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Analysis of Time Series to Examine the Impact of the EU Timber Regulation (EUTR) on European Timber Trade

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Zusammenfassung

Die Europäische Holzhandelsverordnung (EUTR) trat im März 2013 in Kraft. Diese Verordnung zielt darauf ab, die Verpflichtung der Marktteilnehmer in der EU zur Vermeidung des Holzhandels aus illegalen Quellen zu stärken. Um die Auswirkungen von EUTR auf Holzhandel zwischen Europa und nichteuropäischen Ländern bewerten zu können, wurden, auf EUROSTAT Daten basierend, umfangreiche Zeitreihenanalysen für den Zeitraum vom Januar 1988 bis August 2016 durchgeführt. Die Zeitreihen wurden sowohl im Zeit- als auch im Frequenzbereich untersucht. Dabei zeigte sich, dass zur mathematisch-statistischen Modellierung der monatlichen Handelsmengen mit Holzprodukten autoregressive AR(1) bzw. Autoregressiv-Moving-Average Modelle ARMA(1, 1) adäquat sind. Die Analyse der partitionierten Abschnitte der Zeitreihen vor und nach Inkrafttreten der EUTR ergab statistisch signifikante Unterschiede, so dass der Einfluss der Holzhandelsverordnung als Interventionseffekt im Holzhandel als wahrscheinlich erachtet wird. Wichtig ist allerdings, dass der Holzhandel wegen EUTR keine quantitativen Einbrüche verzeichnet: der Handel mit allen Holzprodukten weist sogar einen positiven, linearen Trend ab März 2013. Da die Importe der tropischen Holzprodukte vor dem Inkrafttreten der EUTR rückläufig waren, kann die Stagnation des Holzhandels mit den tropischen Holzprodukten nach EUTR auf eine Unsicherheit der Marktteilnehmer und eine Art von ‚wait-and-see‘ Verhalten hindeuten. Festgestellt wurde auch eine auffällige Veränderung der Zeitreihen im Frequenzbereich: die vor EUTR deutliche 3, 4, 6 und 12 monatliche Zyklen bei Importmengen aus den tropischen Ländern konnten in den Zeitreihen nach Inkrafttreten der EUTR nicht mehr nachgewiesen werden.

Schlüsselworte: illegale Holznutzung, Zeitreihenanalyse, Interventionsmodell

Abstract

The objective of the EU Timber Regulation (EUTR), enforced since March 2013, is for importers and exporters to commit to reducing the risk of trading timber products from illegal sources in the EU. EUROSTAT time series on monthly trade with wood products from January 1988 to August 2016 were used to monitor the law's impact. The time series, subdivided into sections before and after the implementation of EUTR, were investigated in time and frequency domains. The analyses in the time domain indicated the adequateness of the AR (1) and ARMA (1, 1) models. As the confidence intervals for their estimates before and after EUTR do not overlap, the respective time series are considered as different and the influence of EUTR legislation probable (also confirmed by the significant models with EUTR as intervening event). Long term variation of the monthly time series (March 2013 to August 2016) show an increasing linear trend for all wood products and for wood products with tropical woods excluded. Since EU imports of tropical wood were falling before EUTR, the stagnant imports thereafter are judged as uncertainty and time the markets need to adapt to a new legislative situation. The analyses in frequency domain based on inference from periodogram revealed cycles of 3, 4, 6 and 12 months, except for time series of tropical wood imports after EUTR. If cycles are thought of as inherent to import time series, this lack in tropical wood imports can be an indication of a 'wait-and-see' attitude of importers as a consequence of EUTR.

Key words: illegal logging, time series analysis, periodogram, intervention model

1 Introduction

The most important prerequisite for the responsible exploitation of forests is the sustainability of the management. Despite endeavours aimed at ensuring sustainable development in line with international regulations, it has not yet been possible to prevent organizations involved from bringing timber from illegal logging on the European markets. Illegal logging is not only a factor impairing and destabilizing forest ecosystems but also a cause for disturbed markets and their mechanisms worldwide. Bearing this in mind, the European Union launched the Forest Law Enforcement, Governance and Trade (FLEGT) Action Plan 2003. This plan consists of two major elements: Voluntary Partnership Agreements (VPAs) commenced in 2004 and aimed at cooperation between countries producing and exporting tropical wood products on the one hand, and countries importing these products on the other. The second element of FLEGT, the EU Timber Regulation (EUTR), was adopted 2010 and entered into force in March 2013. Other legislative activities to combat illegal logging and to control trade with illegally sourced wood products are the Lacey Act Amendment in USA (in Food, Conservation, and Energy Act 2008) or the Illegal Logging Prohibition Act in Australia (2012). Since the interlinkage between countries strongly integrated in international trade is complex, it remains uncertain, if imposed (political) measures will induce intended effects. The enforcement of EUTR is a legislative intervention in logging and trading with wood products. Therefore, it is important to examine the effects of EUTR by asking whether EUTR reduced trade with illegally sourced wood products, left the system unchanged or led to unintended, possibly negative effects.

Most studies published to date on this subject bring the quantitative aspect of illegal logging and trade with illegally sourced wood products into focus. Noteworthy among them are studies conducted by Dieter (2009) and Dieter et al. (2012) that estimated the quantities of illegally logged wood products in EU markets using Input-Output-Analysis. An analysis by Weimar et al. (2015) is also quantitatively oriented. The study quantifies the amount of wood products traded in Europe and estimates the shares of imports covered by EUTR at about 90 % and 75 % in terms of imported quantities and values, respectively. In consequence, Weimar et al. (2015) recommend that more products be included in EUTR. A study by Jonsson, Giurca et al. (2015) is also quantitatively designed. It examines the impact of the policy measures including EUTR on European and global timber markets. In conclusion, this study finds that it is not possible to say that the policy measures have reduced illegal logging (Jonsson, Giurca et al. 2015).

In contrast to the above studies, the approach presented in this paper dispenses largely with the quantitative evaluation of illegally sourced wood products in logging and trade. Instead, the present study is aimed at evaluating time dependent trade data to find out whether analyses of time series are capable of detecting possible changes in trade development of wood products covered by EUTR. In other words the question pursued here is: are the time series of EU imports before and after EUTR the same? This rather imprecise expression arises from the non-quantitative analysis of time series since an intervention event such as EUTR may leave the quantity of imports unchanged but causes the time series to follow another pattern.

