er estimert med bruk av nylig utviklede SSP-scenarioer fra IPCC og inntektselastisitetene beregnet i oppgaven. Resultatet viser at fremtidig økonomisk vekst vil påvirke etterspørselen etter trelast betydelig.

TABLE OF CONTENTS

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1. INTRODUCTION

1.1 Sawnwood production and consumption overview

Forest resources supply a large industrial sector with a range of products. Globally the majority of wood removals are wood fuel. About half of wood removals are used for energy purposes, such as firewood, but this vary significantly between countries depending on their resource supply and their degree of economic development. The forest product with the highest economic importance is sawtimber and its main further processing into sawnwood. This thesis will focus on the demand for coniferous sawnwood. The term sawnwood includes planks, beams, boards, laths etc. that exceed 6 mm in thickness, except for wooden flooring, sleepers and mouldings, and is subdivided into coniferous- and non-coniferous sawnwood (FAO, 2017). Coniferous wood (or softwood) encompasses wooden materials from species that are botanically classified as Gymnospermae. Examples of such species are *Abies spp.*, *Araucaria spp., Cedrus spp., Chamaecyparis spp., Cupressus spp., Larix spp., Picea spp., Pinus spp., Thuja spp., Tsuga spp.,* etc.

The 2017 global production of sawnwood amounted to 485 million m^3 and the global trade to 153 million m^3 (FAO, 2018a). Coniferous sawnwood contributes to approximately 70 percent of the annual total production of sawnwood (FAO, 2018b). The main part of production takes place in Asia and the Pacific, Europe and North America where it has been growing consecutively in the 2012-2017 period. In Africa, Latin-America and the Caribbean, the production is modest. The main importing regions are Africa and the Asia-Pacific region with a net import of 7 million m^3 and 46 million m^3 respectively. The main exporting regions are Europe and North-America with a net export of 46 million m^3 and 4 million m^3 respectively. At country level, the largest producers of sawnwood are USA, China, Canada, Russia and Germany. Together, these countries contributed to over half of the total production in 2016 (FAO, 2017).

In Europe, the market share of coniferous sawnwood is around 90 percent (Hurmekoski et al., 2015). Most of its end use is different construction applications. Less significant end uses are packaging, furniture production and joinery. Table 1 display the countries with the largest production, import, export and apparent consumption (production + import – export) in 2017. USA is both the largest producer and importer and thus the largest consumer. The largest exporter is Canada, whereas Russia exports a larger share of its production (74 percent) making their consumption low relative to other major countries.

Table 1 Top 5 largest producers, importers, exporters and consumers by countries in 2017. Source: FAO (2018a)

Country	Production	Import quantity	Export quantity	Consumption
United States of America	57 600 000	26 695 038	2 889 844	81 405 194
Canada	48 159 258	740 985	31 075 582	17 824 661
China	38 361 000	26 148 486	128 494	64 380 992
Russian Federation	37 819 636	22 336	27 971 388	9 870 584
Germany	22 050 255	4 738 011	7 519 050	19 269 216
United States of America	57 600 000	26 695 038	2 889 844	81 405 194
China	38 361 000	26 148 486	128 494	64 380 992
United Kingdom	3 728 180	7 079 193	194 426	10 612 947
Japan	8 606 000	6 124 313	-	14 730 313
Germany	22 050 255	4 738 011	7 519 050	19 269 216
Canada	48 159 258	740 985	31 075 582	17 824 661
Russian Federation	37 819 636	22 336	27 971 388	9 870 584
Sweden	18 310 000	485 465	13 110 654	5 684 811
Finland	11 700 000	537 364	9 357 517	2 879 847
Germany	22 050 255	4 738 011	7 519 050	19 269 216
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Japan	8 606 000	6 124 313	-	14 730 313

Figure 1a show a steady increase in consumption in USA and China during 2013-2017. China's consumption grew by 38 percent while USA's consumption grew with 18 percent over the period. The consumption in the other major consuming countries have remained stable, but on a much lower level. The average consumption growth during the period in the top five countries is 14 percent. The imports grew by 38 percent and 31 percent in China and USA, respectively (fig. 1b). On average, imports grew by 20 percent in the top five countries. Canada is the second largest producer and the largest exporter (fig. 1c and 1d). The country with the highest relative growth in export is Russia with 32 percent. Of the top 5 producers, USA and China have an average net import of 20.7 and 20.5 million m^3 respectively while Canada, Russia and Germany have an average net export of 29.3, 23.6 and 2.3 million m^3 respectively.

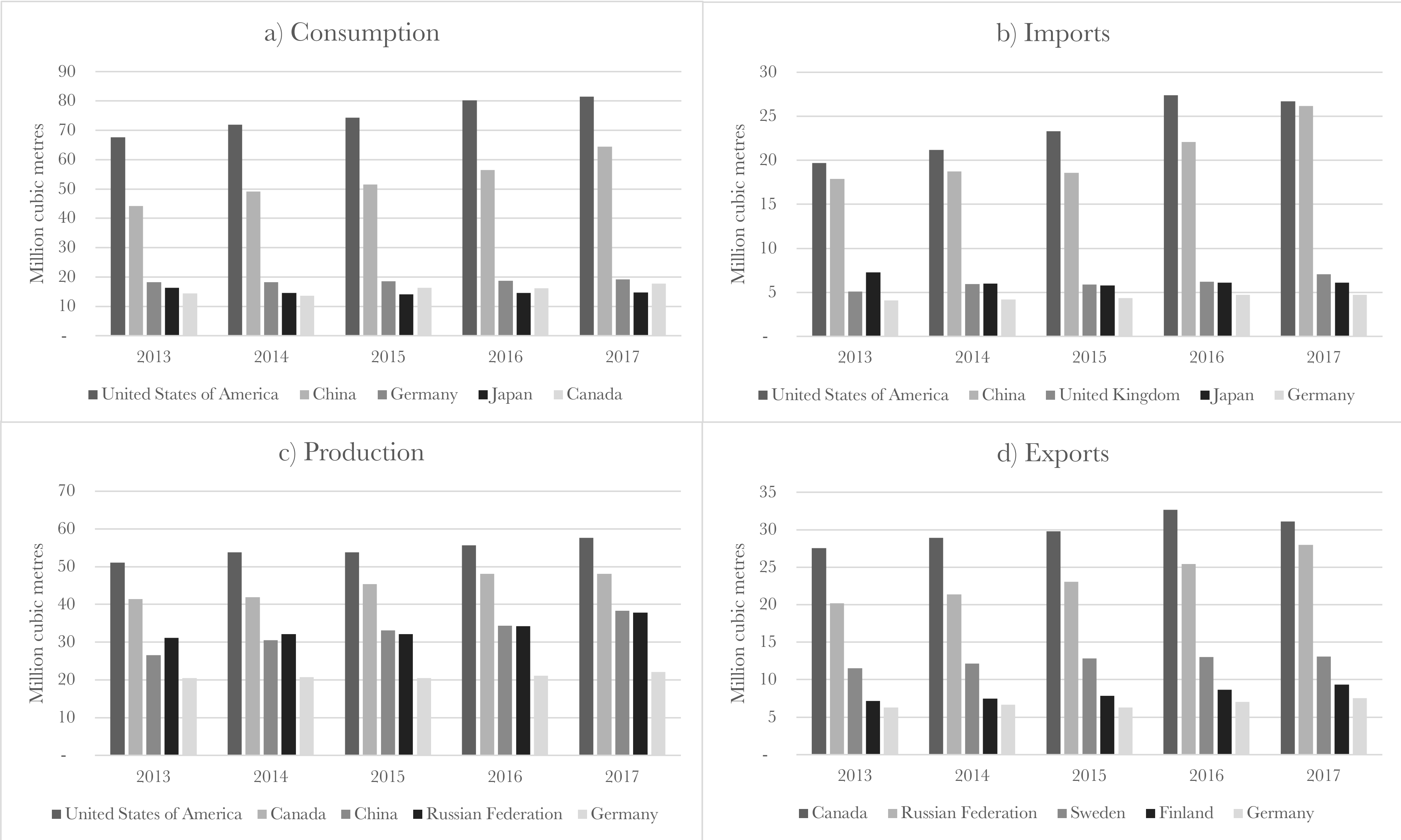

Figure 1 Consumption, imports, production and exports for the five largest countries over the period 2013-2017. Source: FAO (2018a)

Sawnwood is considered a contributor to reach goals of climate change mitigation. Wooden construction materials are renewable and can be produced with less energy than alternative products such as concrete or steel. Wooden constructions can store carbon for a long period. This has led to a recommendation for use of more wood in construction in order to mitigate climate change (Sathre and O'Connor, 2010).

1.2 Previous research

Some previous studies are available on the demand for sawnwood, but only few studies consider the demand for coniferous sawnwood in particular. The main method used for estimating elasticities and other demand indicators is panel data econometrics. The results of some studies are contradicting. The most recent global study discussed is Buongiorno (2015).

The most relevant studies are summarized in chapter 1.2.1. Chapter 1.2.2 discusses the recent research related to the problems with data quality of the FAOSTAT forestry database (FAO, 2018a). This publicly available database provided by the Food and Agriculture Organization of the United Nations (FAO) is the main source of harmonized global data on the forest product markets.

1.2.1 Studies on demand of sawnwood

Simangunsong and Buongiorno (2001) estimated international demand equations for forest products and compared econometric methods of acquiring them. They formulated static and dynamic models and used variants of classic methods such as Pooled OLS, Least Squares with Dummy Variables (LSDV), also known as Fixed Effects, and error component models, as well as more modern shrinkage estimators. Their data set for sawnwood consisted panel data on consumption, price and income from 62 countries over a relatively long time period, from 1973 to 1997. Sawnwood and coniferous sawnwood was not differentiated and all the countries in the world were included into a single panel. For each country, apparent consumption (production + imports – exports) defined the quantity demanded. Prices were estimated as the weighted average of import and export values. These data were obtained from FAOSTAT. Prices and GDPs were measured in real 1985 dollars. GDPs, exchange rates and deflators were obtained from the World Bank Development Indicator Database. Pooled OLS and random effects rely on two opposite assumptions, namely homogeneity or complete heterogeneity of elasticities. As neither of the assumptions were found to be realistic, shrinkage estimators were applied to find an estimator somewhat in the middle. In the static model, it is assumed that demand adjusts immediately to output and prices. In the dynamic model, demand adjusts from one year to the next at a certain rate. Thus, the dynamic model can provide short-term and long-term elasticities. For the static model, the Stein-rule shrinkage estimator was applied. For the dynamic model, an iterative empirical Bayes estimator was applied. That way, each country OLS estimator shrank towards the mean of the estimates across all countries.

In the static model, the coefficients were -0.20 and -0.22 for price elasticity from POLS and LSDV respectively. For GDP elasticities the similar coefficients were 1.04 and 0.50. AR(1) correction was applied to compensate for serial correlation. The mean Stein-rule shrunk coefficients were -0.18 and 0.55 for price and GDP respectively. In the dynamic model, the mean Bayesian shrunk coefficients were -0.06 and 0.35 for price and GDP respectively. The corresponding long-term coefficients were -0.11 and 0.69. The results with the lowest RMSE was the Stein-rule estimators from the static model. This suggests that for forecasting purposes, the static model is better suited than the dynamic despite the higher in-sample R^2.

Michinaka et al. (2010) used cluster analysis on the 180 countries in the Global Forest Products Model (Buongiorno et al., 2003) before estimating price and GDP elasticities of demand with panel data analysis for each cluster. The rationale for applying cluster analysis is efficiency due to the large dataset and the fact that reliability and availability of data varies among countries. The countries were grouped by per capita GDP, forest coverage and per capita consumption of sawnwood. Data sources were FAO and The World Bank from 1992 to 2007. Although earlier data were available, the significant structural changes in the world economy following the late 1980's and early 1990's was considered as a source of distortion. Prices were normalized to real terms in 2005 US dollars. The countries were divided into 8 clusters from similarities in the above-mentioned variables. Elasticities were estimated from Pooled OLS, Fixed Effects and Random Effects regressions in a static and a dynamic model.

The long-term price elasticities ranged from -0.12 to -1.63 while long-term GDP elasticities range from 0.27 to 1.26. For the countries with a low per capita level of sawnwood consumption and GDP, the forest coverage was suggested to explain the differences between price and GDP elasticities among them. In countries with higher per capita sawnwood consumption, elasticities were found to be affected more by per capita GDP. In general, countries with high consumption but low forest coverage, tended to have a higher price elasticity than other clusters. This rejected the assumption that elasticities are homogenous in time and space dimensions. The RMSE test results show that the fixed effects method in this study performs better than the Pooled OLS and random effects methods.

Hurmekoski et al. (2015) identified factors affecting the demand for coniferous sawnwood in Europe. They examined per capita consumption as a function of domestic prices and GDP per capita for 17 countries in the period 1980-2012 and formulated different ad hoc model specifications with additional explanatory variables to identify its drivers. In addition to prices for sawnwood they considered prices for wood-based panels (as a substitute) and concrete (as a compliment) as explanatory variables. In addition to GDP, they included unemployment rate and an index of economic openness in the models. They also considered residential renovation and modernization activity, and residential construction activity as explanatory variables. They applied a Least Square Dummy Variable model (LSDV) and included a lagged dependent variable to compensate for autocorrelation which reported short-run elasticities. Long-run elasticities were computed by dividing the elasticities with one minus the elasticity of the lagged dependent variable. They estimated the elasticities for three alternative sample periods (1980-2012, 1980-1996 and 1997-2012). Two-stage least squares (TSLS) was used to compensate for endogeneity bias. The countries were grouped by similarities in consumption per capita, GDP per capita and growing stock of coniferous wood per capita.

In the conventional baseline model with domestic price, GDP per capita and lagged consumption per capita, most price elasticities were not statistically significant, and some had positive signs which is not in accordance with the economic theory. The domestic price seemed to be more significant in group 1 (Austria, Estonia, Finland, Norway and Sweden). Price elasticities varied in the different time periods and thus did not remain constant in time. In the ad hoc model, the construction activity was identified as a significant determinant in all countries but those in group 1. The consumption appeared to be inelastic with regard to construction activity, compared to the level of income. Moreover, construction activity and GDP had individual effects, which implicates that they do not necessarily occur simultaneously. The effect of income seemed to be largest in group 1 and group 2 (France, Germany and Italy). Based on this model, price changes seemed to have small effects on the sawnwood consumption. The insignificance of prices suggests that the price-differences in construction materials may not have a significant impact on consumption due to long traditions in construction methods.

Buongiorno (2015) investigates to what extent price and income elasticities of demand for forest products has changed in the past two decades and their dependence on the countries' income level. FAOSTAT data on production, import, exports and prices and GDP data from the World Bank was normalized to real 2013 U.S. dollars. The data from 1992-2013 was divided into two time periods (1992-2003 and 2004-2013) and high- and low-income countries using dummy variables. The variables were converted to first differenced natural logarithms to eliminate unobserved differences between countries that might affect consumption and to avoid non-stationarity. He then estimated projections for demand from 2012-2065 using the Global Forest Product Model based on an IPCC scenario.

The pooled regression parameters for sawnwood was -0.17 and 0.24 for price and income elasticities of demand respectively. The results indicated that for sawnwood the data should be pooled across all countries and years and that there were no significant differences across income level and time periods.

Rougieux and Damette (2018), unlike most other articles on the subject, explicitly take the issue of non-stationarity in time-series and panel data into account. They estimated demand elasticities for price and GDP through a cointegration approach for Europe on paper products, coniferous sawnwood and wood panels. They built 3 balanced panel datasets and focused on a panel with 15 countries over 34 years. Prices were given in Euro, converted from US dollars using a fictive euro currency from the US. Federal Reserve for the years preceding 1998. Data were obtained from the FAO Forestry Production and Trade Database and The Federal Reserve Economic Database. Consumption, price and GDP were tested for stationarity with Carrion-i-Silvestre, Del Barrio-Castro, and López-Bazo (2005) test for stationarity. Those variables who could be considered non-stationary were tested for cointegration relationships with the Westerlund (2007) test. They estimated price and GDP elasticities with dynamic OLS (DOLS) and the pool mean group (PMG) approach.