2 Database

Trade data on wood products of the statistical office of the European Union (EUROSTAT) were used for all analyses presented in this paper. For statistical analyses, data relevant for this study were extracted from this database and transformed into SAS software system for data analysis. Trade data can be subdivided into amounts of goods exported and imported. Ideally, the quantity of exports from one country retrieved from the database must quantitatively be the same as that in the respective importing country. A simple method to prove this balance is to regress the corresponding import and export quantities. The absolute concordance between imports (y) and exports (x) is given with slope $\beta_1 = 1$ and intercept $\beta_0 = 0$ in the linear equation $y = \beta_0 + \beta_1 x$.

Table 1: Estimated regression coefficients for the data used in the study

Data traded between	Products involved	Confidence intervals (95 %) Slope (β_1)	Intercept (β_0)	R^2
EU countries	all wood products	(0.825, 0.848)	(1.688, 1.915)	0.984
	wood products included in EUTR	(0.829, 0.852)	(1.639, 1.863)	0.984
	non tropical timber	(0.826, 0.849)	(1.681, 1.913)	0.983
	tropical timber	(0.345, 0.413)	(0.016, 0.022)	0.584
	non tropical timber included in EUTR	(0.829, 0.853)	(1.637, 1.862)	0.984
	tropical timber included in EUTR	(0.345, 0.413)	(0.016, 0.022)	0.584
EU and non EU countries	all wood products	(0.814, 0.889)	(1.203, 1.415)	0.851
	wood products included in EUTR	(0.805, 0.881)	(0.496, 0.670)	0.848
	non tropical timber	(0.744, 0.812)	(1.029, 1.215)	0.854
	tropical timber	**(2.126, 2.797)**	(0.239, 0.288)	0.378
	non tropical timber included in EUTR	(0.741, 0.809)	(1.034, 1.221)	0.852
	tropical timber included in EUTR	**(2.013, 2.660)**	(0.238, 0.285)	0.371

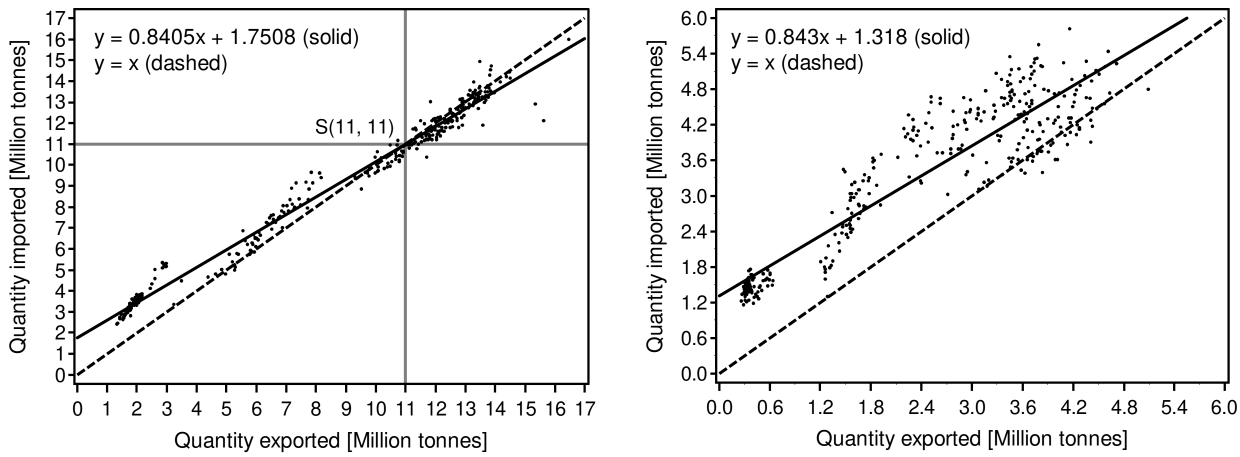
Source: own analyses

The results reported in Table 1 show that in no subsets of data considered a complete concordance between the exported and imported quantities of wood products can be observed, since the confidence limits for slopes lie beyond unity and the intercept is in all cases different from zero. The most cases listed in Table 1 indicate more or less pronounced discrepancy in the data towards higher quantities declared as exported. Whereas the values of the slopes lie in most cases at 0.8, i.e., they deviate only slightly from unity, the quantities of wood products recorded as imports by the EU countries exceed the exports declared by non EU countries by factors ranging from 2.1 to about 2.8 (bold typed in Table 1). This discrepancy can be caused by different factors. The most probable reasons for distorted export-import balance can be (Allafi and Schemer 2018): different information given by trading partners (importers and exporters), trade transactions over third parties, belated reporting, erroneous product assignment or coding, information blocked for secret or confidential reasons, missing data due to different reporting thresholds in individual countries, etc.

Although the influence of the above factors on disparities between export and imports cannot be separated, a closer look at the quantitative aspects of the disparities between exports and imports may be revealing. As already stressed, the relationship between imports and exports indicates that in most of the cases the imports reported and included in the database are lower than exports.

Figure 1: Examples of the disparities between imports and exports

Export/Import within EU countries: only EUTR **Export/Import with non EU countries: only EUTR**



Source: own illustrations

As can be seen at the left of the graph in Fig. 1, this is not always the case. The direction of differences between exports and imports depends on the magnitude of the goods traded. The intersection between the ideal regression line and the linear equation based on real data is a turning point indicating the type of biasedness. In the example depicted in Fig. 1, the export/import relationship indicates that up to 11 Mio. Tons of the imports are inclined to lie above exports. For the magnitudes of traded products larger than 11 Mio, this bias tends to reverse. The extent of each part of the bias could be quantified by the area of the triangles on the left and right, with the common point on which the ideal and data based line intersect. Employing vector calculus, the area of the triangle in perpendicular coordinate system is

$$P = \frac{1}{2}\begin{vmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ 1 & x_3 & y_3 \end{vmatrix}$$

In the example of Fig. 1 for the case imports > exports is

$$P_{i>e} = \frac{1}{2}\begin{vmatrix} 1 & 0 & 0 \\ 1 & 0 & 1.7508 \\ 1 & 11 & 11 \end{vmatrix} = \frac{1}{2}\begin{vmatrix} 0 & 1.7508 \\ 11 & 11 \end{vmatrix} = -9.6294 = -9.6$$

and for imports < exports

$$P_{i<e} = \frac{1}{2}\begin{vmatrix} 1 & 11 & 11 \\ 1 & 17 & 17 \\ 1 & 17 & 16.0393 \end{vmatrix} = \frac{1}{2}\begin{vmatrix} 1 & 11 & 11 \\ 0 & 0 & 0.9607 \\ 1 & 17 & 16.0393 \end{vmatrix} = \frac{1}{2}\cdot(-0.9607)\begin{vmatrix} 1 & 11 \\ 1 & 17 \end{vmatrix} = -2.8821 = -2.9$$

The negative values are due to the orientation of vectors in the parallelogram involved. By interchanging two columns or two rows in the determinants, the results will be positive. This would mean that based on this measure the imports lying above corresponding exports prevail in the database. In contrast to this case, the example depicted in the right part of Fig. 1 shows a clear systematic difference between exports and imports. Obviously, in trade between EU and non EU countries, not all transactions are declared, presumably on the export side of non EU countries into the EU (Allafi and Schemer 2018).

3 Statistical concepts of the time series analysis

It is not spectacular to recognize that most economic phenomena, including trade, are dynamic, i.e., dependent on time. Since the objective of science is to attain knowledge on the behaviour of the objects under investigation and on their relationship to other objects which also may undergo temporal changes, special statistical methods have been developed and established as time series analyses.

Table 2: Statistical concepts of time series analysis versus practical questions they can solve

Theoretical aspects of time series: statistical attributes and methods	**Practical relevance: description, modelling and testing of hypothesis**
Mean, variance and correlation stationarity	Striking low or high values: erroneous data or outliers? Differing quantities traded: overall trend or only varying amplitudes? Marked jumps or smooth sections: explainable? Dependency between neighbouring values: recognisable pattern?
Analyses and statistical inference in time domain, time series as stochastic process.	Quantifying long term trends, Recognizing pattern of seasonal fluctuations, Fitting autoregressive models, Forecasting future from the past, Partitioning long time series based on the anticipated effects of economic or legal events, Comparison of the predicted with the reported data to find out possible differences in time series of the wood products traded before and after enforcing legal measures qualitatively and in type of stochastic model, indication of sudden influences changing time series.
Analyses and statistical inference in frequency domain, periodogram, Fourier transform decomposing time series into superposition of sine and cosine waves at different frequencies, spectral analysis.	How strong is the cyclical behaviour of trade data? Are there visual and hidden periodicities in trade data? Do the intervening factors strengthen, upset or remove the cyclical components?

Source: own analyses

As can be seen from Table 2 the statistical concepts and methods of time series analysis make it possible to solve a large number of practical questions provided that reliable data observed over time are available. In the following the basic concepts of modelling time dependent data will be outlined. To understand and properly interpret the results an elementary knowledge of theory of time series analysis is indispensable. The basics of this theory are given in the current text, whilst more theoretical aspects are moved to the appendices A, B, C and D.

3.1 Time domain

In the following an attempt is made to link the concept of stochastic process to the practical analysis of time series. As already stressed above the way of presenting the theory does not observe the mathematic stringency. It only touches upon a few aspects of the theory needed to understand and interpret models calculated later. Rigorous mathematical treatises of time series are given by Brockwell and Davis (2006) or Shumway and Stoffer (2006). The attempts to answer the question about what a time series is, may lead to thinking of it as a stochastic process consisting of random variables (**X_t**) ($t \in T$) defined at the discrete time points $t = 0, \pm1, \pm2, \pm3, \ldots, \pm N$. As it is unknown what values the random variable can take on the individual time points we should be able to consider a realization of the stochastic process given by a concrete time series and denoted by **x_t**. Further, it is sensible to assume that under similar or comparable economic conditions, repeated measurements of **x_t** would produce, due their stochastic character, a set of different realizations of the stochastic process characterized by the mean function

$$\mu_t =: E(X_t) \tag{1}$$

and the variance function

$$\sigma_t^2 =: Var(X_t) \tag{2}$$

The both functions quantifying the mean level of the stochastic process and the variation of all possible realizations scattered over the mean function are important but not exhausting characteristics of the stochastic process. Imaging real stochastic process e.g. the development of products traded over a long time period is naturally to assume a dependence between the random variables (**X_t**) and (**X_s**) taken at the different time points from ($s, t \in T$) which lead to the two further characteristics of a stochastic process, the covariance

$$\gamma(s,t) =: cov(X_s, X_t) = E((X_s - \mu_s)(X_t - \mu_t)) \tag{3}$$

and correlation function

$$\rho(s,t) =: corr(X_s, X_t) = \frac{cov(X_s, X_t)}{\sigma_s \cdot \sigma_t} \tag{4}$$

Since in practice only one realization of a stochastic process is available, the above characteristics must be stationary, which means in particular:

$$\begin{array}{ll} \mu_t =: \mu & \mu \text{ constant for all } t \in T \\ \sigma_t^2 =: \sigma^2 & \sigma \text{ constant for all } t \in T \\ \gamma(s,t) =: \gamma(s-t) & \text{constant for all } s, t \in T \end{array} \tag{5}$$

The stationarity as defined in (5) implies that the mean and the variance of a given time series do not change in randomly selected parts of a time series. In other words, a stationary time series does not exhibit a trend and its values oscillate uniformly over the mean along the time axis. Also, the covariance, respectively the correlation structure of stationary time series, depends only on the lag τ = s – t, not on the part of the time series considered. If the conditions (5) are fulfilled, the characteristics of a stationary time series simplify to

$$
\begin{aligned}
&\sigma_t^2 = \gamma(t,t) = \gamma(s,s) = \gamma(0) = \sigma^2 \\
&\rho(0) = 1 \\
&\rho(\tau) = \frac{\gamma(\tau)}{\gamma(0)} \\
&-\gamma(0) \leq \gamma(\tau) \leq \gamma(0) \\
&-1 \leq \rho(\tau) \leq 1
\end{aligned}
\tag{6}
$$

The stationarity conditions outlined here give rise to the simplest stochastic model, called white noise process. It consists of uniformly distributed and uncorrelated random variables $(\varepsilon_t)(t \in T)$ with the properties

$$
\left.\begin{aligned} \mu_t &= \mu \\ \sigma_t^2 &= \sigma^2 \end{aligned}\right\} for\ all\ t
$$

$$
\gamma(\tau) = \begin{cases} \sigma^2\ for\ \tau = 0 \\ 0\ otherwise \end{cases} \tag{7}
$$

$$
\rho(\tau) = \begin{cases} 1\ for\ \tau = 0 \\ 0\ otherwise \end{cases}
$$

The stochastic process with parameters and properties described above appears to be appropriate for the statistical modelling of time dependent data. In addition to the common characteristics μ and σ^2 it is described by the covariance and correlation defined in (3) and (4). They quantify the dependencies inherent in the time series and reveal the structure of these dependencies, which play a decisive role in specification appropriate models based on the time series sampled. The covariance and correlation (3) and (4) can be estimated from only one time series by

$$
\hat{\gamma}(\tau) = \sum_{t=1}^{N-\tau} (x_t - \bar{x})(x_{t+\tau} - \bar{x}) \tag{8}
$$

$$
\hat{\rho}(\tau) = \frac{\hat{\gamma}(\tau)}{\hat{\gamma}(0)} = \frac{\sum_{t=1}^{N-\tau}(x_t - \bar{x})(x_{t+\tau} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2} \tag{9}
$$