For sawnwood, the DOLS approach yielded a GDP elasticity of 0.356 and a positive price elasticity of 0.663 while the PMG approach yielded a GDP elasticity of 0.214 and a price elasticity of -0.366. They argue that price elasticities are unstable over time and excluded the DOLS estimates from the further simulations. The overall simulations showed a lower consumption growth than previously expected by 2030 and that GDP elasticities from previous studies were overestimated. The tensions predicted between biomass-based materials and bioenergy may therefore be less immediate than previously thought.

To summarize the findings in the above-mentioned articles and some earlier studies, Table 2 display the price- and income elasticities of demand for coniferous and non-coniferous sawnwood available from the literature. Note that the estimates from Hurmekoski et al. (2015) are not statistically significant.

Table 2 Price- and income elasticities available in literature. Studies prior to year 2000 are from Simangunsong and Buongiorno (2001), table 10. a) indicate elasticities of demand for coniferous sawnwood, b) for sawnwood in general.

Study	Price	GDP
Buongiorno (1979) 43 countries [a)] 1963-1973	-0.21	0.71
Wibe (1984) 103 countries [a)] 1970-1979	-0.72	1.57
Buongiorno & Chang (1986) 10 countries [a)] 1961-1981	-0.24	1.41
Baudin & Lundberg (1987) major consuming countries [a)] 1961-1981	-1.13	0.85
Brooks et al. (1995) 8 countries [a)] 1964-1991 (a: high income, b: low income)	0.38 a) -0.46 b)	0.16 a) 0.28 b)
Simangunsong and Buongiorno (2001) 62 countries [b)] 1973-1997	-0.18	0.55
Michinaka et al. (2010) 82 countries [b)] 1992-2007	-0.12 to -1.63	0.27 to 1.26
Hurmekoski et al. (2015) 17 countries (Europe) [a)] 1997-2012	0.27	0.20
Buongiorno (2015) 180 countries [b)] 1992-2013	-0.17	0.24
Rougieux and Damette (2018) 15 countries (Europe) [a)] 1980-2013	-0.37	0.21
Median	-0.23	0.42

1.2.2 Recent studies on the accuracy of international forest statistics

Kallio and Solberg (2018) identified inconsistencies in the FAOSTAT database for several countries. The database is the primary source of data on production, imports and exports, that are needed to estimate the apparent consumption levels, and is used in all the above-mentioned articles. Firstly, the data were examined with three simple tests: "(i): Is the wood production at least as high as the net exports? (ii): Is the reported production of chips, particles and wood residues (too) high compared to the production of solid wood products? (iii): Are the apparent levels of wood use high enough for the reported production of forest industry products?" The latter test is most relevant to this study. They used minimum and maximum conversion factors to determine if the inputs needed for production of forest industry products were under-reported. To improve the consistency and precision and to identify regions with mismatching supply and production, a Linear Programming formulation was used. This made it possible to define the magnitude of deviation of the plausible values from those given in the statistics. In the case of sawnwood, plywood and veneer, the production in a country was related to the apparent sawlog supply based on the statistics of harvest and trade volumes.

Generally, it was assumed that at least 1.5 m^3 of sawnlogs under bark were required to produce one unit of sawnwood, veneer or plywood. The maximum amount of sawlogs that was allowed to be used for these products was 2.8 m^3.

The deficits in logs availability in some countries were substantial and, in a few cases, enormous. China has a deficit of more than 160 million m^3 in 2015 and 2016 which indicate that at most 0.65 m^3 of logs has been used per m^3 of sawnwood or plywood. Vietnam, Turkey and Venezuela also greatly surpass the million mark with 7, 1.7 and 1.1 million m^3 respectively. For all forest industry production, Iran, Malaysia, Romania, Ukraine and Thailand all have a deficit of more than a million m^3. The LP test suggests that even more countries (7-15) have deficits larger than one million m^3 during 2007-2016. This includes countries such as Canada and Germany who presumably could be considered to have resources to collect and provide reliable data. Deficits much smaller than 1 million m^3 can have an important magnitude, compared to the roundwood harvests. Several countries were also found to a have a surplus of reported roundwood supply, 8-10 of them of more than 1 million m^3.

Buongiorno (2018) used goal programming to estimate consumption data on industrial roundwood and paper-making fibres for 180 countries on average from 2013 to 2015. The optimum for the programming problem revealed whether the consumption of the input was over- or under reported compared to the estimate. They used upper- and lower bounds from UNECE for the input-output coefficients, making the estimates as close as possible to the reported consumption. For industrial roundwood, having sawnwood as one of the outputs, 17 countries had an under reporting of more than 1 million m^3. The largest national under reporting was for China with 237.4 million m^3. This is a relative discrepancy of 57 %. The second largest national under reporting in absolute terms were USA with 35.2 million m^3 (10 %) followed by Vietnam, Japan and Thailand with 17.6, 13.6, and 10.6 million m^3 respectively. In total, the world had an under reporting of 368 million m^3 and an over reporting of 16 million m^3 which indicates that an overall under reporting is taking place. For the countries with under reported consumption, the most efficient technology was assumed, thus the differences may be even larger.

Buongiorno argues that production is the least accurate statistic since trade statistics are regulated by custom duties and are also reported in other countries' trade flows. For China, in particular, the under reporting of imports adds up to 8.5 million m^3 less than the exports to China reported from other countries. While the discrepancy is of a significant magnitude, it's much less than the total discrepancy for consumption. If the errors from trade are ignored, some of the underestimation of consumption could be due to illegal logging. This could be plausible for China, Vietnam and Thailand, but less so for USA, Japan and Germany. Illegal logging has also been suspected in Russia, but this study found that the reported apparent consumption was plausible and that the discrepancy between exports reported from Russia and the worlds' reported imports from Russia was below 1 million m^3. In sum, the study concludes that the discrepancies between reported and estimated consumption of the input goods seem to be due to plain errors in the data collection. However, the production statistics of the outputs, such as sawnwood, pulp and paper were kept at their reported level and the errors in individual forest-based products were not investigated.

Obviously, reliable data collection is challenging. The products are often produced in numerous small units which are prone to measurement errors. The reasons for these inconsistencies may be numerous and identifying the sources of data error would be a more than challenging exercise on its own. However, being aware of the inconsistencies is important when making inferences on relevant data analysis.

1.2.3 Implications for the choice of topics

Simangunsong and Buongiorno (2001) is a frequently cited study in the literature as it elegantly formulates the underlying economic theory and concerns a variety of forest products. The elasticities estimated are assumed to be applicable for the global economy and thus represents an average of elasticities that is found to differ across countries in other studies. However, the study is very general and does not differentiate coniferous- and non-coniferous sawnwood. Also, the study is already relatively old and lots of new data has accumulated since 2001. In contrast, Michinaka et al. (2010) estimates demand elasticities for different groups of countries. Also, in this study sawnwood is not differentiated into coniferous- and non-coniferous products. As mentioned in the introduction, coniferous sawnwood make up approximately 70 % of the global production of sawnwood, so it is possible that the elasticities do not differ substantially between these two assortments. However, a similar study focusing on coniferous sawnwood may offer more insight to different levels of demand for this product category.

Hurmekoski et al. (2015) is one of few studies attempting to estimate country-specific elasticities of demand and they confine the scope of their article to European countries. Few countries had statistically significant elasticities and some of them had contradictive signs to what is expected from economic theory. These problems are not discussed thoroughly. A new attempt on a global scale followed by a review of the data quality and the reliability of the estimates might offer some explanation to these problems.

Buongiorno (2015) concludes that there are no significant differences in elasticities of demand across time periods and high- or low-income countries for sawnwood in his study of 180 countries. He based his inferences on data that are first-differenced in order to remove unobserved differences possibly affecting consumption. This might isolate the effect of income but also removes any other source of heterogeneity. An overall homogeneity is thus the inexplicit assumption. 20 percent of the countries were in the high-income category, which would amount to 36 out of 180 countries. The threshold deciding low or high income was 15 000 USD, presumably the median GDP per capita across countries. Having a GDP above the median could be the only thing these countries have in common. The elasticities of -0.17 and 0.24 for price and income respectively may be representative for the world average, but the rejection of heterogeneity is not convincing.

As suggested by Rougieux and Damette (2018), a topic not offered much attention in the present literature is the stationarity of the variables in question. If the variables are found to be stationary in levels, the literature is likely to be reliable. If not, the previously estimated global elasticities of demand may be results of spurious regressions. Their study only provides estimates for Europe.

The data used is prone to contain errors and the econometric methods for estimating demand elasticities need to be applied with careful consideration. The recent studies on the reliability of the FAOSTAT data motivates awareness about the quality of the underlying data. Most of the studies described above seem to ignore issues of data quality in order to get larger samples. In this thesis it is assumed that preliminary measures for generating a credible sample are necessary. However, countries with large discrepancies such as China and Russia should not be omitted from the study as they are large actors in the industry as well as the global economy. A study on coniferous sawnwood demand with an in-depth assessment of the data quality is relevant and likely to be a valuable contribution to the existing research on the subject.

1.3 Objectives

This thesis aims at providing new results regarding the global demand for coniferous sawnwood. Based on the findings in section 1.2. and particularly the implications in section 1.2.3, the main objectives of this thesis are to estimate and compare new elasticities of demand from using various types of statistical methods and taking into consideration uncertainty in the data input provided by the international statistics. The elasticities are further used to quantify future outlooks for the consumption of coniferous sawnwood using the SSP scenarios used by IPCC.

To delineate this broad study into the format of a master's thesis, the objectives are divided into the following sub-objectives::

1. Estimate individual or representative elasticities of demand on a country level, emphasizing the quality of the underlying data.
2. Assess whether the elasticities of demand are homogenous across countries or regions.
3. Compare the findings with the present literature on the subject.
4. Project future coniferous sawnwood consumption based on GDP and population prognoses in the Shared Socioeconomic Pathways (SSP) used by the Intergovernmental Panel on Climate Change (IPCC).

1.4 Outline of the thesis

The remaining part of the thesis is structured as follows: In chapter 2 data and methods are described. In chapter 3 the results are presented and discussed. In chapter 3.1 country-specific elasticities of demand are estimated with classic time series methods while assessing the quality of the underlying data. Reversed regressions are applied to evaluate the precision of the elasticities. In chapter 3.2 countries with sufficient data quality are grouped by various assumptions to generate representative demand elasticities with panel data estimators. It is assumed that forest coverage, income level and production share of consumption affects the elasticities of demand. In chapter 3.3 prognoses for the future consumption of sawnwood are presented, based on combining SSP assumptions with the income elasticities estimated in this thesis. This gives an illustrative application of parts of the thesis' results, while at the same time quantifying possible future sawnwood consumptions under different IPCC narratives.

Section 3.4 then gives an overall, more generic discussion of the results. Finally, chapter 4 provides conclusions and suggestions for interesting future research concerning this topic.

2. MATERIALS AND METHODS

In this chapter the underlying economic theory will be discussed, the characteristics of the dataset and its necessary conversions presented, and the choices made for model specification are explained.

2.1 Economic theory

The following theoretical models are based on the study of Simangunsong and Buongiorno (2001). We consider a country's factor demand function derived by the cost minimization problem defined in Varian (1992) aggregated from all firms in the country. It can be expressed as:

(1) $\min\limits_{y,z}(yp_y + zp_z)$ for the Cobb-Douglas technology:

(2) $ay^b z^c = g$

where y is the amount of sawnwood demanded, z is the amount of other inputs, g is the industry production and a, b and c are positive parameters. Solving the first order conditions for *y* gives the static derived demand function:

(3) $y(p_y, p_z, g) = \beta_1 (\frac{p_y}{p_z})^{\beta_2} g^{\beta_3}$

where β_1 equals $a^{-\frac{1}{b+c}}(b/c)^{\frac{c}{b+c}}$, β_2 is the negative elasticity of demand with respect to prices relative to the price of other inputs, $-\frac{c}{b+c}$ and β_3 is the positive elasticity of demand with respect to output $\frac{1}{b+c}$.

Taking the natural logarithm, we get the expression:

(4) $\ln(y_t) = \ln \beta_1 + \beta_2 \ln(p_t) + \beta_3 \ln(g_t) + \varepsilon_t$

where y_t is the input demand by a country at time *t*, $p_t = \frac{p_y}{p_z}$ is the real price of sawnwood at time t as p_y is the current price of sawnwood and p_z is proxied by the CPI deflator. The output, g_t is in this study proxied by GDP per capita[1].

The parameters β_2 and β_3 are elasticities, which indicate the relative change in the dependent variable due to a one percent change in the explanatory variable.

[1] GDP = Gross domestic product is the market value of all final goods and services produced annually.

The price elasticity of demand (PED) can generally be expressed as:

$$(5)\ \epsilon_p = \frac{\partial y}{\partial p} * \frac{p}{y}$$

From economic theory, it is expected that the price elasticity of demand is negative for normal goods. That is, demand decrease when price increases. For the rare "Veblen" or "Giffen" goods, demand increase when price increases. In these cases, the demand functions illustrated in Figure 2 would look like the functions in Figure 3.

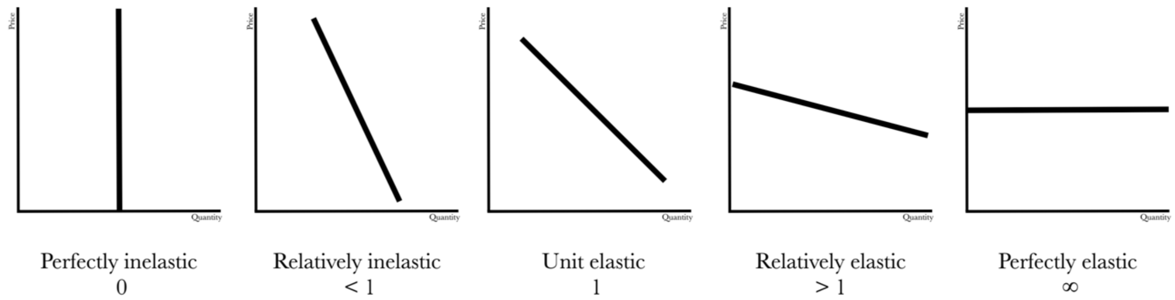

Figure 2 Price elasticity of demand with expected negative sign. Price on vertical axis, quantity demanded on horizontal axis.

The GDP elasticity of demand (YED) can be expressed as:

$$(6)\ \epsilon_g = \frac{\partial y}{\partial GDPC} * \frac{GDPC}{y}$$

The income elasticity of demand is expected to be positive for normal goods. That is, if income increases, the demand for a normal good increase. The demand curve depicted above will shift outwards by the slope of the functions in Figure 3. If the income elasticity of demand is negative, the good is classified as an inferior good.

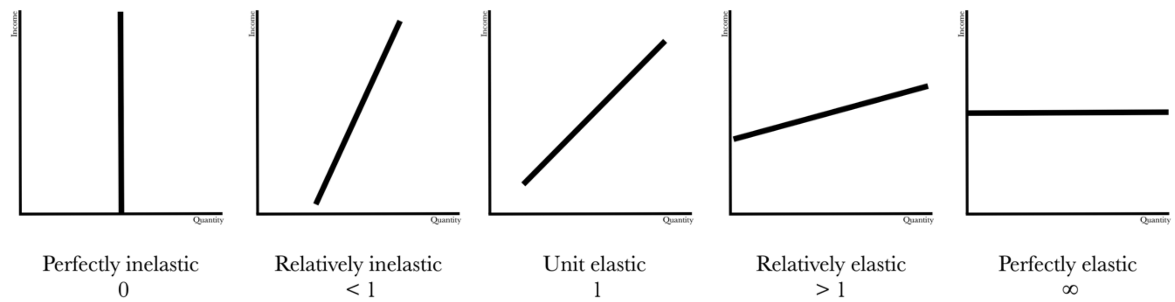

Figure 3 Income elasticity of demand with expected positive sign. Income on vertical axis, quantity demanded on horizontal axis.

For both elasticities, a coefficient value between 0 and 1 indicates that the good is inelastic. This indicates a good where demand is insensitive to a change in the independent variable. For income elasticities, these goods are regarded as normal necessities. Coefficients with a value greater than 1 indicates that the good is elastic. These goods are regarded as normal luxuries. In this case the percentage change in demand is greater than the percentage change in price or income.

2.2 Data

The dataset contains annual country-specific observations for the last 28 years. The data for production, import quantity, import value, export quantity and export value for 1990-2017 are obtained from the FAOSTAT database (FAO, 2018a). Data on midyear population were obtained from The World Bank (The World Bank, 2019).

Per capita consumption was estimated as production plus net trade divided by population:

$$(7)\ CPC = \frac{production + imports - exports}{population}$$

Import and export values from FAOSTAT are given in current thousands of US dollars. Domestic prices were approximated as the weighted average of import and export values:

$$(8)\ P_d = \frac{import\ value + export\ value}{import\ quantity + export\ quantity} * 1000\$$$

While this variable is labelled "domestic price", one should be aware that it is an average of Cost, Insurance and Freight (CIF) import prices and Free on Board (FOB) export prices (FAO, 2018c). This implies that the prices are measured at the nearest port. To be able to get constant monetary terms, historical exchange rates from US dollars to local currency were obtained from the World Bank along with country specific consumer price indexes. The base year was set to 2015 for all countries and once the prices were converted to LCU and deflated, it was converted back to constant US dollars using the 2015 exchange rates. For countries who changed their currency to Euro, the currency was divided by the respective euro conversions the preceding years. The World Bank provided data for GDP. Constant GDP per capita was obtained by dividing the current total GDP on the midyear population and deflating by the same factor as for prices.

Preparing the data, one immediately become aware of missing or irrational entries for many countries. Quantities are given in cubic meters and some countries have conspicuously low values such as imports of 2 m^3 per year. Some countries have negative apparent consumption in one year or more. As a first step of validating the data, countries with an annual average consumption of less than 10 000 m^3 over the 28-year period were excluded from the dataset. Of the 220 countries available, 80 countries fell under this threshold.

Table 3 Omitted countries due to (1) low apparent consumption, (2) negative apparent consumption, (3) lack of price or GDP data. Source: FAO (2018a)

Country	Code	Country	Code	Country	Code
Afghanistan	3	Georgia	2	Palau	1
American Samoa	1	Ghana	1	Papa New Guinnea	2
Andorra	1	Gibraltar	1	Paraguay	1
Angola	1	Greenland	1	Peru	2
Antigua & Barbuda	1	Grenada	1	Pitcairn Islands	1
Armenia	2	Guadeloupe	3	Réunion	3
Aruba	1	Guinea	1	Rwanda	3
Azerbajan	3	Guinea-Bissau	1	Saint Helena	1
Bangladesh	1	Guyana	1	Saint Kitts and Nevis	1
Benin	1	Iraq	3	Saint Pierre and Miquelon	1
Bhutan	3	Kazakhstan	3	Saint Vincent and the Grenadines	1
Bolivia	1	Kiribati	1	Saint-Martin (French Part)	1
Bosnia Herzegovina	2	Lao People's DR	1	Sao Tome and Principe	1
British Virgin Islands	1	Lebanon	3	Senegal	1
Brunei Darussalam	1	Lesotho	1	Serbia	3
Burkina Faso	1	Liberia	1	Seychelles	1
Burundi	3	Libya	3	Sierra Leone	1
Cabo Verde	1	Liechtenstein	1	Solomon Islands	1
Cambodia	1	Luxembourg	3	Somalia	3
Cameroon	1	Madagascar	1	South Sudan	3
Cayman Islands	3	Malaysia	2	Sri Lanka	1
C. African Republic	1	Maldives	1	Sudan	3
Chad	1	Mali	1	Suriname	1
Comoros	1	Marshall Islands	1	Syrian Arab Republic	3
Congo - Brazzaville	1	Martinique	3	Tajikistan	3
Cook Islands	1	Mauritania	1	Timor-Leste	1
Côte d'Ivoire	1	Micronesia	1	Togo	1
Cuba	3	Montenegro	1	Tokelau	1
Djibouti	1	Montserrat	1	Tonga	1
Dominica	1	Mozambique	2	Turkmenistan	3
DPR Korea	3	Myanmar	3	Turks and Caicos Islands	1
DR Congo	1	Namibia	2	Tuvalu	1
Equatorial Guinea	1	Nauru	1	Uganda	3
Eritrea	1	New Caledonia	3	United Arab Emirates	3
Eswatini	2	Nicaragua	2	United Republic of Tanzania	1
Falkland Islands	1	Niger	1	Uzbekistan	3
Faroe Islands	1	Nigeria	1	Vanuatu	1
French Guiana	1	Niue	1	Viet Nam	2
French Polynesia	3	Norfolk Island	1	Wallis and Futuna Islands	1
Gabon	1	Northern Mariana Islands	1	Yemen	3
Gambia	1	Oman	3	Zimbabwe	3

Some countries had negative apparent consumption. Countries where this remained over more than two years were omitted from the dataset. Some countries, namely Estonia, Latvia, Peru, Singapore and Slovakia had one or two years with negative apparent consumption amongst more reliable figures. To remedy these errors, Latvia and Slovakia had alternative statistics in the UNECE FAO-Database (UNECE/FAO, 2018). The other countries were modified by averaging the consumption in the years prior and after the negative year. Some countries had missing price or GDP data. This includes non-reported import or export values, no available CPI data or no available GDP data from the World Bank. Since many of the European countries had missing data in 1990-1992, likely due to the breakup of the Soviet Union, the time span of the sample was reduced to 25 years, from 1993 through 2017. Table 3 display all the 123 omitted countries. In all, 92 countries passed the criteria for making balanced panels with 25 periods each. Although the countries have data for all variables over all periods, the credibility of the data varies. Some countries have close to zero average consumption per capita (e.g. Ethiopia) and the standard deviations are very large for many countries (see Appendix I: Descriptive statistics).

FAO labels their data as "official data", "unofficial figure", "FAO estimate" and "previous year". In some of the panels, FAO estimates and previous year are repeatedly used. While this may be the "best bet", it is unlikely that the exact same quantity is produced, imported or exported over several years and technically, it artificially deflates the variances in the samples. In the further analysis, this source of uncertainty will be emphasized.

2.3 Statistical methods

In the following sections, an overview of the methods and model specification used in each part of the thesis is presented. For part I, the results of the preliminary tests for stationarity is included as well as the post-estimation tests for model misspecification, heteroscedasticity and autocorrelation and the precautions they lead to in interpreting the data. The results from the tests have implications for the model specifications. For part II, the preliminary panel data tests for stationarity and poolability and their results are presented. The stationarity test has implications for the time-periods and sub-samples, and the poolability test has implications for the choice of the panel data model specification. In part III pragmatic relative adjustments were made to align the results to the models.

2.3.1 Part I: Country-individual elasticities of demand

According to the literature, demand elasticities may vary significantly between countries. It therefore makes sense to measure the country-specific price- and GDP elasticities. To achieve this, classic time series regressions are applied. STATA is used for diagnostic tests and estimations. Firstly, the variables are transformed into logarithmic values. Consumption per capita, domestic prices and GDP per capita is tested for stationarity with the Augmented Dickey-Fuller Unit Root test (Dickey and Fuller, 1979). The test can be described as fitting the following regression to the variable (STATA, 2013):

(9) $\Delta y_t = a + \beta y_{t-1} + \delta t + \zeta_1 \Delta y_{t-1} + \cdots + \zeta_k \Delta y_{t-k} + \varepsilon_t$

where Δy_t is the differentiated variable in question, y_{t-1} is a lagged observation and β is the parameter to be tested, δt is a time trend and *k* is the number of differentiated lags included. The null hypothesis $H_0\colon \beta = 0$ implies that the variable has a unit root and is thus non-stationary. When testing for trend stationarity, the default restriction of the time trend is lifted.

In all countries, the null hypothesis of a unit root cannot be rejected for either one or more of the variables. The presence of a unit root implies that the variables are non-stationary. Stationary processes are vital in order to apply regression analysis. A non-stationary process violates the 1st OLS assumption of linearity and weak dependence. The results are spurious regressions and the inability to apply the central limit theorem and the law of large numbers. The logarithmic first differences are found to be stationary for all countries. This implies that the differences are weakly dependent processes that satisfies the central limit theorem. These variables can be interpreted as proportionate growth rates and the parameters from regressions are approximations to the elasticities of demand (Wooldridge, 2013, p. 386). Differencing time series also removes any linear time trend.

The model specified is a multiple first differences log-log autoregressive model. For each country, consumption is expressed with the following model:

(10) $\Delta\ln(CPC)_t = \ln\ \beta_1 + \beta_2 \Delta\ln(Pd_t) + \beta_3 \Delta\ln\ (GDPC_t) + \sigma\, \Delta\ln(CPC_{t-1}) + \varepsilon_t$

Where the dependent variable is the change in coniferous sawnwood consumption per capita (from equation 9) from time *t-1* to *t*, β_1 is the intercept, $\beta_2$is the short-term price elasticity of demand, $\Delta\ln(Pd_t)$ is the change in domestic price (from equation 10) from time *t-1* to *t*, β_3 is the short-term income elasticity of demand, $\Delta\ln\ (GDPC_t)$ is the change in GDP per capita from time *t-1* to *t*, σ is the change from the lagged consumption growth, $\sigma\, \Delta\ln(CPC_{t-1})$ is the change in consumption from time *t-2* to *t-1* and ε_t is an error term. The lagged consumption variable is included to control for autocorrelation. The model is run for each of the 92 countries in the sample. While price and income are expected to be decisive factors for predicting consumption, the model used may have less explanatory power for some countries than for others. Other less observable factors, such as government programs, building traditions and the availability of sawnwood may be equally or more decisive. A variable for these factors who can apply to each country in the sample is obviously not available. Instead, countries where the model performs poorly are identified with post estimation tests.

The link test for model specification (Pregibon, 1980) regress the dependent variable on the squared predictions of the model. If the model is correctly specified, the squared prediction has no explanatory power. If the squared prediction is significant, either the dependent variable or an independent variable is incorrectly specified or there may be an omitted variable, among other possible explanations. Thus, estimates from a regression with a specification error should be interpreted with caution.

Another post estimation test is the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity. It is assumed that the residuals have a constant variance. This is tested by regressing the squared OLS residuals on the explanatory variables and obtain the Lagrange Multiplier statistic (Wooldridge, 2013):

$$(11)\ LM_{BP} = n * R_u^2$$

Where n is the sample size and R_u^2 is the R^2 from the regression of the squared predictions. If the *LM* statistic is below a critical value in the $\mathcal{X}_k^2$-distribution, the null hypothesis of constant variance holds (Cook and Weisberg, 1983). If not, the standard errors reported in the model are underestimated which may result in exaggerated statistical significance. To remedy this, robust standard errors are applied for countries having issues of heteroscedasticity.

A problem typically associated with time series regression is autocorrelation or serial correlation. Serial correlation occurs when the errors of two or more observations are related. In economic time series the autocorrelation is often caused by inertia (Gujarati and Porter, 1999). In plain English, successive observations are likely to be interdependent or correlated. Serial correlation may also be a result of model specification errors. Since the lagged consumption is included, the appropriate test is the Breusch-Godfrey test for higher order serial correlation (Godfrey, 1994).

The test regresses the OLS residuals on the explanatory variables and lagged residuals and calculates the *LM* statistic as (Wooldridge, 2013):

$$(12)\ LM_{BG} = (n - q)R_u^2$$

Where q is the number of lagged residuals. The null hypothesis is no serial correlation. The consequence of serial correlation is that the least squares estimators are not efficient, although they are linear and unbiased. The estimated variances are biased, leading to underestimated standard errors and unreliable t- and F- statistics. Models with an indication of serial correlation should therefore be interpreted with care.

Due to the variable data quality mentioned earlier, price and GDP elasticities are re-estimated by using consumption as an explanatory variable and price and GDP as dependent variables in a reversed regression:

$$(13)\ \Delta\ln(Pd)_t = \ln\gamma_1 + \gamma_2\,\Delta\ln(CPC_t) + \gamma_3\Delta\ln\,(GDPC_t) + \gamma_4\,\Delta\ln(CPC_{t-1}) + u_t$$

Where γ_2 is the inverse price elasticity of demand (or demand elasticity of price), such that ${\gamma_2}^{-1}$ is a lower bound estimate of the price elasticity of demand, given that the coefficient is negative. Similarly, for income:

$$(14)\ \Delta\ln(GDPC)_t = \ln\gamma_1 + \gamma_2\Delta\ln(Pd_t) + \gamma_3\Delta\ln\,(CPC_t) + \gamma_4\Delta\ln(CPC_{t-1}) + u_t$$

Where ${\gamma_3}^{-1}$ is an upper bound estimate of the income elasticity of demand.

The "true" value of the elasticities is expected to lie between the demand elasticities and the elasticities of demand and the difference between the two elasticities is an indicator of uncertainty. Reversed regressions are used to confirm or contradict results from direct regressions by e.g. Goldberger (1984) and Fornell et al. (1991).

Since lagged consumption is included in the model, R^2-values are not suitable for evaluating the goodness-to-fit. We therefore have to rely on the statistical significance of the coefficients and assess the accuracy of the predictions made for each country. The time-span of the study is from 1993-2017. To be able to verify the results, 2015-2017 is left for evaluation and with the inclusion of the lagged variable, the actual time span of the model is 21 years.

The predictions from the model for 2015 to 2017 are compared to the reported apparent consumption for each country. To make the data easier to interpret, the differenced log predictions are converted to integer values and multiplied by the midyear population, reporting the predicted consumption in cubic metres for the whole country. The mean absolute deviation can be defined as:

$$(15)\ MAD = \left(\sum_{t=1}^{n} |A_t - P_t|\right)/n$$

Where A_t is the actual apparent consumption and P_t is the predicted apparent consumption. Since the mean absolute deviation in this case will be affected by the size of the population, it is not a very good measure of the efficiency of the model. Therefore, the mean average percentage error is used as a relative measure (de Myttenaere et al., 2016). This can be defined as:

$$(16)\ MAPE = \left(\sum_{t=1}^{n} \left|\frac{A_t - P_t}{A_t}\right|\right) \frac{100\%}{n}$$

2.3.2 Part II: Panel data estimation

In part I, each country is treated individually and as pure time series data. Including the countries as explanatory dummy variables, the data set contains time-series panel data. The relevant variables, prices and GDPs, are reported annually, making the number of observations in the time dimension small. Panel data methods alleviates the problems of small datasets to some degree by adding degrees of freedom and increasing the efficiency of statistical methods as well as a country-specific dimension. The aim of using panel data estimators is to generate representative elasticities of demand for the countries included in this thesis.

One option is to include all countries in one model to get averaged results for the world total. Explaining the global demand for a good with two indicators would be an over-simplification. Another approach is to divide the sample into subsamples by identifiable attributes. These are often referred to as clusters, groups or categories. In this study, the subsamples will be referred to as categories. In the literature considering forest products, grouping of countries is a subject that is dedicated some attention (Hurmekoski et al., 2015, Michinaka et al., 2010). Countries have been grouped by high or low income, economic development, consumption level and forest coverage. For the 92 countries included in this study, forest coverage, GDP per capita and the production share of consumption are used for division into seven categories.

Forest coverage data were obtained from the FAO Global Forest Resource Assessment (2015) and converted into the percentage share of forested land on total land area, both measured in hectares. GDP per capita and data for production and consumption were already available in the dataset. The average per capita GDPs in the period 2015-2017 were divided into five 0.2-percemtiles while the production share of consumption was calculated as a percentage share of average production and consumption the last ten years. For each attribute, the countries were ranked from 1 to 5 relying on the 20-percentiles in the ranges 1; < 20%, 2; 20-40%, 3; 40-60%, 4; 60-80% and 5; > 80%.

GDP per capita was weighted heavier than forest coverage and production share of consumption. The average per capita GDPs ranged from USD 3 330-39 248 between the 20th and the 80th percentile. The average GDP is USD 20 328 with a standard deviation of USD 18 892. Medium GDP is thus a large interval as the highest GDP (USD 82 039) are 6 times the median (USD 13 511). The forest coverage share is meant to describe the availability of raw material but does not explicitly refer to the access to coniferous lumber as such data were not available. A high forest coverage could just as well consist of tropical tree species. For this reason, forest coverage was used with careful consideration when deciding categories.

A high production share of consumption indicates that the country is either self-sufficient with sawnwood or exporting parts of its production. A low production share of consumption indicates that it is reliant on imports. Net exporting countries typically have values well above 100 %. The main purpose of this variable is identifying countries with low self-sufficiency.