Obviously, the above expressions are functions with lag τ as argument taking discrete values $\tau = 1, 2, 3, \dots, N-1$. The functions (8) and (9) are nothing but auto-covariance (AC) and autocorrelation function (ACF). The latter can be considered as a measure to predict a specific value x_t from the adjacent or other values, far from x_t by the lag τ. Furthermore, the structure and appearance of ACF, that, according to (6), can take any value from the interval [-1,1], is the main criterion for defining, selecting and judging the most appropriate theoretical model to fit a specific time series.

3.2 Frequency domain

In conjunction with time, it is worth investigating whether the quantity of products traded shows a long term development referred to as trend. Different statistical models are available to analyse the trend. Apart from theoretical details, the common feature of these models is the regression approach with a time variable given at equidistant time points and a quantity assumed to depend on time. This approach is very popular since it enables one to ascertain, whether the development of goods sold or purchased shows a recognizable trend justifying statistical models in time domain. However, the lack of trend does not necessarily mean that a time series is only white noise and it is nothing but random points. Besides trends, time series may show more or less regular periods, important from economic point of view often caused by other factors or phenomena accompanying trade activities. Regular and easily recognizable periods in time series can be described by trigonometric functions like

$$\left.\begin{aligned} f(x) &= \mathrm{A}\cdot\sin x \\ g(x) &= \mathrm{B}\cdot\cos x \end{aligned}\right\} \; x \,\epsilon\, [0, 2\pi],\ \ with\, f(x)\ \in [-1,1]\ and\ g(x) \in [-1,1],\ \ if\ A = B = 1 \tag{10}$$

In the above simplest form, they describe a variable oscillating within the amplitudes A and B. The periods in time series can already be seen in time domain, i.e., by plotting the variable investigated against time. But in most cases time series consist of both trend and periodic components. The latter, often not visible at first glance, are referred to as hidden periodicities. The approximation of time series by superimposed (linearly combined) harmonic oscillations, themselves not important, produces a term that quantifies the presence of harmonic waves in time series as a function of the frequency. This measure, called periodogram, is

$$I(\lambda) = N\big(C^2(\lambda) + S^2(\lambda)\big) \tag{11}$$

$$\begin{aligned} C(\lambda) &= \frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})\cos(2\pi\lambda t) \\ S(\lambda) &= \frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})\sin(2\pi\lambda t) \end{aligned} \tag{12}$$

The terms C (λ) and S (λ) are nothing but co-variances between the time series x_t $(t = 1,2,\cdots N)$ and the harmonic waves at frequency λ. A mathematically strong formal derivation of periodogram is based on complex vector space and Fourier analysis, which are not available here. A less elegant method to arrive at periodogram is to seek the special linear combination of sine and cosine waves by minimizing the squared error. The outline of this method is given in Appendix C. The analyses of the time series in this paper in frequency domain were carried out by using the procedure SPECTRA implemented in SAS/ETS 9.2 (2008).