Table 4 Categories used for grouping

Category	Forest coverage	GDP per capita	Production share
1	low	low	low
2	low/medium	medium	low
3	low/medium	medium	medium
4	low	medium/high	low
5	medium	medium/high	medium/high
6	low	high	low
7	high	high	high

Table 4 display the characteristics of the countries in the different categories. The countries identified with low data quality in part I are categorized but omitted from the further calculations in order to prevent distortion. However, knowing their category, the estimated elasticities can be used as proxies for these countries. Table 5 display the countries included in the categories.

Table 5 Country subsamples. Countries in black are included in the model.

Category	Country	Sample size
1	Egypt, Jordan, Mauritius, Morocco, Philippines, Albania, Algeria, Botswana, El Salvador, Ethiopia, Haiti, Indonesia, Kenya, Malawi, Mongolia, Pakistan, Republic of Moldova, Saint Lucia, Tunisia, Ukraine	5
2	Dominican Republic, Hungary, Jamaica, Panama, Samoa, Former Yugoslav Republic of Macedonia, Nepal, Thailand	6
3	Brazil, China, Costa Rica, Croatia, Honduras, Latvia, Lithuania, Mexico, Poland, Romania, Russian Federation, Turkey, Argentina, Belarus, Belize, Colombia, Ecuador, Fiji, Greece, Guatemala, India, South Africa, Trinidad and Tobago, Uruguay, Zambia	12
4	Bahrain, Cyprus, Israel, Italy, Saudi Arabia, Barbados, Kuwait	5
5	Belgium, Bulgaria, Chile, Czechia, Estonia, France, Japan, Portugal, Republic of Korea, Singapore, Slovenia, Spain, Bahamas, Slovakia, Venezuela (Bolivarian Republic of)	15
6	Denmark, Iceland, Netherlands, Qatar, United Kingdom	5
7	Australia, Austria, Canada, Finland, Germany, Ireland, New Zeeland, Norway, Sweden, Switzerland, United States of America	11

For each category, a dummy variable was given to the countries included. The corresponding values for consumption, prices and GDP was treated accordingly, generating 21 new variables. While some earlier studies on sawnwood demand assume stationarity, econometric literature suggests that presence of unit roots should be tested. In particular, a stationary dependent variable is of uppermost importance to obtain reliable results. In part I, the country specific data was found to be stationary only in first differences by the Augmented Dickey-Fuller Test. For the new variables, the Levin, Lin and Chu unit root test, which is a similar test with adaptations for panel data, were applied.

Table 6 Levin, Lin and Chu unit root test results for each category

		Category						
		1	2	3	4	5	6	7
Consumption per capita	Adj. t	-2.309	-2.175*	-5.414	-1.599*	-6.333	-2.390	-1.894
	p-value	0.011	0.015	0.000	0.055	0.000	0.008	0.029
Prices	Adj. t	-2.471	-2.309	-1.411	-3.185	-3.434	-1.981	-2.737
	p-value	0.007	0.010	0.079	0.001	0.000	0.024	0.003
GDP per capita	Adj. t	-1.132	-1.839*	-3.165*	-1.719	-3.2345	-3.338	-3.278
	p-value	0.129	0.033	0.000	0.043	0.000	0.000	0.000
	Time period	1995-2015	1996-2017	1993-2017	1998-2017	1993-2017	1993-2017	1993-2017
	Years	21	22	25	20	25	25	25

* = trend stationary

Table 6 displays the results of the unit root test for each category in logarithmic values. It reveals that not all variables are stationary across countries. A heuristic approach was applied to deal with non-stationarity as the time-span was reduced with one year in either end of the 1993-2017 period until at least two of the variables were found to be stationary or trend stationary while attempting to minimize the time reduction in the most recent years. In this process, Argentina, Barbados, Colombia and Kuwait were omitted from their categories due to dubious patterns in consumption.

A unit root with pure random walk cannot be rejected for GDP per capita in category 1, while Consumption and Prices have strong evidence of stationarity in 1995-2015. In category 2, consumption and GDP per capita is found to be trend stationary in 1996-2017. In category 3, GDP per capita is found to be trend stationary and in category 4, consumption is trend stationary in 1998-2017. All variables are stationary in categories 5, 6 and 7. Trend stationarity will be controlled for in the relevant regressions and all parameters are given robust standard errors to control for autocorrelation.

Both Simangunsong and Buongiorno (2001) and Michinaka et al. (2010) used fixed effects models to estimate price and income elasticities of demand. The former study found a static fixed effects model to be best suited for forecasting purposes while the latter favored a dynamic model. Fixed Effects models allow for some heterogeneity between the countries as it allows the time invariant variable, or intercept, to vary. This way unobserved demographic and geographic factors do not affect the estimated coefficients. Although the countries within each category have resembling characteristics, many factors such as geography, age of population, size of households and corruption were not emphasized directly. Because only within-country variations are used to estimate the parameters, most of these stable factors are controlled for (Allison, 2009). The rationale for choosing a Fixed Effects model is logical but may not be applicable for all categories. While model specification should be connected to fundamental knowledge of the data, the assumptions associated with the choice of model should be tested. An alternative to the Fixed Effects model is the Random Effects model which assumes that the specific individual effects are uncorrelated to the independent variables. If this is the case, the Fixed Effects estimates are still consistent, but the Random Effects estimates are more efficient. Both Fixed Effects and Random Effects are models that assume individual effects. An opposite assumption is that the parameters do not differ significantly between countries. In this case they would fit in a Pooled OLS model.

For each category of countries, the following static demand model is applied:

$$(17)\ \ln(CPC_{it}) = \ln\beta_0 + \beta_1 ln(Pd_{it}) + \beta_2 ln(GDPC_{it}) + u_{it}$$

where the dependent variable CPC_{it} is coniferous sawnwood consumption per capita in country *i* at time *t* and the parameters β_1 and β_2 are long-term elasticities of demand.

Firstly, the Pooled OLS (POLS) model assuming no individual effects is estimated:

$$(18) y_{it} = \beta' X_{it} + u_{it}$$

The Random Effects (RE) model can be expressed as:

$$(19)\ y_{it} = \alpha + \beta' X_{it} + v_i + u_{it}$$

where v_i denotes random disturbance from the individual country.

To decide whether to use POLS or RE, the Breusch and Pagan Lagrange Multiplier Test for Random Effects was run with the null hypothesis that the variance of $u_{it} = 0$ (Breusch and Pagan, 1980). Rejecting the null hypothesis implies that a Random- or Fixed Effects model is preferred over POLS.

The Fixed Effects (FE) model can be expressed as:

$$(20) y_{it} = \alpha_i + \beta' X_{it} + u_{it}$$

where the constant, α_i is the time invariant coefficient containing the specific characteristics of each country, β denotes the parameters for $'X_{it}$, which is a vector of independent variables and u_{it} is an error term. Fixed Effects regressions are subtracting the average over time for all elements in the equation:

$$(21)\ \overline{X}_\iota = \frac{1}{T}\sum_{t=1}^{T} X_{it} \rightarrow \bar{y}_i = \alpha_i + \beta' \overline{X}_i + \bar{u}_i$$

The time demeaned equation can be expressed as:

$$(22)\ \ln(\widetilde{CPC}_{it}) = \beta_1 \ln(\widetilde{Pd}_{it}) + \beta_2 \ln(\widetilde{GDPC}_{it}) + \tilde{u}_{it}$$

where parameters β_1 and β_2 are the average price and income elasticities of demand for each category. Notice that the time invariant coefficient is cancelled out in the subtraction. This implies that the intercepts of the demand functions are allowed to vary, while the slopes are assumed equal for all countries within each category.

To help decide whether to use the Fixed Effects or Random Effects, the Hausman test (Hausman, 1978) is applied to the regression results. In this context, the $\mathcal{X}^2$ distributed Hausman test statistic can be formulated as:

$$(23)\ H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'[Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})]^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE})$$

Michinaka et al. (2010) found a dynamic model to be better than a static model according to RMSE-values[2]. In addition to the static demand model above, a dynamic demand model is applied:

$$(24)\ \ln(CPC_{it}) = \ln\beta_0 + \beta_1 ln(Pd_{it}) + \beta_2 ln(GDPC_{it}) + \sigma\, ln(CPC_{it-1}) + u_{it}$$

where the parameters β_1 and β_2 are short-term elasticities of demand. The long-term elasticities of demand are calculated as the ones found in and Simangunsong and Buongiorno (2001):

$$(25)\ \beta_{iLT} = \frac{\beta_i}{1-\sigma}$$

where β_i is the price or income elasticity of demand from the dynamic model and σ is the parameter of the lagged apparent consumption. The long-term elasticities of demand should in theory resemble those of the static model.

To assess whether the significant country-specific elasticities from part I differ significantly from the panel data models from part II, a Chow test on poolability was run. To be able to compare the estimates, the elasticities was tested against a POLS model with first differenced logs, letting their intercepts (country dummies) vary. The Chow test can be described as:

$$(26)\ F(k, \sum N_i\ - 2*k) = \frac{ess_C - \sum_{i=1}^{n} ess_i/k}{\sum_{i=1}^{n} ess_i/\sum_{i=1}^{n} N_i - 2*k}$$

where ess_C is the error sum of squares from the combined model (POLS), $\sum_{i=1}^{n} ess_i$ is the total error sum of squares from the separate regressions *i*, k is the number of estimated parameters and $\sum_{i=1}^{n} N_i$ is the total of the number of observations from the separate regressions *i* (Gould, 1999, Wooldridge, 2013).

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[2] Root Mean Square Error: $\sqrt{\frac{1}{NT}\sum_i \sum_i (\hat{y}_{it} - y_{it})^2}$

2.3.3 Part III: Projections of future demand using IPCC´s SSPs

The data for the Shared Socioeconomic Pathways was retrieved from the International Institute for Applied Systems Analysis' online database (IIASA, 2016). The data consisted of country-specific GDP and population projections under five different scenarios (SSP 1-5). The scenarios will be discussed in more detail in section 2.4.

The predicted consumption up to 2030 given the relative change in per capita GDP and population growth is calculated. The Shared Socioeconomic Pathways have GDPs given in real PPP-adjusted[3] 2005 USD. Although the elasticities are estimated from CPI-adjusted 2015 USD, they are assumed to be applicable as they are relative measures. A pragmatic adjustment was done to the population values as the ones used for 2015 in the SSPs were prognoses. The predictions for following years were adjusted by the relative difference to the observed 2015 midyear population from the World Bank used previously in this thesis. The GDP per capita change (Dellink et al., 2017) and the following change in per capita consumption relative to 2015 is calculated for the 92 countries included in the thesis. For each country the change in per capita consumption is calculated as:

$$(27)\ \Delta CPC_i = YED_i * \Delta GDPC_i$$

where YED_i is the representative income elasticity of demand and $\Delta GDPC_i$ is the change in per capita GDP from 2015 to 2025 or 2015 to 2030 for country *i*.

Finally, the change in consumption per capita is multiplied with the population prognosis (Kc and Lutz, 2017) and the consumption is summarized in the regions Africa, Asia, Europe, North America, South America (including the Caribbean), Oceania and the World total. Supply and prices are assumed ceteris paribus. This is not an attempt to model a state of equilibrium, but rather estimate the possible future demand from a present point of view.

[3] PPP = Purchase Power Parity

2.4 Part III: A summary of the different Shared Socioeconomic Pathways

In order to predict the global future development related climate change policies, five different pathways with their respective narratives have recently been formulated by the climate change research community. In this thesis, the illustrative cases with the interpretation from OECD were used (Dellink et al., 2017). The Shared Socioeconomic Pathways (SSPs) represents combinations of challenges for mitigation and adaptation of climate changes (Riahi et al., 2017). One of the purposes of these pathways is to produce scenarios for future GHG emissions and land use change driven by urbanization, population and GDP trends (Crespo Cuaresma, 2017, Dellink et al., 2017, Kc and Lutz, 2017). It is possible that the consumption of sawnwood will be affected by the varying emphasis given to climate change mitigation and adaptation. Yet, here the consumption projections are solely tied to population and GDP developments in to the SSPs. A more detailed description of the different narratives can be found in O'Neill et al. (2017).

SSP 1 "Taking the Green Road" (van Vuuren et al., 2017) is an environmentally desirable and optimistic scenario where both challenges to mitigation and adaptation are low. The increased environmental awareness and a move towards a less resource-intensive lifestyle globally, represents a break with the recent history where emerging economies has adapted the resource-intensive habits of industrialized economies. The economic growth is high in low- and medium income countries and medium in high-income countries, and the global trade is moderate. A premise for this scenario is that the various "green economy" and environmental strategies found in emerging and industrialized countries turns out to be successful and efficient.

SSP 2 "Middle of the Road" (Fricko et al., 2017) is the business-as-usual-scenario and represents medium challenges to mitigation and adaption. In this scenario, there are some improvements in energy efficiency and the intensity of resource use. Fossil fuel dependency decreases, but unconventional sources of fossil energy are used without reluctance. The population growth is moderate, but investment in education is not high enough to slow down fertility rates in low-income countries. Global inequality and technological progress are only improving slowly and environmental systems experience degradation.

SSP 3 "Regional Rivalry – A Rocky Road" (Fujimori et al., 2017) is an undesirable, but not unlikely scenario where both mitigation and adaption challenges are high. Inequality across countries potentially sparks severe conflicts. This scenario would imply a reversion of some of the ongoing globalization trends. Regional rivalries weaken the international institutions and slows the progress toward development goals. Economic growth is slow and global trade is strongly constrained. Environmental strategies are given less priority in a world with seemingly more imminent challenges.

SSP 4 "Inequality – A Road Divided" (Calvin et al., 2017) is an asymmetric scenario where the challenges to mitigation are low and the challenges to adaption are high. Among the drivers for global economic development is the growth of the global middle class. In this scenario, the growth is slowed down leading to persisted and increased inequality, especially within countries. The economic growth per capita is low in low-income countries and moderate in medium- and high-income countries and the international trade is moderate.

SSP 5 "Fossil-fuelled Development – Taking the Highway" (Kriegler et al., 2017) assumes high challenges to mitigation and low challenges to adaption. In this scenario, there is a rapid overall growth in the global economy. Progress in emerging economies leads to strongly reduced inequality due to the rapid emergence of the global middle-class. Materialism, tourism, mobility and meat-rich diets are representative for the development in overall consumption as emerging economies adapt to resource and energy intensive lifestyles. The effort in avoiding global environmental impacts is low, due to a perceived trade-off with progress in economic development.

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3. RESULTS AND DISCUSSION

3.1 Part I: Country-individual elasticities of demand

The following tables display the short-term elasticities of demand. Statistically significant elasticities are highlighted in bold letters and the standard errors are given in parentheses. The countries where poor data quality is identified has their elasticities presented in italic. To ease reading, countries are sorted alphabetically in regions.

Table 7 Elasticities of demand for countries in Africa. PED denotes the price elasticity of demand, YED denotes the income elasticity of demand. Standard errors given in parentheses. Bold numbers indicate p-value < 0.05, italic numbers indicate poor data quality. Error codes indicate serial correlation (sc), robust standard errors (r) and model misspecification (ms).

Country	Posttest	PED	SE	YED	SE
Algeria		*-0.007*	(0.271)	*-0.213*	(0.458)
Botswana		***-0.636***	(0.174)	*-1.094*	(1.132)
Egypt		-0.155	(0.258)	-1.762	(1.973)
Ethiopia		*-0.586*	(0.366)	*2.178*	(1.480)
Kenya	ms sc	*0.013*	(0.075)	*0.101*	(0.920)
Malawi	r	*0.046*	(0.022)	*-0.004*	(0.044)
Mauritius	ms	**-0.401**	(0.123)	0.597	(2.956)
Morocco	r	**-0.544**	(0.158)	-1.168	(1.215)
South Africa	r	*-0.054*	(0.056)	*-0.984*	(0.835)
Tunisia		*0.079*	(0.230)	*1.547*	(1.261)
Zambia	ms r sc	*-0.115*	(0.083)	*0.407*	(0.532)

Of the 11 countries in Africa, 3 countries have significant price elasticities. The signs are as expected from economic theory and indicate a relatively price-inelastic demand. 8 of these countries have poor data quality which may explain the lack of significant estimates. The elasticities of Botswana, though significant, should be interpreted with caution due to the low data quality indicated.

Of the 19 countries in Asia, only one country has a significant price elasticity of demand and 6 countries have significant income elasticities of demand. The median significant income elasticity is 2.986 indicating that demand is highly income-elastic. In Oceania, New Zeeland and Samoa report significant income elasticities of demand.

Table 8 Elasticities of demand for countries in Asia and Oceania. PED denotes the price elasticity of demand, YED denotes the income elasticity of demand. Standard errors given in parentheses. Bold numbers indicate p-value < 0.05, italic numbers indicate poor data quality. Error codes indicate serial correlation (sc), robust standard errors (r) and model misspecification (ms).

Country	Posttest	PED	SE	YED	SE
Bahrain		0.189	(0.584)	0.907	(1.656)
China	ms r	-0.381	(0.413)	2.847	(1.404)
India		*0.017*	(0.394)	*-5.162*	(6.224)
Indonesia	r	-0.107	(0.214)	-2.828	(1.916)
Iran	r	-0.544	(0.559)	3.776	(2.044)
Israel		-0.498	(0.335)	-0.777	(1.746)
Japan	r sc	0.229	(0.157)	**2.030**	(0.744)
Jordan	sc	-1.341	(1.083)	-1.190	(4.588)
Kuwait		**-0.465**	(0.219)	**0.864**	(0.342)
Mongolia		*0.900*	(0.849)	*0.879*	(1.761)
Nepal		*-0.009*	(0.021)	*0.028*	(0.232)
Pakistan	ms r	*0.046*	(0.064)	*0.386*	(0.346)
Philippines	r	-1.417	(1.004)	18.036	(14.99)
Qatar		-0.083	(0.630)	-0.375	(0.865)
Republic of Korea		-0.138	(0.264)	**3.942**	(1.011)
Saudi Arabia		-0.108	(0.296)	0.417	(0.525)
Singapore		-0.474	(0.295)	2.632	(1.848)
Thailand		*-0.122*	(0.507)	***3.976***	(1.475)
Turkey	sc	-0.186	(0.101)	0.668	(0.329)
Australia		-0.175	(0.354)	-0.600	(1.156)
Fiji		*0.262*	(0.130)	*-0.898*	(1.631)
New Zealand	sc	0.150	(0.261)	**2.832**	(1.110)
Samoa		-0.155	(0.368)	**6.221**	(2.752)

Of the 35 European countries, 14 countries have price elasticities that are significant with a confidence level of 95 % or more. 10 countries have significant income elasticities and 5 countries have significant elasticities for both price and income. The median values of the significant income elasticities are 0.687 and 3.232 respectively. This indicates that demand is relatively price-inelastic and highly income-elastic. Many of the countries have positive price elasticities, which is opposite of what economic theory would suggest. This phenomenon can also be found in the studies concerning Europe in the literature review. Hurmekoski et al. (2015) suggests that price is a more significant determinant in the Nordic countries while GDP is a more significant determinant in the rest of Europe.

Table 9 Elasticities of demand for countries in Europe. PED denotes the price elasticity of demand, YED denotes the income elasticity of demand. Standard errors given in parentheses. Bold numbers indicate p-value < 0.05, italic numbers indicate poor data quality. Error codes indicate serial correlation (sc), robust standard errors (r) and model misspecification (ms).

Country	Posttest	PED	SE	YED	SE
Albania		*0.026*	(0.929)	*-1.896*	(3.393)
Austria	ms	**0.704**	(0.331)	2.230	(1.267)
Belarus		*0.173*	(0.168)	*0.218*	(0.911)
Belgium		0.278	(0.150)	0.614	(0.986)
Bulgaria		0.772	(0.486)	-1.861	(2.876)
Croatia		**-0.234**	(0.098)	0.425	(0.763)
Cyprus		**-0.308**	(0.120)	**3.360**	(1.466)
Czechia		-0.021	(0.251)	1.366	(1.012)
Denmark		**-0.848**	(0.156)	**4.285**	(1.730)
Estonia	ms sc	-0.708	(0.994)	2.739	(1.487)
Finland	sc	**1.097**	(0.305)	1.620	(1.065)
France	sc	0.008	(0.108)	**3.602**	(0.507)
Germany	r	**1.004**	(0.346)	0.418	(1.624)
Greece		*-0.346*	(0.213)	***2.547***	(1.069)
Hungary	r	**-0.715**	(0.271)	**2.556**	(0.793)
Iceland	r	-0.369	(0.531)	1.579	(2.038)
Ireland	ms	0.257	(0.200)	**2.830**	(0.736)
Italy	sc	0.119	(0.140)	**3.463**	(0.538)
Latvia		-0.435	(0.598)	1.114	(0.871)
Lithuania	ms	**1.839**	(0.745)	-1.066	(0.705)
Netherlands		**0.329**	(0.149)	**1.530**	(0.525)
Norway		0.348	(0.227)	0.762	(0.400)
Poland	ms	**-0.620**	(0.291)	**4.489**	(1.468)
Portugal		**0.687**	(0.226)	-0.818	(1.846)
Republic of Moldova	ms r	*0.385*	(0.725)	*0.166*	(0.733)
Romania		-0.421	(0.982)	1.653	(1.341)
Russian Federation		0.100	(0.253)	0.312	(0.229)
Slovakia		***0.958***	(0.267)	*2.856*	(2.265)
Slovenia		1.114	(0.642)	0.070	(3.413)
Spain	r sc	-0.173	(0.345)	**3.232**	(0.975)
Sweden	sc	**1.793**	(0.642)	2.409	(1.957)
Switzerland		-0.357	(0.396)	1.298	(1.393)
FYR Macedonia		**-0.911**	(0.172)	1.536	(1.944)
Ukraine		*-0.599*	(0.532)	*2.321*	(1.360)
United Kingdom	ms r	-0.254	(0.402)	0.416	(1.429)

Germany, Netherland and Portugal have positive price elasticities, apparently high data quality and no indication on errors from the post estimation tests. If this is true, consumption in these countries increases with price. Most of these countries are producing more than to their own use. Therefore, one explanation may be that sawnwood is reprocessed into other end products (such as wooden flooring, sleepers and mouldings) in the same country and then exported under another product category, increasing the apparent consumption and thus creating an apparently positive correlation. Another explanation may be reversed causality: increased consumption leads to an increase in price and is picked up by the model at a later point in time. An increase in price may arise from foreign demand, increasing the production more than is eventually exported and the remaining stock is picked up as apparent consumption. The same explanations may be valid for Austria, Finland, Lithuania and Sweden. However, the post estimation tests indicate that the elasticity estimates are unreliable.

Of the 21 countries in Latin America, 7 have significant price elasticities and 2 have significant income elasticities. The median price elasticity is -1.148 indicating a near-unitary price-elastic demand. In North America, USA reports a theoretically suspicious positive price elasticity of demand and a high income elasticity. These estimates fail both the link-test and the Breusch-Godfrey test and should consequently be interpreted with caution.

Table 10 Elasticities of demand for countries in Latin America and The Caribbean and North America. PED denotes the price elasticity of demand, YED denotes the income elasticity of demand. Standard errors given in parentheses. Bold numbers indicate p-value < 0.05, italic numbers indicate poor data quality. Error codes indicate serial correlation (sc), robust standard errors (r) and model misspecification (ms).

Country	Posttest	PED	SE	YED	SE
Argentina	ms	0.276	(0.341)	-0.923	(0.993)
Bahamas		*-0.078*	(0.572)	*-0.242*	(2.175)
Barbados	r	**-1.169**	(0.271)	2.218	(1.585)
Belize		*-0.170*	(0.205)	***9.549***	(3.971)
Brazil	ms	0.111	(0.082)	**1.309**	(0.340)
Chile		0.067	(0.241)	0.656	(0.427)
Colombia		-0.218	(0.282)	1.245	(2.851)
Costa Rica	sc	-0.236	(0.403)	0.311	(5.696)
Dominican Republic	sc	**-0.358**	(0.169)	2.554	(1.315)
Ecuador		*-0.130*	(0.194)	*0.474*	(0.285)
El Salvador	r sc	***-1.299***	(0.445)	*-1.029*	(4.179)
Guatemala		*0.406*	(0.772)	*-2.181*	(5.448)
Haiti		*-0.627*	(0.424)	*-1.199*	(2.929)
Honduras	sc	**0.680**	(0.258)	0.412	(1.139)
Jamaica		**-1.148**	(0.142)	0.721	(1.130)
Mexico	r	**-0.491**	(0.147)	0.746	(0.843)
Panama		**-1.359**	(0.549)	4.811	(5.845)
Saint Lucia	sc	*-0.311*	(0.243)	*0.384*	(1.163)
Trinidad and Tobago	r sc	*-0.667*	(0.316)	*-0.029*	(0.620)
Uruguay	sc	*-0.132*	(0.258)	*-1.926*	(1.309)
Venezuela (BR)		*-0.353*	(0.363)	*2.294*	(1.445)
Canada		0.189	(0.344)	2.094	(1.263)
United States of America	ms sc	**0.297**	(0.138)	**3.148**	(1.156)

As previously mentioned, there are uncertainties and possible errors in the variables. This means that the results given above, although they are significant and from an apparently correctly specified model, may not be reliable. To create a lower and upper bound for the elasticities, reversed regressions are applied. These regressions keep the signs and significance of the direct regressions but reports larger coefficient values. If the intervals between the lower and the upper bounds are large, the direct elasticities should be interpreted with caution.

Table 11 Direct and inverse elasticities of demand. Reverse elasticities are the inverses of the parameters from the reversed regressions.

	PED direct	Deviation	PED reverse	YED direct	Deviation	YED reverse
Austria	0.704	2.491	3.195			
Belize				9.549	26.422	35.971
Botswana	-0.636	-0.761	-1.397			
Brazil				1.309	1.416	2.725
Croatia	-0.234	-0.655	-0.889			
Cyprus	-0.308	-0.754	-1.062	3.360	10.227	13.587
Denmark	-0.848	-0.461	-1.309	4.285	11.171	15.456
Dominican Republic	-0.358	-1.271	-1.629			
El Salvador	-1.299	-0.767	-2.066			
Finland	1.097	1.354	2.451			
France				3.602	1.137	4.739
Germany	1.004	0.688	1.692			
Greece				2.547	7.162	9.709
Honduras	0.680	1.562	2.242			
Hungary	-0.715	-0.809	-1.524	2.556	7.059	9.615
Ireland				2.830	3.052	5.882
Italy				3.463	1.345	4.808
Jamaica	-1.148	-0.283	-1.431			
Japan				2.030	7.316	9.346
Kuwait	-0.465	-1.649	-2.114	0.864	2.166	3.030
Lithuania	1.839	4.828	6.667			
Mauritius	-0.401	-0.605	-1.006			
Mexico	-0.491	-0.271	-0.762			
Morocco	-0.544	-0.86	-1.404			
Netherlands	0.329	1.074	1.403	1.530	2.875	4.405
New Zealand				2.832	6.972	9.804
Panama	-1.359	-3.543	-4.902			
Poland	-0.620	-2.189	-2.809	4.489	7.676	12.165
Portugal	0.687	1.189	1.876			
Republic of Korea				3.942	4.123	8.065
Samoa				6.221	19.486	25.707
Slovakia	0.958	1.193	2.151			
Spain				3.232	4.898	8.130
Sweden	1.793	3.671	5.464			
Thailand				3.976	8.747	12.723
FYR Macedonia	-0.911	-0.522	-1.433			
United States of America	0.297	1.019	1.316	3.148	6.753	9.901

Table 11 illustrates the difference between the statistically significant elasticities from the direct regressions and the inversed elasticities from the reverse regressions. Many estimates, though statistically significant, are undeniably uncertain. In fact, most of the deviations may be considered large as a deviation of 0.5 may change the observed elasticity from being relatively inelastic to relatively elastic.

Table 12 lists the mean absolute errors in cubic meters and the mean average percentage errors for the 92 countries. The plus/minus column indicates whether the model over- or underpredicted the consumption.

At first glance, some countries stand out with extremely high MAPE-figures. In all three years, the production of coniferous sawnwood in Ecuador is reported to be 9215 m^3, which is a quarter of the 2014 production and a tenth of the 2013-production. This could help explain the relative error figure of 88 %. Jordan (56 %) is solely reliant on imports has apparently reduced them with 143 % from 2014 to 2017. Mongolia (63%) has reported identical quantities for production, imports and exports over longer periods and have apparently reduced their consumption by 238 % from 2010 to 2017. Qatar (95 %) have similar reductions. Singapore (49 %) has reported a production of 5000 m^3 every year since 1992. This is a relatively insignificant quantity of sawnwood and a fraction of its current consumption: from 2014-2017 the apparent consumption increased from 7053 m^3 to 69 641 m^3. Venezuela has faced an escalating economic, political and recently humanitarian crisis which escalated in 2015 due to low oil prices. The high relative deviations may therefore be an indication of unreliable data, rather than a bad model. However, neither of these countries have significant elasticities of demand and the results should therefore not be given much attention.

USA has an absolute deviation of more than one million cubic metres, but a small relative deviation (3 %) Canada and China have equally high absolute deviations and MAPE-figures of 10 % and 12 % respectively. These are the top 3 producers of coniferous sawnwood and although the quantities are substantial, the model seems to have a satisfactory fit to the data. USA and China are also the 1st and 2nd largest consumers, followed by Germany (1%), Japan (6%) and Canada. Even in some countries with non-significant elasticities, such as Norway (4 %) and Switzerland (3 %) the model seems to perform well. In Russia the model under-predicts the consumption by 10%. Russia has had an average growth in reported exports of 9% annually over the last 3 years while the consumption has declined by 3% annually.

Table 12 Prediction errors for 2015-2017 MAD = mean absolute deviation, MAPE = mean average percentage error. Bold letters indicate one or more significant elasticities of demand.

Country	+/-	MAD	MAPE	Country	+/-	MAD	MAPE
Albania	+	16 320	22 %	**Japan**	-	891 722	6 %
Algeria	+	309 813	16 %	Jordan	+	99 905	56 %
Argentina	+	58 457	4 %	Kenya	+	3 363	1 %
Australia	+	152 556	3 %	**Kuwait**	+	11 151	14 %
Austria	+	260 730	5 %	Latvia	-	106 038	10 %
Bahamas	-	1 066	32 %	**Lithuania**	-	71 207	8 %
Bahrain	+	27 285	59 %	Malawi	-	4 245	11 %
Barbados	-	2 329	34 %	**Mauritius**	+	4 697	23 %
Belarus	+	393 914	37 %	**Mexico**	-	469 322	12 %
Belgium	-	179 310	11 %	Mongolia	-	18 324	63 %
Belize	-	4 179	17 %	**Morocco**	+	129 145	12 %
Botswana	+	6 604	17 %	Nepal	-	1 274	6 %
Brazil	+	198 604	3 %	**Netherlands**	-	286 584	13 %
Bulgaria	-	42 560	9 %	**New Zealand**	+	77 225	3 %
Canada	-	1 728 975	10 %	Norway	-	124 779	4 %
Chile	+	429 214	8 %	Pakistan	+	61 954	10 %
China	-	7 109 968	12 %	**Panama**	+	2 847	9 %
Colombia	+	8 777	8 %	Philippines	+	211 079	51 %
Costa Rica	+	42 744	38 %	**Poland**	+	176 787	4 %
Croatia	-	32 701	14 %	**Portugal**	+	195 714	26 %
Cyprus	-	1 615	5 %	Qatar	+	86 690	95 %
Czechia	+	251 090	8 %	**Republic of Korea**	-	235 535	5 %
Denmark	+	51 507	3 %	Republic of Moldova	-	29 366	17 %
Dominican Republic	+	42 513	38 %	Romania	-	804 039	28 %
Ecuador	+	9 163	88 %	Russian Federation	-	910 107	10 %
Egypt	+	1 446 242	33 %	Saint Lucia	-	4 434	24 %
El Salvador	-	6 005	14 %	**Samoa**	+	1 848	28 %
Estonia	+	378 062	21 %	Saudi Arabia	+	266 874	16 %
Ethiopia	-	29 469	30 %	Singapore	+	20 333	49 %
Fiji	+	32 426	38 %	**Slovakia**	+	174 998	23 %
Finland	-	348 470	12 %	Slovenia	-	105 601	15 %
France	-	393 210	5 %	South Africa	+	69 129	4 %
Germany	-	195 808	1 %	**Spain**	-	216 420	9 %
Greece	-	32 567	11 %	**Sweden**	+	597 667	11 %
Guatemala	-	32 757	41 %	Switzerland	-	34 695	3 %
Haiti	-	12 187	16 %	**Thailand**	+	64 373	26 %
Honduras	+	34 344	37 %	**FYR Macedonia**	-	4 816	11 %
Hungary	-	121 896	17 %	Trinidad and Tobago	+	26 244	141 %
Iceland	-	14 594	27 %	Tunisia	+	58 318	16 %
India	-	124 945	5 %	Turkey	-	554 917	8 %
Indonesia	+	40 275	41 %	Ukraine	-	68 893	23 %
Iran	+	272 907	36 %	United Kingdom	-	565 807	6 %
Ireland	+	117 127	29 %	**United States of America**	+	2 635 425	3 %
Israel	+	10 413	3 %	Uruguay	-	18 621	13 %
Italy	-	187 558	4 %	Venezuela (BR)	+	356 392	54 %
Jamaica	-	8 472	13 %	Zambia	-	10 582	7 %

According to the conventional demand model applied on the currently available data, elasticities of demand seem to vary considerably among countries and within regions. Price and income seem to be only partial determinants of consumption, suggesting the presence of omitted variables or errors in the reported data. Of the 92 countries in question, only 37 reported statistically significant elasticities in one form or another. The inverse elasticities indicate that even the statistically significant estimates are uncertain. The dataset for each country is inevitably small, as they consist of annual data over a relatively short period of time, even though it contains the longest GDP dataset available. The reasons for the lack of significant estimates may also be market imperfections and errors in the underlying data. Either way, classic time series regressions on independent countries does not seem to be an efficient way of measuring elasticities of demand. In part II, alternative methods for measuring representative elasticities of demand will be carried out with the help of panel data estimations.