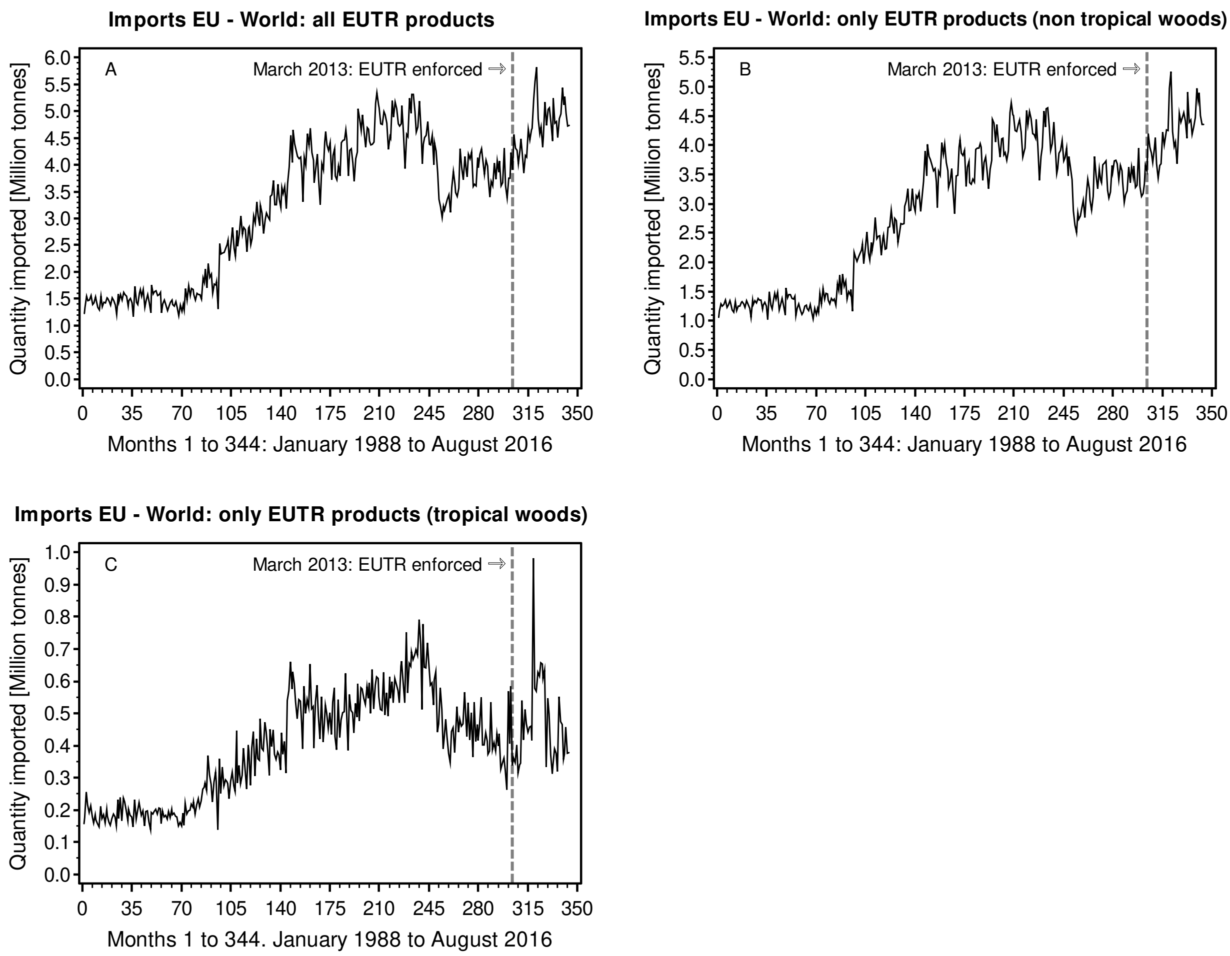
4 Results

As shown and discussed in Chapter 2, the logical balance between exports and imports is more or less distorted in EUROSTAT data. The question ensuing here is which data are likely to be more reliable: import or export data. The decisive point speaking in favour of import data is, that with EUROSTAT data, the EU member states are always declarants and therefore obliged to report the quantities imported from countries outside the EU to their custom and tax offices. This procedure is considered as suitable to answer the questions asked in this paper. The EUROSTAT data used consists of 344 months, ranging from January 1988 to August 2016. Since time series are supposed to differ depending on the kind of wood products traded, separate analyses were conducted covering the following three categories (Fig. 2):

- A: all wood products
- B: only non-tropical wood products
- C: only tropical wood products

The above data categories correspond with commodity codes for wood and wood products, including pulp, paper and paperboard, as defined in the trade classification of the Combined Nomenclature (CN), henceforth referred to as wood products. These were primarily qualified as tropical according to the description of the commodity. Beyond this criterion, wood products imported from tropical countries were also classified as tropical.

Figure 2: Imports of the EUTR products by EU from non EU countries



Source: own illustrations

4.1 Descriptive analysis of the fragmented time series

Fig. 2 shows that the import values vary in the investigated time period. The magnitudes of the products imported by the EU do not only reveal long term variation but also recognizable monthly variation manifested by the serrated shape of imports. Moreover, cyclical components can be recognized. Without formal statistical proof, the graphs support the assumption that the time series on imports are not stationary according to the definitions (5) and (6) given in Chapter 3.1.

Prior to further discussion, marked data points in the time series should be identified, trying (as far as possible) to explain what factors or events can possibly have caused them. A striking high import value occurred in Time Series A in month 321 (corresponding with September 2014). Another peculiarity of the time series depicted in Fig. 2 is the abruptly changing levels of the goods imported. The elevated magnitudes of the imported products occur between December

1995 and January 1996 (current months 96/97), which may be explained by the fact that Austria, Finland and Sweden joined the EU in 1995. Before January 1996, the imports of the EU countries do not show a significant trend. Moreover, their variation is rather modest when compared with the subsequent months: From January 2001 (month 157) the time series began to undulate with discernibly increased amplitude. A sharp decrease in products imported by EU countries occurred in January 2009 (month 253), which may be due to the economic recession in 2008. A trend, i.e., long term variation, is visible as well but it is not always present along the whole time axis. Marked trends occur only in particular segments of the time series, so that one would be reluctant to assess them as being driven by the same, constant factors. Even if the long term variation of the whole time series could be smoothed by moving averages, splines, or explained by polynomial regression, separate analyses of distinctive segments should be preferred. By subdividing the whole time series from January 1988 to August 2016, and separately analysing their segments, a part of variation will be accounted for prior to the detailed analyses. Moreover, it can be examined whether the boundaries of the segments coincide with particular months, years, periods or events that are likely to be connected with events exerting influence on the temporal development of wood products imported by EU. The appearances of their plots support the idea and necessity to subdivide the entire time series into segments. However, the boundaries of the segments for the times series A, B and C are not set arbitrarily or only by visual inspection. The decision about the point at which a subseries should start, and where it should stop, are based on quadratic form proposed by Cook (1979), measuring distance between regression coefficients estimated with and without possibly influential observations. In the following, each time series shown in Fig. 2 will be fragmented. Whereas the last two fragments to the left and right of March 2013, marking the enforcement of EUTR, will be analysed in detail later, all earlier subseries have only been examined with regard to possible trends by fitting linear or quadratic equations, which was considered sufficient for trend description. Finally, the segments of these time series were detrended and investigated in the frequency domain to find indications for possible periods.

Time series A: all wood products

Time series A, covering imports of all EUTR products, consists of four segments of different lengths (Table 3). Regressed on months, the imports show linear or quadratic trends with R^2 ranging between 0.082 and 0.810. Assuming the adequateness of linear and quadratic trends for the segments analysed, there are positive linear trends with significant $\hat{\beta}_1$ and concave parabolic trends with approximate confidence intervals for estimates. The only exception is the lack of any trend in the period Jan 1994 and Dec 1995.

Table 3: Segmented time series A from Fig. 2: parameters of the linear/parabolic equations fitting trend of imports

No.	Time	N	Trend: $Imports = \beta_0 + \beta_1 t$ $Imports = \beta_0 + \beta_1 t + \beta_2 t^2$ Parameter	Estimate	95 % CI	P-value	R^2	Monthly periods
1	1/ 1988 –12/1993	72	$\hat{\beta}_0$	1.3547	(1.2679, 1.4416)	< 0.0001	0.157	2, 12
			$\hat{\beta}_1$	0.0089	(0.0035, 0.0144)	0.0021		
			$\hat{\beta}_2$	-0.0001	(-0.0002, -0.0001)	0.0008		
2	1/1994 – 12/1995	24	$\hat{\beta}_0$	1.0241	(0.0712, 1.9770)	0.0468	0.082	12
			$\hat{\beta}_1$	0.0080	(-0.0032, 0.0193)	0.1757		
3	1/1996 – 11/2001	71	$\hat{\beta}_0$	-0.6677	(-1.1265, -0.2089)	0.0057	0.810	4, 12
			$\hat{\beta}_1$	0.0300	(0.0266, 0.0335)	< 0.0001		
4	12/2001 – 8/2009	93	$\hat{\beta}_0$	-23.8936	(-29.4694, -18.3178)	< 0.0001	0.539	12
			$\hat{\beta}_1$	0.2707	(0.2180, 0.3234)	< 0.0001		
			$\hat{\beta}_2$	-0.0006	(-0.0008, -0.0005)	< 0.0001		

Source: own analyses

Time series B: only non-tropical wood products

The time series of non-tropical wood products covered by EUTR was subdivided into six segments excluding the last two intended for comprehensive analyses (Table 4). A pronounced linear trend can be observed out of these six segments between Jan 1996 and Nov 1999. The monthly imports tend to decrease in 1995. The trend of imports from Aug 1993 to Dec 1994, smoothed by parabola with its maximum at t = 0.6215/0.008 = 77.69, corresponds well with the highest import recorded at t = 78, i.e., in Jun 1994.