Table 13 summarizes the levels of statistical significance for the country-specific elasticities of demand.

Table 13 Levels of statistical significance for country-specific elasticities. Pale stars indicate that the signs are opposite than expected.

Country	Price	Income	Country	Price	Income
Austria	*		Japan		*
Belize		*	Kuwait	*	*
Botswana	**		Lithuania	*	
Brazil		**	Mauritius	**	
Croatia	*		Mexico	**	
Cyprus	*	*	Morocco	**	
Denmark	***	*	Netherlands	*	*
Dominican Republic	*		New Zealand		*
El Salvador	*		Panama	*	
Finland	**		Poland	*	*
France		***	Portugal	*	
Germany	*		Republic of Korea		**
Greece		*	Samoa		*
Honduras	*		Slovakia	**	
Hungary	*	**	Spain		**
Ireland		**	Sweden	*	
Italy		***	Thailand		*
Jamaica	***		FYR Macedonia	***	
			United States of America	*	*

*** p < 0.001, ** p < 0.01, * p < 0,05

3.2 Part II: Panel data estimation

Chapter 3.1 sought to estimate elasticities of demand using classic time series methods. A problem with time-series data in general is the small variation between observations. As this thesis emphasizes, the error in measurements and reporting will have large impacts on the reliability of the estimators. Collinearity is also a typical problem with time-series data, which occurs when independent variables are strongly correlated to each other. This leads to inflated variances to the regression coefficients. Thus, the statistical significance of the coefficients may be affected. Panel data may reduce this problem to some degree by including countries with similarities (Simangunsong and Buongiorno, 2001). In this section, the results from the panel data models are presented and interpreted.

Table 14 display the results from the Lagrange Multiplier Test for Random Effects. The null hypothesis of no unobserved effects is rejected in all categories.

Table 14 Breusch and Pagan Lagrange Multiplier Test for Random Effects results

Category	Chi sq	p-value
1	235.89	0.000
2	782.77	0.000
3	1594.33	0.000
4	98.63	0.000
5	2424.90	0.000
6	536.13	0.000
7	2193.50	0.000

Table 15 display the regression results from the static Fixed Effects model.

Table 15 Static fixed effects estimators, standard errors in parentheses. Panel size refers to number of countries and years. R^2 from within regression.

		Price elasticity of demand		Income elasticity of demand			
Category	Panel size	Estimate	SE	Estimate	SE	R2	Time period
1	5x21	-0.601	(0.176)	2.617	(4.587)	0.470	1995-2015
2	6x22	-0.852	(0.052)	3.839	(0.052)	0.562	1996-2017
3	12x25	-0.138	(0.146)	0.918	(0.291)	0.585	1993-2017
4	5x20	-0.359	(0.084)	1.299	(0.477)	0.613	1998-2017
5	15x25	-0.079	(0.291)	2.804	(0.777)	0.454	1993-2017
6	5x25	-0.100	(0.319)	2.008	(0.232)	0.552	1993-2017
7	11x25	0.515	(0.396)	0.334	(0.381)	0.381	1993-2017

Price elasticities are significant in category 1, 2 and 4 at a confidence level of 95 % or higher. All categories are found to be relatively inelastic with regards to prices. The low-income countries and those who have a low forest coverage and self-sufficiency seems to be most elastic both with regards to prices and income. High income countries with a high level of self-sufficiency report a positive price elasticity, though not statistically significant. Countries with a high dependence on imports have price elasticities that comply with economic theory, regardless of their income. The income elasticities of category 2, 3, 4, 5 and 6 are statistically significant at a confidence level of 95 % or higher. The income elasticity in category 3 is reportedly near-unitary elastic while those of the other categories are relatively elastic.

In section 3.3.2, the concept of random effects was discussed briefly. To decide which model assumption is the most correct, the Hausman test was applied for each category. In category 2 and 7, the null hypothesis of no covariance between the random disturbance and the independent variables could not be rejected. Neither of the models could estimate significant elasticities of demand in category 7. Table 16 display the results from the POLS, Random Effects and Fixed Effects regressions. The bold figures indicate the statistically significant and recommended parameters.

Table 16 Elasticities of demand from static models. Robust standard errors in parentheses

	1	2	3	4	5	6	7
Price elasticity of demand							
POLS	-2.866	-0.948	-1.077	-0.804	-0.488	-1.546	-0.368
	(0.964)	(0.673)	(0.566)	(0.132)	(0.770)	(0.448)	(0.633)
Random Effects	-1.120	**-0.815**	0.119	-0.620	-0.125	-0.115	0.491
	(0.322)	(0.128)	(0.193)	(0.054)	(0.297)	(0.307)	(0.399)
Fixed Effects	**-0.601**	-0.852	-0.138	**-0.359**	-0.079	-0.100	0.515
	(0.176)	(0.052)	(0.146)	(0.084)	(0.291)	(0.319)	(0.396)
Income elasticity of demand							
POLS	0.484	-0.746	0.558	0.929	-0.224	-1.278	-0.516
	(0.688)	(1.070)	(0.430)	(0.359)	(0.772)	(1.176)	(0.549)
Random Effects	0.935	**1.174**	0.969	1.109	2.491	1.942	0.285
	(0.579)	(0.535)	(0.226)	(0.278)	(0.754)	(0.238)	(0.339)
Fixed Effects	2.617	3.839	**0.918**	**1.299**	**2.804**	**2.008**	0.334
	(4.587)	(1.107)	(0.291)	(0.477)	(0.777)	(0.232)	(0.381)

Overall the Fixed Effects model was the best suited for most of the categories, but there is a considerable difference in income elasticity of demand for category 2 between the Fixed Effects parameter and the Random Effects parameter.

Table 17 Dynamic fixed effects model results, robust standard errors in parentheses

	Price elasticity of demand			Income elasticity of demand				
Category	Short-term	SE	Long-term	Short-term	SE	Long-term	CPC t-1	SE
1	-0.438	(0.156)	-0.954	0.721	(2.34)	1.569	0.540	(0.049)
2	-0.725	(0.102)	-1.505	3.000	(0.708)	3.967	0.244	(0.128)
3	-0.191	(0.088)	-1.230	0.388	(0.141)	0.797	0.577	(0.085)
4	-0.329	(0.036)	-0.549	0.971	(0.327)	1.620	0.401	(0.144)
5	-0.028	(0.254)	-0.072	1.102	(0.514)	2.804	0.607	(0.080)
6	-0.142	(0.215)	-0.231	1.310	(0.336)	2.131	0.385	(0.096)
7	0.244	(0.129)	1.296	0.052	(0.072)	0.275	0.812	(0.095)

Table 17 display the results from the dynamic Fixed Effects model. Price elasticities are significant at a confidence level of 95 % or higher in categories 1, 2, 3, and 4. Income elasticities are significant at a confidence level of 95% or higher in categories 2, 3, 4, 5 and 6.

The medium-income countries seem to have the highest elasticities with regards to prices. In the long term, the price elasticity of the medium income countries (category 3) changes from relatively inelastic to relatively elastic. Countries with higher income seem to remain inelastic in the long term. The countries in category 2 seem to have a more income-elastic demand compared to countries with a similar income level in category 3. Countries in category 2 have a low production share of consumption and may consider coniferous sawnwood as a luxury good. Similarly, the countries in category 6 have remarkably different elasticities compared to those in category 7. These results are in compliance with the notion that a low production share of consumption affects the elasticities of demand. The results are less clear when comparing categories 4 and 5. Both categories have a medium to high income. Forest coverage and self-sufficiency seem have less effect in these countries. Other factors may explain the differences between the two.

Both models are applicable as long as precautions about the statistical significance are taken. As the R^2 values of the dynamic model are not suited for inferences due to the lagged dependent variable, root mean square errors are used to compare the models. Table 19 list the RMSE-values for the respective models. A low RMSE is favourable when deciding which models to apply. The dynamic model reports the lowest RMSE values for all categories. In addition, the dynamic model reports more statistically significant elasticities at a higher confidence level. The long-term elasticities from the dynamic model resembles those of the dynamic model and the lower RMSE-value suggests that the dynamic model is more accurate.

Table 18 RMSE values from the static and dynamic models

Category	Static Fixed Effects	Dynamic Fixed Effects
1	0.541	0.453
2	0.379	0.365
3	0.339	0.263
4	0.234	0.210
5	0.449	0.368
6	0.255	0.237
7	0.203	0.115

In Table 16 Random Effects was found to give the best estimate for the elasticities in category 2 based on the Hausman test. The income elasticity of demand from RE is considerably lower than the one from FE and is more in accordance with the results from the other categories. Therefore, the long-term price elasticity (-0.815) and the long-term income elasticity (1.174) from the static Random Effects regression is recommended for this category.

The estimates from the Fixed Effects regressions seem to be more reliable than those from the country-individual regressions. Although they vary in time periods, the estimated elasticities are based on the most present data available and with relatively large panels of data with a time span of at least 20 years. The results can be compared to the ones found in the available literature (Hurmekoski et al., 2015, Michinaka et al., 2010, Rougieux and Damette, 2018, Simangunsong and Buongiorno, 2001).

In Michinaka et al. (2010), elasticities of demand varied considerably between the clusters. This is also found to be true in this study. The demand is relatively inelastic to prices, especially in the short-term, while most income elasticities are relatively elastic both in short- and long-term. In general, demand for coniferous sawnwood seems less elastic with regards to prices and more elastic with regards to income compared to what they suggest. Their results consider all sawnwood (coniferous and non-coniferous), however. Brooks et al. (1995) estimated elasticities to be higher in low-income countries than in high-income countries. Judging by the results in Table 17, this is the case with regards to prices. The elasticities in category 7 with high-income and high-producing countries are not statistically significant and the price elasticity has a counter-intuitive sign. Hurmekoski et al. (2015) reported similar results when analysing sawnwood demand for the period 1997-2012 in Europe.

Rougieux and Damette (2018) argue that spurious results are likely to be found in most of the available literature as few of the articles mention stationarity or present appropriate unit root test results. As previously mentioned, stationarity is of vital importance for the reliability of the estimates. While the articles from Simangunsong and Buongiorno (2001), Michinaka et al. (2010) and Hurmekoski et al. (2015) are valuable contributions to the literature on econometric research of the demand for sawnwood, none of them addresses the issue of non-stationarity explicitly. That way, their results may or may not be valid as the presence of unit roots are not accounted for. Simangunsong and Buongiorno (2001) concerns a very large panel which is likely to be stationary, but it is nevertheless not accounted for. Buongiorno (2015) uses first differenced variables which are very likely to be stationary and offers thus the most reliable estimate of the overall elasticities of demand. In this thesis, stationarity is tested and remedies for avoiding non-stationary processes are accounted for, albeit with less significant results. The econometric methods are not the most refined or complicated, but the results are thoroughly evaluated. Hopefully, future studies on the subject will address this issue with more care and not leave the reader in doubt of whether fundamental assumptions of the methods used are violated or ignored.

Table 19 summarizes the elasticities of demand estimated in this study.

Table 19 Summary of long-term price and income elasticities of demand (PED, YED). Bold letters indicate p-value < 0.05. Model indicates dynamic Fixed Effects or static Random Effects.

Category	Country	PED	YED	Model
1	Egypt, Jordan, Mauritius, Morocco, Philippines, Albania, Algeria, Botswana, El Salvador, Ethiopia, Haiti, Indonesia, Kenya, Malawi, Mongolia, Pakistan, Republic of Moldova, Saint Lucia, Tunisia, Ukraine	**-0.954**	1.569	FE dyn
2	Dominican Republic, Hungary, Jamaica, Panama, Samoa, Former Yugoslav Republic of Macedonia, Nepal, Thailand	**-0.815**	**1.174**	RE stat
3	Brazil, China, Costa Rica, Croatia, Honduras, Latvia, Lithuania, Mexico, Poland, Romania, Russian Federation, Turkey, Argentina, Belarus, Belize, Colombia, Ecuador, Fiji, Greece, Guatemala, India, South Africa, Trinidad and Tobago, Uruguay, Zambia	**-1.230**	**0.797**	FE dyn
4	Bahrain, Cyprus, Israel, Italy, Saudi Arabia, Barbados, Kuwait	**-0.549**	**1.620**	FE dyn
5	Belgium, Bulgaria, Chile, Czechia, Estonia, France, Japan, Portugal, Republic of Korea, Singapore, Slovenia, Spain, Bahamas, Slovakia, Venezuela (Bolivarian Republic of)	-0.072	**2.804**	FE dyn
6	Denmark, Iceland, Netherlands, Qatar, United Kingdom	-0.231	**2.131**	FE dyn
7	Australia, Austria, Canada, Finland, Germany, Ireland, New Zeeland, Norway, Sweden, Switzerland, United States of America	0.244	0.275	FE dyn

Rougieux and Damette (2018) found countries in Europe to have relatively inelastic elasticities of demand for coniferous sawnwood (-0.37 and 0.21 for price and income respectively). Buongiorno (2015) estimates the global price elasticity of demand to be -0.17 and the global income elasticity of demand to be 0.24. Their income elasticities show the most resemblance to the income elasticity reported for category 7 which is representative for high-income countries with high production, though statistically insignificant. In general, the statistically significant elasticities of demand are higher in this thesis.

Table 20 display the results of the Chow test for poolability. Most of the countries with significantly different elasticities had positive price elasticities, large deviations between direct and reversed regressions or violated the post estimation tests carried out in part I. The fact the country-specific estimates differ does not necessarily mean that they are qualitatively better. Categories 1, 2, 4, 5 and 6 cannot reject the null hypothesis of poolability.

Category 3 contains some countries where elasticities are suggested to be better explained by the country-individual regressions. Brazil has a higher income elasticity of demand (1.309) but violated the White-test for misspecification. Croatia has a lower price elasticity of demand in absolute terms than the group (-0.234). The same is found for Mexico (-0.491). In category 7, Austria, Germany, Sweden and USA have positive price elasticities of demand. The very significant rejection of the poolability may explain the lack of significance in the Fixed Effects model.

Table 20 Poolability of elasticities.

Category	Countries	F-stat	p-value
1	Mauritius, Morocco	0.36	0.699
2	Dominican Republic, Hungary, Jamaica, Panama, Samoa	0.70	0.649
3	Brazil, Croatia, Honduras, Lithuania, Mexico, Poland	3.69	0.001
4	Cyprus, Italy	0.77	0.516
5	France, Japan, Portugal, Republic of Korea, Spain	0.24	0,944
6	Denmark, Netherlands	1.42	0.231
7	Austria, Germany, Ireland, New Zealand, Sweden, USA	18.86	0.000

3.3 Part III: Projections of future demand using IPCC's SSPs

The elasticities of demand estimated in part II are applicable to a variety of economic modelling instruments, such as various forest sector models. As mentioned in the introduction, the use of sawnwood is considered to be an important mean to meet the challenges of climate change. To provide an illustrative example of using this thesis' results, they are combined with the GDP predictions following the shared socioeconomic pathways.

Table 21 Predicted consumption from Shared Socioeconomic Pathways in million cubic metres. Source: IIASA(2016)

Region	SSP Scenario				
Year	1	2	3	4	5
Africa					
2015	11.604	11.604	11.604	11.604	11.604
2025	22.454	21.869	21.300	21.320	23.065
2030	30.885	28.651	26.634	27.526	33.056
Asia					
2015	83.539	83.539	83.539	83.539	83.539
2025	144.398	138.419	134.832	138.740	151.239
2030	182.909	165.465	155.495	167.886	201.275
Europe					
2015	101.996	101.996	101.996	101.996	101.996
2025	133.368	131.002	126.669	131.363	138.540
2030	152.769	146.464	137.166	148.580	165.051
North America					
2015	90.648	90.648	90.648	90.648	90.648
2025	104.201	103.341	99.437	102.861	108.076
2030	110.942	109.134	102.221	108.650	118.443
South America					
2015	19.519	19.519	19.519	19.519	19.519
2025	31.891	31.313	30.666	30.749	32.702
2030	39.614	37.399	35.264	36.431	42.329
Oceania					
2015	7.229	7.229	7.229	7.229	7.229
2025	8.628	8.578	8.195	8.520	9.006
2030	9.364	9.223	8.537	9.165	10.091
World					
2015	314.535	314.535	314.535	314.535	314.535
2025	444.941	434.523	421.100	433.552	462.627
2030	526.482	496.337	465.317	498.238	570.245

The SSP projections for 2025 and 2030 are used to predict consumption for regions and the world total, represented by the 92 countries in this study. Prices are assumed ceteris paribus. The income elasticities of demand from the dynamic Fixed Effects model is applied with the exception of category 2 which uses the Random Effects estimate from the static model. The elasticities for the countries in category 1 and 7 (1.569 and 0.275 respectively) are not statistically significant but are nonetheless used as likely estimates. The figures representing Oceania should be interpreted with caution as the region is dominated by Australia and New Zealand, both with the low and non-significant income elasticity of demand from category 7.

Scenarios 1 and 5 leads to the greatest increase in coniferous sawnwood consumption. In scenario 1, the population growth is relatively low, the global trade is moderate, and the inequalities are reduced among and across countries. The main difference to scenario number 5 is the lower economic growth in high-income countries and a lower global trade. A retardation of economic growth and reduced world trade decreases the demand for sawnwood in scenario 3, compared to the "business as usual" scenario 2. Comparing a more sustainable future in scenario 1 with scenario 2, the 2030 demand for coniferous sawnwood is increased with 30 million cubic metres. The highest demand for sawnwood is found when there is a virtually unrestricted economic growth in scenario 5. The 2030 demand is 105 million cubic metres higher in this scenario compared to the lowest projection in scenario 3.

Table 22 Consumption growth rates of coniferous sawnwood under SSP scenarios. Source: IIASA(2016)

Region	SSP Scenario				
Year	1	2	3	4	5
Africa					
2015-2025	66 %	63 %	61 %	61 %	69 %
2025-2030	32 %	27 %	22 %	26 %	36 %
Asia					
2015-2025	55 %	50 %	48 %	51 %	59 %
2025-2030	24 %	18 %	14 %	19 %	29 %
Europe					
2015-2025	27 %	25 %	22 %	25 %	31 %
2025-2030	14 %	11 %	8 %	12 %	18 %
North America					
2015-2025	14 %	13 %	9 %	13 %	18 %
2025-2030	6 %	5 %	3 %	5 %	9 %
South America					
2015-2025	49 %	47 %	45 %	45 %	52 %
2025-2030	22 %	18 %	14 %	17 %	26 %
Oceania					
2015-2025	18 %	17 %	13 %	16 %	22 %
2025-2030	8 %	7 %	4 %	7 %	11 %
World					
2015-2025	35 %	32 %	29 %	32 %	39 %
2025-2030	17 %	13 %	10 %	14 %	21 %

Table 22 display the growth rates of the predicted consumption in the periods 2015-2025 and 2025-2030. In all scenarios, the relative growth in consumption is highest in Africa, followed by Asia and South America.

The apparent 2015 consumption of the 123 countries omitted in this study sum up to 8.3 million cubic metres, most of which in Asia. This is a rough estimate as the data quality in these countries is uncertain. If the omitted countries have the same relative growth as their regions, the additional world consumption can range from 12.2 million to 14.8 million cubic metres in 2030 (scenario 3 and 5 respectively).

3.4 Overall discussion

In part I, the challenges of estimating country-individual elasticities of demand were revealed. Both the availability and the quality of data impose challenges with obtaining reliable results. Domestic studies of consumption in individual countries would perhaps require more explanatory variables than prices and GDP, such as construction activity, prices of substitutes, unemployment rates and population density. To gather these data for all countries would be a considerable endeavour.

Part II is a panel data study of the same data as in part I, utilizing the acquired knowledge of the dataset to divide the sample of countries into categories. With Fixed Effects and Random Effects models, reliable estimators were obtained. These can be used as proxies for country-specific elasticities of demand and may add updated estimates to the limited amount of literature on the subject. It is found that low- or medium-income countries are more sensitive to changes in price, and that medium- or high-income countries are more sensitive to changes in income. The results also imply that countries with low production relative to its consumption or a low access to raw materials are more sensitive to changes in income when the income level is either medium or high. Unlike the majority of the previous studies, this study has addressed the issue of non-stationarity. The results suggest that a reassessment of the elasticities of demand available in the literature is needed as the reported elasticities differ substantially. This is also likely to be the case with other forest product groups.

In part III the future demand for coniferous sawnwood assuming constant prices was projected using the recently developed SSP scenarios. None of the scenarios represent explicit policies for the use of sawnwood, but the demand will increase in the future simply due to the increasing GDP and population in all the scenarios. The future rate of the global economic growth will have significant impacts on the demand for sawnwood. The supply of wood products and the policies favouring or discouraging the use of wood products will be additional factors affecting the demand eventually.

This thesis has had a strong emphasis on the uncertainties associated with the data. It is evident that the statistics of forest products has its imperfections so the data should be treated accordingly. A focus on the quality of the available underlying data is vital when simulating consumer behaviour e.g. in forest sector models. This thesis may be a contribution to the growing literature on this subject.

The findings in this thesis are likely to be relevant to forest owners making forest management decisions, the sawnwood industry, and various interest groups including policy makers focusing on the forest sector or environmental guidelines at national or international level. The main end-users of sawnwood, the construction industry, is path dependent and building techniques are evolving slowly (Mahapatra and Gustavsson, 2008). Meanwhile, new techniques are under development for use of timber e.g. in multi-storey timber-framed buildings. As these innovations diffuse in the market, contemporary reassessments of demand indicators are relevant.

4. CONCLUSION AND IDEAS FOR FUTURE RESEARCH

Individual and representative elasticities of demand for each country in the sample of 92 countries were estimated using econometric methods. The sample includes the countries that have an annual apparent coniferous sawnwood consumption of at least 10 000 m^3 and for which the data on GDP and population were available for the period used in the estimations. The sample represents 97% of the global consumption of coniferous sawnwood in 2015. The estimates from the panel data regressions seem more reliable than those from the country-individual regressions. Although they vary in time periods, the estimated elasticities are based on the most present data available and with relatively large panels of data with a time span of at least 20 years. According to the conventional demand model applied on the currently available data, elasticities of demand vary greatly among countries and within regions.

In this thesis, stationarity is tested and remedies for handling non-stationary processes are accounted for. Though some of the elasticities of demand are not statistically significant, the results are thoroughly evaluated with regards to stationarity. Assuming that the results found in the literature are valid, the elasticities of demand from this study in general are higher in comparison. Hopefully, future studies on the subject will address this issue with more care and not leave the reader in doubt of whether fundamental assumptions of the methods used are violated or ignored.

This thesis has considered coniferous sawnwood, which is only one of multiple forest end products. Similar studies can be done on other end products, independently or in combinations. Here the focus has been on price and income elasticities of demand, but other interesting elasticities could be cross-price elasticities to various other construction materials or the elasticities of supply. The assumptions taken in categorizing the countries in this thesis led to different results than those in other relevant studies and is above all a suggestion for determining clusters or groups of countries. The elasticity estimates obtained for the panels of very-low or very-high income countries were not statistically significant. It should, under different assumptions, be possible to get reliable estimates for these countries.

The variables are proved to have issues with non-stationarity. In part I, this was remedied by first differencing the variables. In part II, some categories were found to have stationary panels only when adjusting the time periods. There are more exhaustive remedies for dealing with non-stationarity, such as the cointegration analysis performed by Rougieux and Damette (2018).

The prices used in this study are thought to be the best estimates available for a global study and is similar to the ones used in the present literature. Some alternative prices are available, and it could be tested if they were more efficient for purposes of estimating elasticities under the assumption that the different countries face the same prices. An example is the monthly average Global price of Soft Sawnwood from the International Monetary Fund, available from the U.S. Federal Reserve (IMF, 2019).

This thesis has assumed that elasticities of demand differ among countries and reports evidence to support this assumption. Whether these or more generalized estimates on the overall global consumption are the most useful and efficient ones depends on the use of the elasticities and is a question beyond the scope of the thesis. However, the results found in this thesis may be of some use regarding the answer to this question.

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Appendix I: Descriptive statistics

Table 23 Descriptive statistics of variables country A-I. Mean, standard deviation and var.coefficient. Source: FAO(2018a)

	Consumption per capita			Price			GDP per capita		
Country	Mean	SD	% SD	Mean	SD	% SD	Mean	SD	% SD
Albania	0.013	0.011	80 %	226.44	173.056	76 %	2788.416	992.641	36 %
Algeria	0.034	0.014	42 %	241.647	29.388	12 %	3170.433	1159.063	37 %
Argentina	0.021	0.010	49 %	115.435	108.301	94 %	5133.625	6358.031	124 %
Australia	0.179	0.019	11 %	448.48	116.997	26 %	43976.576	6817.592	16 %
Austria	0.597	0.064	11 %	239.457	20.431	9 %	40860.309	3488.129	9 %
Bahamas	0.109	0.163	150 %	397.058	450.752	114 %	30820.670	6546.239	21 %
Bahrain	0.040	0.013	31 %	268.324	94.792	35 %	19995.688	4784.725	24 %
Barbados	0.141	0.146	104 %	756.691	290.115	38 %	18646.991	2273.749	12 %
Belarus	0.120	0.043	36 %	140.89	130.954	93 %	3114.148	1964.308	63 %
Belgium	0.179	0.018	10 %	254.748	31.186	12 %	38023.505	2872.238	8 %
Belize	0.036	0.022	60 %	371.596	185.833	50 %	4598.194	195.631	4 %
Botswana	0.013	0.008	62 %	476.13	230.544	48 %	5362.160	1075.656	20 %
Brazil	0.035	0.006	18 %	219.897	65.302	30 %	6624.121	1680.955	25 %
Bulgaria	0.033	0.021	64 %	201.222	98.790	49 %	5175.199	1393.896	27 %
Canada	0.484	0.089	18 %	270.634	76.509	28 %	38777.568	4640.519	12 %
Chile	0.238	0.048	20 %	227.482	25.538	11 %	9514.386	3020.186	32 %
China	0.017	0.012	72 %	335.035	123.274	37 %	4020.330	2682.671	67 %
Colombia	0.003	0.002	59 %	466.589	295.596	63 %	4453.077	1096.566	25 %
Costa Rica	0.009	0.008	84 %	406.791	133.494	33 %	8605.285	1887.475	22 %
Croatia	0.064	0.026	41 %	211.003	118.777	56 %	10039.430	2248.217	22 %
Cyprus	0.075	0.039	51 %	217.872	90.964	42 %	17180.023	2107.239	12 %
Czechia	0.241	0.046	19 %	225.819	50.776	22 %	15018.050	2376.940	16 %
Denmark	0.402	0.157	39 %	237.291	69.457	29 %	49524.682	3977.996	8 %
Dominican Republic	0.025	0.007	29 %	310.477	105.172	34 %	4680.920	1209.600	26 %
Ecuador	0.012	0.011	90 %	478.442	283.119	59 %	12217.986	13427.956	110 %
Egypt	0.038	0.013	33 %	274.545	111.198	41 %	2551.757	547.190	21 %
El Salvador	0.009	0.006	63 %	320.323	165.959	52 %	3190.543	307.533	10 %
Estonia	0.756	0.489	65 %	260.039	42.273	16 %	11882.111	4467.873	38 %
Ethiopia	0.000	0.000	52 %	481.678	166.033	34 %	381.137	148.247	39 %
Fiji	0.058	0.022	38 %	455.376	232.799	51 %	3946.861	554.650	14 %
Finland	0.776	0.199	26 %	238.567	23.211	10 %	38450.122	5678.804	15 %
France	0.142	0.017	12 %	253.69	22.682	9 %	34319.067	2528.401	7 %
Germany	0.212	0.025	12 %	232.878	24.663	11 %	36930.623	2680.575	7 %
Greece	0.050	0.020	39 %	258.187	64.679	25 %	20502.405	3061.099	15 %
Guatemala	0.011	0.008	73 %	363.429	104.544	29 %	3652.821	176.484	5 %
Haiti	0.004	0.003	69 %	412.284	163.257	40 %	848.058	117.521	14 %
Honduras	0.032	0.011	32 %	338.462	70.190	21 %	2026.938	242.435	12 %
Hungary	0.074	0.024	33 %	190.384	40.783	21 %	10372.356	1775.010	17 %
Iceland	0.258	0.055	21 %	272.964	45.851	17 %	43791.022	7110.744	16 %
India	0.003	0.003	84 %	278.441	115.627	42 %	1153.088	353.836	31 %
Indonesia	0.001	0.000	31 %	442.106	292.917	66 %	2090.107	863.889	41 %
Iran	0.007	0.005	69 %	207.929	111.459	54 %	4906.049	1349.623	28 %
Ireland	0.198	0.106	54 %	238.722	56.522	24 %	43473.527	11794.393	27 %
Israel	0.050	0.018	35 %	317.103	61.038	19 %	29796.837	3854.897	13 %
Italy	0.100	0.016	16 %	243.246	41.571	17 %	31419.157	1945.629	6 %

Table 24 Descriptive statistics of variables country A-I. Mean, standard deviation and var.coefficient. Source: FAO(2018a)