Table 4: Segmented time series B: parameters of the linear/parabolic equations fitting trend of imports with non-tropical wood products

No.	Time	N	Trend: $Imports = \beta_0 + \beta_1 t$ $Imports = \beta_0 + \beta_1 t + \beta_2 t^2$ Parameter	Estimate	95 % CI	P-value	R^2	Monthly periods
1	1/ 1988 –7/1993	67	$\hat{\beta}_0$	1.1811	(1.1024, 1.2597)	< 0.0001	0.108	12
			$\hat{\beta}_1$	0.0076	(0.0022, 0.0129)	0.0071		
			$\hat{\beta}_2$	-0.0001	(-0.0002, -0.0001)	0.0082		
2	8/1993 – 12/1994	17	$\hat{\beta}_0$	-22.7347	(-34.2330, -11.2363)	0.0017	0.643	2
			$\hat{\beta}_1$	0.6215	(0.3180, 0.9249)	0.0013		
			$\hat{\beta}_2$	-0.0040	(-0.0060, -0.0020)	0.0015		
3	1/1995 – 12/1995	12	$\hat{\beta}_0$	4.1399	(1.9457, 6.3342)	0.0041	0.351	2
			$\hat{\beta}_1$	-0.0288	(-0.0530, -0.0046)	0.0422		
4	1/1996 – 11/1999	47	$\hat{\beta}_0$	-0.2146	(-0.6698, 0.2406)	0.3604	0.760	3, 12
			$\hat{\beta}_1$	0.0229	(0.0192, 0.0267)	< 0.0001		
5	12/1999 - 11/2005	72	$\hat{\beta}_0$	1.5758	(0.9240, 2.2275)	< 0.0001	0.389	6, 12
			$\hat{\beta}_1$	0.0123	(0.0087, 0.0159)	< 0.0001		
6	12/2005 – 1/2009	38	$\hat{\beta}_0$	-89.9070	(-141.6000, -38.2140)	0.0017	0.539	12
			$\hat{\beta}_1$	0.8268	(0.3852, 1.2683)	0.0008		
			$\hat{\beta}_2$	-0.0018	(-0.0028, -0.0009)	0.0006		

Source: own analyses

Time series C: only tropical wood products

The development of only tropical wood products looks comparatively simple. The first segment of its time series (Jan 1988 to Dec 1995) shows a moderate linear trend of imports (Table 5). In the subsequent 144 months, corresponding with the period Jan 1996 to Dec 2007, the imports of tropical wood products increased by 0.0023. In the next 23 months the imports went down by factor 0.0154. In both cases the factors can be assumed to be significant and the percentage of long term variation explained by linear equation is relatively high.

Table 5 Segmented time series C from Fig. 2: parameters of the linear equations fitting trend of imports with tropical wood products

No.	Time	N	Trend: $Imports = \beta_0 + \beta_1 t$					Monthly periods
			Parameter	Estimate	95 % CL	P-value	R^2	
1	1/ 1988 –12/1995	96	$\hat{\beta}_0$	0.1660	(0.1510, 0.1810)	< 0.0001	0.207	2
			$\hat{\beta}_1$	0.0007	(0.0004, 0.0009)	< 0.0001		
2	1/1996 – 12/2007	144	$\hat{\beta}_0$	0.0901	(0.0418, 0.1384)	0.0004	0.657	2
			$\hat{\beta}_1$	0.0023	(0.0021, 0.0026)	< 0.0001		
3	1/2008 – 11/2009	23	$\hat{\beta}_0$	4.1800	(3.3029, 5.0571)	< 0.0001	0.774	2
			$\hat{\beta}_1$	- 0.0154	(-0.0190, -0.0118)	< 0.0001		

Source: own analyses

As showed in the last columns of the above three tables, the imports often appear to undergo bimonthly or yearly cycles. Based only on periodogram and not tested, these and other periods are only tentative, i.e., they cannot be considered as being inherent in the examined subseries.

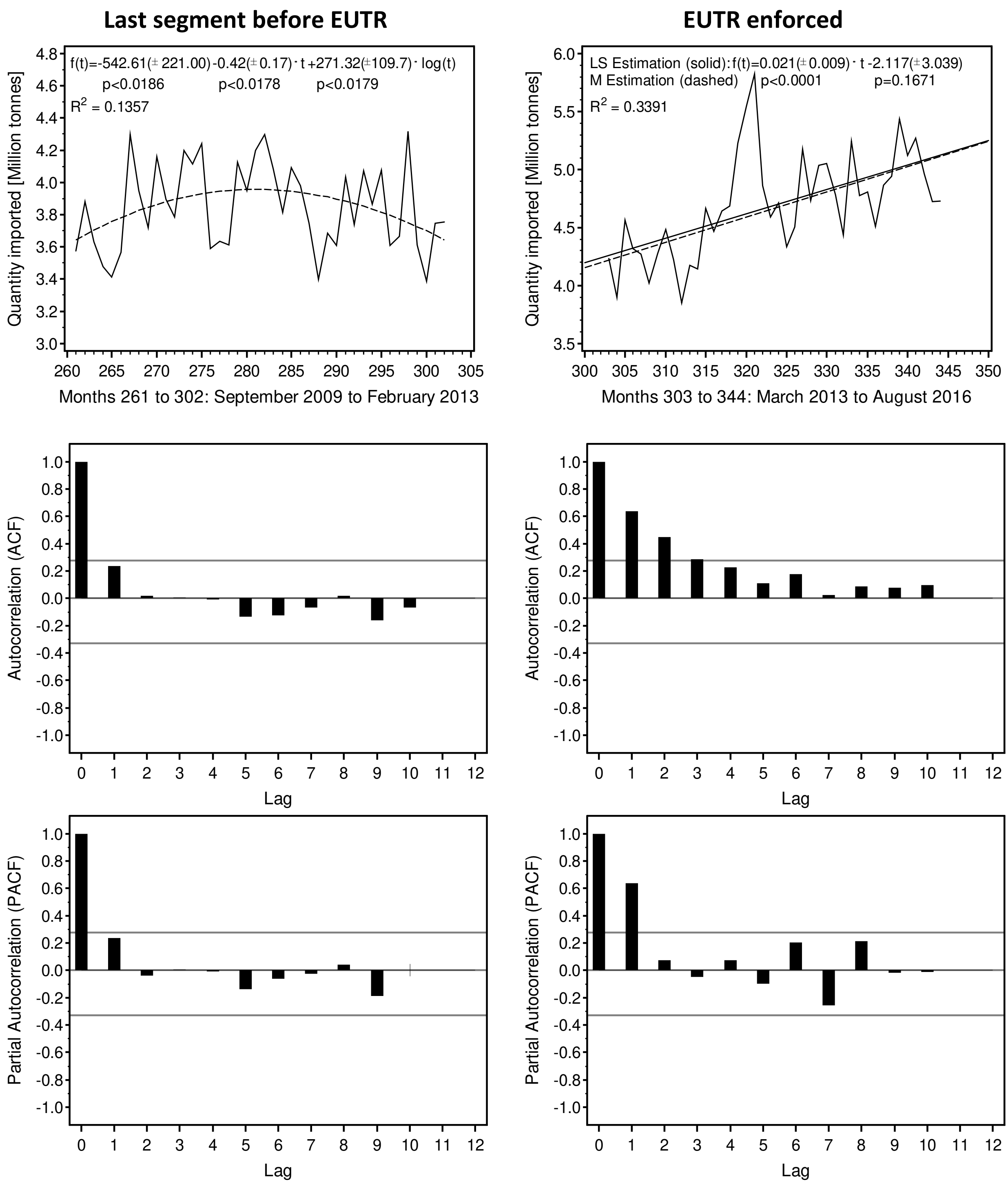
4.2 In-depth analyses of imports before and after EUTR enforcement