	Consumption per capita			Price			GDP per capita		
Country	Mean	SD	% SD	Mean	SD	% SD	Mean	SD	% SD
Jamaica	0.044	0.026	59 %	420.592	119.755	28 %	5244.608	294.931	6 %
Japan	0.170	0.055	32 %	294.18	31.010	11 %	34317.012	772.627	2 %
Jordan	0.022	0.012	56 %	279.097	73.362	26 %	3478.953	611.881	18 %
Kenya	0.005	0.002	39 %	585.626	345.186	59 %	1204.132	123.808	10 %
Kuwait	0.038	0.020	53 %	285.983	116.058	41 %	39182.573	12366.124	32 %
Latvia	0.410	0.202	49 %	180.632	50.702	28 %	9273.673	3737.968	40 %
Lithuania	0.196	0.071	36 %	240.112	84.173	35 %	9277.469	3874.813	42 %
Malawi	0.002	0.001	22 %	281.737	359.400	128 %	253.554	97.366	38 %
Mauritius	0.013	0.007	53 %	360.385	192.977	54 %	7253.687	1591.596	22 %
Mexico	0.033	0.009	26 %	252.524	116.917	46 %	8235.977	877.235	11 %
Mongolia	0.065	0.054	83 %	252.857	115.536	46 %	2233.022	1263.555	57 %
Morocco	0.027	0.009	35 %	265.486	85.229	32 %	2292.017	413.779	18 %
Nepal	0.001	0.000	10 %	364.12	167.360	46 %	536.780	132.813	25 %
Netherlands	0.151	0.023	15 %	248.817	28.382	11 %	42154.188	4474.997	11 %
New Zealand	0.536	0.071	13 %	393.792	88.852	23 %	33176.916	4224.344	13 %
Norway	0.554	0.049	9 %	274.187	25.720	9 %	61345.536	13987.189	23 %
Pakistan	0.003	0.000	15 %	267.267	132.307	50 %	1065.691	272.332	26 %
Panama	0.003	0.002	76 %	402.881	127.028	32 %	8607.452	3010.522	35 %
Philippines	0.001	0.002	137 %	512.505	177.447	35 %	2154.887	511.987	24 %
Poland	0.085	0.020	24 %	232.509	27.587	12 %	9085.231	2485.331	27 %
Portugal	0.066	0.014	21 %	221.054	41.856	19 %	18431.370	1778.685	10 %
Qatar	0.038	0.019	51 %	303.078	75.541	25 %	62945.674	21285.344	34 %
Republic of Korea	0.081	0.014	17 %	361.776	135.518	37 %	21137.991	4632.079	22 %
Republic of Moldova	0.029	0.014	46 %	165.583	224.610	136 %	1253.621	390.969	31 %
Romania	0.044	0.044	100 %	250.258	88.227	35 %	5850.153	2486.693	43 %
Russian Federation	0.076	0.028	37 %	187.087	135.577	72 %	6557.432	2589.711	39 %
Saint Lucia	0.084	0.019	22 %	422.052	188.311	45 %	7951.762	1073.940	14 %
Samoa	0.053	0.032	60 %	512.16	99.248	19 %	3595.154	536.787	15 %
Saudi Arabia	0.052	0.016	30 %	252.741	50.270	20 %	18347.472	5688.421	31 %
Singapore	0.004	0.003	86 %	335.981	148.292	44 %	44757.345	8121.043	18 %
Slovakia	0.121	0.090	74 %	349.785	182.615	52 %	13126.125	2475.090	19 %
Slovenia	0.140	0.092	65 %	193.814	45.783	24 %	18563.748	3086.544	17 %
South Africa	0.034	0.005	16 %	225.08	95.663	43 %	4491.127	1075.772	24 %
Spain	0.085	0.029	34 %	240.579	50.793	21 %	25278.634	2977.444	12 %
Sweden	0.537	0.114	21 %	240.041	18.565	8 %	41332.400	7052.044	17 %
Switzerland	0.194	0.031	16 %	415.991	75.365	18 %	74444.654	6021.126	8 %
Thailand	0.003	0.001	35 %	268.908	77.508	29 %	4452.158	1019.184	23 %
FYR Macedonia	0.037	0.022	60 %	193.765	72.595	37 %	3496.436	953.242	27 %
Trinidad & Tobago	0.043	0.015	35 %	577.475	283.717	49 %	19234.911	5669.948	29 %
Tunisia	0.038	0.007	19 %	209.433	28.899	14 %	3143.233	699.037	22 %
Turkey	0.058	0.014	24 %	208.165	77.725	37 %	8072.704	1942.323	24 %
Ukraine	0.015	0.011	71 %	106.895	30.183	28 %	1529.892	626.023	41 %
United Kingdom	0.148	0.018	12 %	285.724	35.205	12 %	40659.424	5049.344	12 %
USA	0.280	0.061	22 %	268.838	52.722	20 %	51277.565	4007.399	8 %
Uruguay	0.026	0.008	30 %	361.465	79.794	22 %	11696.837	2370.033	20 %
Venezuela (BR)	0.012	0.010	81 %	1217.691	695.801	57 %	32824.921	7074.574	22 %
Zambia	0.015	0.008	57 %	449.521	303.363	67 %	1000.699	229.850	23 %

Appendix II: Part I Unit Root Tests

Table 25 ADF Unit Root test for logarithmic variables

	Random Walk 5 % critical value = -3.000			Trend 5 % critical value = -3.600		
Country	CPC	Pd	GDPC	CPC	Pd	GDPC
Albania	-2.316	-1.964	-1.881	-3.339	-2.441	-3.442
Algeria	-0.228	-3.303	-0.558	-2.839	-3.298	-2.237
Argentina	-2.802	-0.758	-3.899	-3.232	-2.513	-0.475
Australia	-2.269	-0.297	-1.115	-3.5	-3.682	-0.987
Austria	-3.352	-1.468	-2.475	-2.873	-2.373	-0.474
Bahamas	-1.408	-0.692	-2.267	-1.663	-1.792	-1.437
Bahrain	-2.94	-2.169	-0.968	-3.969	-2.306	-2.046
Barbados	-1.66	-2.768	-1.162	-2.872	-3.379	-0.453
Belarus	-2.033	-4.493	-0.706	-2.474	-3.999	-6.373
Belgium	-3.538	-2.778	-2.628	-3.158	-3.551	-0.694
Belize	-4.018	-2.68	-1.238	-3.896	-3.121	-2.103
Botswana	-0.758	-2.277	-0.852	-1.73	-2.277	-2.409
Brazil	-2.902	-1.358	-1.623	-1.643	-2.231	-2.607
Bulgaria	-2.032	-2.719	0.07	-3.19	-3.715	-2.956
Canada	-1.323	-1.005	-1.8	-1.03	-1.42	-1.764
Chile	-2.271	-2.606	-0.308	-1.427	-2.232	-1.657
China	0.095	-1.709	1.002	-1.017	-4.067	-1.842
Colombia	-1.894	-2.032	-0.871	-1.938	-1.932	-3.153
Costa Rica	-1.7	-4.434	0.355	-3.25	-5.078	-2.232
Croatia	-1.371	-3.27	-1.159	-1.096	-3.209	-2.159
Cyprus	-0.894	-2.216	-3.045	-1.652	-3.391	-0.097
Czechia	-1.713	-2.184	-2.264	-2.635	-2.363	-0.945
Denmark	-1.648	-1.63	-2.68	-2.173	-2.316	-1.617
Dominican Republic	-2.037	-3.59	0.067	-3.539	-4.369	-2.358
Ecuador	-1.798	-2.101	-2.36	-5.562	-3.054	-0.771
Egypt	-1.959	-3.995	-0.137	-2.819	-3.647	-3.953
El Salvador	-3.054	-3.107	-0.6	-3.116	-3.032	-2.798
Estonia	-1.406	-3.101	-1.367	-2.513	-3.181	-0.091
Ethiopia	-2.606	-2.31	-0.544	-2.447	-2.716	-1.93
Fiji	-1.947	-3.19	-0.867	-2.727	-3.894	-2.069
Finland	-2.32	-2.86	-3.907	-1.98	-4.423	-0.75
France	-1.238	-1.989	-2.229	-0.762	-1.992	-0.488
Germany	-4.227	-3.015	-0.329	-4.536	-3.816	-2.647
Greece	-0.845	-2.374	-1.197	-1.487	-4.447	0.439
Guatemala	-1.734	-2.816	-1.846	-3.519	-3.023	-1.811
Haiti	-2.158	-1.964	-2.146	-2.308	-2.419	-0.795
Honduras	-2.439	-3.518	-1.165	-3.947	-3.686	-3.045
Hungary	-1.136	-2.953	-1.37	-1.978	-4.383	-0.92
Iceland	-3.028	-2.109	-2.419	-3.12	-1.665	-0.881
India	-2.019	-2.633	0.062	-1.965	-2.899	-1.338
Indonesia	-3.107	-2.288	-0.184	-3.142	-3.339	-1.714
Iran	-1.565	-2.726	-0.856	-1.555	-2.51	-0.84
Ireland	-0.262	-1.659	-3.477	-1.426	-3.204	-1.281
Israel	-2.547	-1.285	-1.055	-2.043	-1.239	-2.733
Italy	-0.654	-1.907	-1.846	-1.171	-2.082	0.036

Table 26 ADF Unit Root test for logarithmic variables cont.

Country	Random Walk 5 % critical value = -3.000			Trend 5 % critical value = -3.600		
	CPC	Pd	GDPC	CPC	Pd	GDPC
Jamaica	-4.66	-3.312	-0.964	-4.29	-4.272	-1.254
Japan	-0.725	-2.314	-1.925	-2.863	-1.868	-2.62
Jordan	-1.796	-2.181	-0.498	-4.157	-2.135	-1.067
Kenya	-1.606	-3.269	-2.312	-0.996	-4.25	-2.233
Kuwait	-1.016	-0.867	-1.343	-0.833	-0.256	-1.333
Latvia	-1.989	-6.767	-0.754	-1.81	-5.767	-1.346
Lithuania	-1.836	-7.344	-3.923	-2.732	-6.155	-4.689
Malawi	-0.834	-3.331	-0.782	-2.343	-4.212	-2.796
Mauritius	-1.325	-2.383	-1.082	-2.008	-3.045	-1.365
Mexico	-1.764	-1.625	-0.825	-1.705	-1.546	-2.832
Mongolia	-1.798	-1.066	-0.074	-1.619	-2.412	-2.154
Morocco	-0.949	-1.725	0.103	-2.077	-2.363	-2.382
Nepal	-1.61	-2.529	0.535	-3.371	-2.402	-2.524
Netherlands	-0.516	-2.13	-2.7	-3.24	-2.952	-0.04
New Zealand	-1.806	-1.567	-1.214	-2.138	-1.992	-1.707
Norway	-3.73	-2.453	-1.415	-3.57	-3.478	-1.614
Pakistan	-3.744	-1.637	-0.857	-3.397	-3.099	-1.736
Panama	-3.606	-4.305	-2.695	-3.809	-4.303	-0.787
Philippines	1.662	-2.777	-0.295	-1.814	-2.632	-2.599
Poland	-1.414	-2.097	-1.881	-2.616	-2.044	-1.782
Portugal	-3.827	-3.857	-2.891	-5.143	-4.782	-0.843
Qatar	-1.78	-3.203	-1.214	-5.213	-3.083	-2.213
Republic of Korea	-3.339	-1.147	-2.451	-3.308	-2.233	-3.109
Republic of Moldova	-1.884	-13.76	-0.136	-2.162	-13.339	-6.862
Romania	-1.659	-3.252	-0.435	-3.411	-2.14	-1.363
Russian Federation	-4.084	-6.432	0.195	-2.604	-10.912	-3.626
Saint Lucia	-2.743	-1.73	-0.914	-4.667	-1.516	-1.771
Samoa	-1.523	-4.124	-6.21	-1.637	-4.021	-5.037
Saudi Arabia	-1.442	-3.39	-0.692	-3.209	-3.686	-2.335
Singapore	-1.798	-2.164	-1.427	-1.912	-2.424	-2.357
Slovakia	-1.174	-1.866	-1.539	-2.318	-2.846	-1.653
Slovenia	-1.752	-2.653	-3.438	-2.479	-2.95	-0.656
South Africa	-1.591	-3.592	-0.469	-1.797	-3.498	-1.128
Spain	0.051	-0.647	-2.262	-1.154	-4.936	0.524
Sweden	-3.658	-4.877	-2.559	-3.883	-4.819	-1.23
Switzerland	-0.975	-1.861	-0.279	-2.536	-2	-2.215
Thailand	-2.115	2.507	-0.164	-4.413	-9.748	-1.416
FYR Macedonia	-2.04	-2.12	-0.776	-1.792	-2.042	-2.262
Trinidad and Tobago	-4.055	-1.013	-1.624	-6.05	-4.666	-1.14
Tunisia	-2.962	-3.787	-1.909	-3.325	-3.761	-0.346
Turkey	-1.577	-2.445	-0.67	-4.889	-2.722	-3.044
Ukraine	-1.937	-2.775	0.263	-2.528	-2.537	-3.465
United Kingdom	-2.402	-1.982	-3.831	-2.544	-1.724	-1.293
United States of America	-0.734	-1.635	-2.194	-1.486	-1.583	-1.352
Uruguay	-2.578	-2.97	0.439	-2.289	-2.926	-0.85
Venezuela (BR)	-0.924	-2.31	-1.227	-2.607	-3.382	-1.577
Zambia	-2.189	-2.319	0.728	-1.594	-2.546	-1.621

Table 27 ADF Unit root test for 1st difference logs

	Random Walk 5 % critical value = -3.000		
Country	CPC	Pd	GDPC
Albania	-5,866	-5,529	-5,244
Algeria	-5,143	-6,824	-10,357
Argentina	-6,822	-7,408	-8,397
Australia	-16,11	-3,904	-14,715
Austria	-8,394	-5,912	-27,561
Bahamas	-5,026	-4,529	-8,355
Bahrain	-7,342	-6,431	-10,692
Barbados	-5,831	-4,664	-8,168
Belarus	-5,661	-4,485	-28,657
Belgium	-16,591	-5,541	-93,029
Belize	-8,571	-7,699	-81,551
Botswana	-5,753	-4,155	-6,03
Brazil	-5,851	-6,504	-20,216
Bulgaria	-6,568	-9,523	-10,571
Canada	-14,395	-7,035	-53,925
Chile	-13,721	-5,441	-42,219
China	-12,301	-6,652	-89,595
Colombia	-5,154	-4,193	-26,378
Costa Rica	-4,958	-6,459	-3,76
Croatia	-4,676	-4,517	-5,071
Cyprus	-5,447	-5,248	-3,202
Czechia	-15,676	-4,116	-17,277
Denmark	-4,288	-4,947	-32,236
Dominican Republic	-14,972	-6,512	-89,492
Ecuador	-6,107	-5,086	-7,608
Egypt	-11,81	-10,416	-39,506
El Salvador	-4,753	-4,648	-8,406
Estonia	-12,002	-5,607	-4,662
Ethiopia	-17,791	-5,109	-53,512
Fiji	-12,579	-7,013	-29,427
Finland	-9,719	-5,963	-46,482
France	-24,085	-5,31	-26,096
Germany	-6,054	-6,506	-8,293
Greece	-7,872	-5,894	-17,817
Guatemala	-5,797	-7,409	-50,167
Haiti	-4,673	-5,809	-27,819
Honduras	-8,383	-5,312	-16,626
Hungary	-8,663	-7,204	-28,136
Iceland	-9,531	-4,281	-19,398
India	-8,131	-6,766	-172,21
Indonesia	-5,682	-6,003	-10,715
Iran	-4,111	-5,285	-3,512
Ireland	-11,812	-4,975	-23,278
Israel	-6,184	-4,543	-4,971
Italy	-9,925	-5,944	-13,086

Table 28 ADF Unit root test for 1st difference logs cont.

	Random Walk 5 % critical value = -3.000		
Country	CPC	Pd	GDPC
Jamaica	-6,382	-5,125	-46,431
Japan	-27,174	-6,408	-94,784
Jordan	-5,226	-3,96	-76,441
Kenya	-4,088	-7,974	-16,009
Kuwait	-8,053	-2,247	-19,669
Latvia	-9,392	-3,171	-18,618
Lithuania	-5,851	-11,008	-19,967
Malawi	-47,959	-7,826	-31,679
Mauritius	-4,924	-6,48	-100,869
Mexico	-4,763	-6,304	-11,158
Mongolia	-4,605	-3,251	-13,77
Morocco	-6,457	-5,232	-30,017
Nepal	-124,808	-5,62	-52,183
Netherlands	-71,514	-4,993	-140,342
New Zealand	-12,308	-12,082	-28,889
Norway	-5,633	-6,529	-4,419
Pakistan	-46,239	-5,261	-80,715
Panama	-6,311	-7,018	-37,18
Philippines	-6,922	-6,092	-106,483
Poland	-16,159	-5,123	-19,631
Portugal	-7,419	-8,278	-2,599
Qatar	-5,228	-7,726	-6,309
Republic of Korea	-6,965	-5,158	-40,789
Republic of Moldova	-12,384	-9,885	-54,759
Romania	-5,326	-15,522	-4,617
Russian Federation	-3,509	-11,68	-5,798
Saint Lucia	-6,75	-4,782	-6,328
Samoa	-4,866	-8,32	-43,338
Saudi Arabia	-4,819	-9,144	-10,418
Singapore	-6,782	-6,352	-7,539
Slovakia	-6,124	-5,25	-47,988
Slovenia	-6,588	-5,746	-10,197
South Africa	-23,172	-7,303	-63,624
Spain	-7,247	-5,247	-37,336
Sweden	-8,053	-6,028	-3,386
Switzerland	-10,605	-13,816	-12,476
Thailand	-14,582	-10,014	-77,801
FYR Macedonia	-5,635	-3,806	-31,502
Trinidad and Tobago	-8,651	-9,817	-6,962
Tunisia	-6,421	-6,005	-63,595
Turkey	-11,221	-4,971	-7,379
Ukraine	-4,692	-3,855	-22,377
United Kingdom	-22,776	-13,712	-79,007
United States of America	-6,093	-5,513	-4,593
Uruguay	-9,206	-6,259	-35,16
Venezuela (BR)	-7,577	-5,049	-7,019
Zambia	-4,914	-13,407	-52,99

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