Pursuing the objective of this paper, the focus of the following analyses will be on a comparison between the sections of the time series before and after enforcement of EUTR. Separate analyses will be carried out for the time series A, B and C as shown in Fig. 2. To verify the hypothesis that the enforcement of EUTR in March 2013 may have affected the subsequent timber trade, the general question is whether the segments of the time series before and after EUTR differ.

Time series A: all wood products

Fig. 3 displays the last two segments of the time series plotted in time domain. The plots on the right-hand side, that show the last section of the time series after enforcing EUTR, display striking high import values with the appearance of outliers. Traced back, the peak in month number 321 (September 2014) can be attributed to extraordinary high imports of EUTR products from Russia declared by the Netherlands, and increased imports by Germany from Norway. In this connection the study by McDermott and Sotirov (2018) with detailed analyses of implementation and impact of EUTR in EU member states should be mentioned. The robust regression developed by Huber (1973) (implemented in ROBUSTREG Procedure of SAS) was applied to keep down the influence of this peak for trend estimates. The robust M estimation based on maximum likelihood yields a regression line lying below that derived from the least squares (LS).

Figure 3: EU imports of all EUTR wood products (time series A) showing two penultimate segments of the whole time series with their ACF and PACF (standard error of estimates in parenthesis)



Source: own illustrations

The trend between September 2009 and February 2013 can be described by a parabola. The regression coefficient with t^2 indicates statistical significance, but only slight causing a flat shape of the parabola. When EUTR came into force in March 2013 the imports follow a linear positive trend. Despite the different trends before and after enforcement of EUTR, the conclusion that this fact may be connected with EUTR impacts on imports can hardly be justified. But this does not mean that both time series are indeed the same, and nothing happened to the imports from March 2013 on, with EUTR in force. In pursuance of this question, the time series will be investigated as realizations of stochastic processes by examining the Autocorrelation and Partial Autocorrelation Functions. Based on the structure of ACF and PACF, models defined in Appendix B were fitted and their adequateness examined. The first step in choosing the suitable model follows the method discussed by Box and Jenkins (1976). The core of the identification technique is the visual inspection of ACF and PACF. As evident from Fig. 3, the ACF and PACF for the last segment before EUTR cuts off at τ = 1, suggesting AR(1), i.e., an autoregressive model of order p = 1. To introduce the criteria to decide which model fits better a given time series, the model of order p = 2 will be considered as well. For p = 2 the Yule-Walker estimates given in Appendix B by the formula B-10 and B-11 are

$$\begin{pmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{pmatrix} \cdot \begin{pmatrix} \varphi_1 \\ \varphi_2 \end{pmatrix} = \begin{pmatrix} \rho_1 \\ \rho_2 \end{pmatrix} = \begin{pmatrix} 1 & 0.23548 \\ 0.23548 & 1 \end{pmatrix} \cdot \begin{pmatrix} \varphi_1 \\ \varphi_2 \end{pmatrix} = \begin{pmatrix} 0.23548 \\ 0.01998 \end{pmatrix}$$

$$\widehat{\boldsymbol{\varphi}} = \widehat{\mathbf{P}}_2^{-1} \widehat{\boldsymbol{\rho}}_2 = \begin{pmatrix} +1.05871 & -0.24930 \\ -0.24930 & +1.05871 \end{pmatrix} \cdot \begin{pmatrix} 0.23548 \\ 0.01998 \end{pmatrix} = \begin{pmatrix} +0.24432 \\ -0.03755 \end{pmatrix}$$

For AR(1) model the $\varphi_1$estimate is 0.2443. According to the formula B-13 in Appendix B the variance-covariance matrix of the estimates is

$$\frac{1}{N[1 - (\hat{\rho}_1 \widehat{\varphi}_1 + \hat{\rho}_2 \widehat{\varphi}_2)]} \cdot \widehat{\mathbf{P}}_{\boldsymbol{p}}^{\mathbf{-1}} = \frac{1}{42\left[1 - \begin{pmatrix} 0.23548 \\ 0.01998 \end{pmatrix} \cdot \begin{pmatrix} +0.24432 \\ -0.03755 \end{pmatrix}\right]} \cdot \begin{pmatrix} +1.05871 & -0.24930 \\ -0.24930 & +1.05871 \end{pmatrix} =$$

$$= \begin{pmatrix} 0.017850 & 0.019490 \\ 0.019490 & 0.019238 \end{pmatrix}$$

From its diagonal elements the 95 % confidence intervals of the estimates are calculated as

$$\widehat{\boldsymbol{\varphi}}_1 = +0.24432 \pm 1.96\sqrt{0.017850} = (-0.01754, +0.50618)$$
$$\widehat{\boldsymbol{\varphi}}_2 = -0.03755 \pm 1.96\sqrt{0.019238} = (-0.30940, +0.23430)$$

Surprisingly, Yule-Walker estimates for both AR(1) and AR(2) include null, which indicates that an autoregressive model chosen by the inspection of ACF and PACF does not describe this time series in an adequate way. The ARIMA SAS procedure (SAS/ETS 9.2 2008) was used for a more detailed check and comparison of both autoregressive models with p=1 and p=2. The Maximum Likelihood (ML) was chosen as estimation method. This method maximizes the logarithm of the likelihood function $L(\boldsymbol{\varphi}, \boldsymbol{\sigma^2})$ by taking the partial derivatives of $\boldsymbol{\varphi}, \boldsymbol{\sigma^2}$ and setting them to zero (details in Brockwell and Davis 2006, p. 256-257). The autoregressive models A(p) with p = 1 and p = 2 are, in accordance with B-4.

$$X_t = \alpha + \varphi_1 X_{t-1} + \varepsilon_t = \alpha + \varphi(B)X + \varepsilon_t$$

$$\alpha = \mu(1 - \varphi_1) = \varphi(B)\mu \tag{13}$$

$$X_t = \alpha + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \varepsilon_t = \alpha + \varphi(B)X + \varepsilon_t$$
$$\alpha = \mu(1 - \varphi_1 - \varphi_2) = \varphi(B)\mu.$$

The model parameters for the time series section before enforcement of EUTR (Fig. 3, left panel) are reported in Table 6.

Table 6: Parameter of AR(1) and AR(2) models from September 2009 to February 2013 before enforcement of the EUTR (in parentheses 95 % CI)

Parameter	Model AR(1)	Model AR(2)
Back shift operator	$1 - 0.2368B^1$	$1 - 0.2463B^1 + 0.0386B^2$
Estimated mean μ	3.8444 (3.7404, 3.9484)	3.8449 (3.7433, 3.9465)
AR(1) estimate	0.2368 (-0.0641, 0.5377)	0.2463 (-0.0676, 0.5602)
AR(2) estimate	-	-0.0386 (-0.3528, 0.2756)
P-values	μ :< 0.0001, AR(1): 0.1229	μ:< 0.0001, AR(1): 0.1241, AR(2): 0.8099
Constant estimate α	2.9340	3.0460
Number of parameters k	2	3
Length of the time series N	42	42
Q_6: white noise time series	4.19	4.19
P-value: time series	0.6516	0.6516
Q_6: white noise residuals	1.20	1.11
P-value: residuals	0.9449	0.8927
Likelihood function L	0.0641	0.0662
AIC(k)	9.4930	11.4297
SBC(k)	12.9683	16.6427

Source: own analyses

The model parameters estimated by Maximum Likelihood (ML) with the procedure ARIMA of SAS are similar to the Yule-Walker estimates obtained above. They confirm that the time series depicted in the left panel in Fig. 3 does not follow the autoregressive models. This conclusion is substantiated by formal tests compiled in Table 6. One of these tests is based on the statistic

$$Q_M = N(N+2)\sum_{\tau=1}^{M}\frac{\hat{\rho}^2(\tau)}{(N-\tau)} \tag{14}$$

derived by Ljung and Box (1978). For $N \to +\infty$ the above statistic follows the $\chi^2_{1-\alpha}(M)$ distribution. The null hypothesis, stating that the time series is a white noise process, is rejected at level α if

$$Q_M > \chi^2_{1-\alpha}(M) \tag{15}$$

In terms of the statistic and its probability given by the formulas (14) and (15) the Q_M calculated for the first six lags is less than $\chi^2_{0.95}(6) = 12.6$ which may speak for uncorrelated time series. The corresponding P-value of 0.6516 indicates that this statement is very probable. For these reasons this time series does not need to be detrended or differenced, i.e., it can be considered as stationary despite the weak parabolic trend. The AR(1) model, even though not significant, produces white noise residuals at a probability of about 94 %. All the P-values given in Table 6 are direct output of the ARIMA procedure, of SAS but they can also be obtained with the SAS probability function[1]. In Table 6 two information criteria are included to judge the competing models AR(1) and A(2):

Akaike's information criterion (Akaike 1981)

$$AIC(k=2) = ln\left[\left(\frac{1}{L}\right)^2\right] + 2k = ln\left[\left(\frac{1}{e^{-2.7465}}\right)^2\right] + 2\cdot 2 = 2\cdot 2.7465 + 4 = 9.4930$$
$$AIC(k=3) = ln\left[\left(\frac{1}{L}\right)^2\right] + 2k = ln\left[\left(\frac{1}{e^{-2.7149}}\right)^2\right] + 2\cdot 3 = 2\cdot 2.7149 + 6 = 11.4298$$

Schwarz's Bayesian criterion (Schwarz 1978)

$$SBC(k=2) = ln\left(\frac{N^k}{L^2}\right) = ln\left(\frac{42^2}{e^{-2\cdot 7465\cdot 2}}\right) = 2\cdot \ln(42) + 2\cdot 2.7465 = 12.9683$$
$$SBC(k=3) = ln\left(\frac{N^k}{L^2}\right) = ln\left(\frac{42^3}{e^{-2.7149\cdot 2}}\right) = 3\cdot \ln(42) + 2\cdot 2.7149 = 16.6428$$

Both information criteria depend on the maximized likelihood function L for the estimates and their number k. Thus, models with lower values of the above criteria should be preferred. Moreover, the mathematical relationship between L and k in AIC and SBC reflects a trade-off between maximized L and the principle of the simplicity and parsimony of the competing models, i.e., the preference of models with few parameter. Taking account of this and supposing the significance of the models presented in Table 6, one would be inclined to see the model A(1) surpassing A(2).

The equation of the autoregressive model AR(1) follows from (13) and Table 6 is

$$X_t = 3.8444(1 - 0.2368) + 0.2368X_{t-1}$$
$$X_t = 2.9340 + 0.2368X_{t-1} \quad (16)$$

[1] 1 - PROBCHI (x, df): 1 - PROBCHI (4.19, 6) = 0.6510, 1 - PROBCHI (1.20, 5) = 0.9449, 1 - PROBCHI (1.11, 4) = 0.8927

As with imports not subjected to EUTR, the time series covering the time with EUTR already enforced the ACF decays from τ = 1 indicating the appropriateness of the A(1) model (right side of Fig. 3). The only difference to imports before EUTR is the linear trend with a higher coefficient of determination as compared with the time before. This fact reflects the ACF decaying slower than the ACF in the left panel of Fig. 3. As stated above the time series covering all wood products imported after enforcing EUTR shows a linear trend. For this reason, the time series was transformed to a nearly stationary state by subtracting the linear trend from the observed values. The autoregressive model A(1) was fitted based on detrended values. As shown in Table 7, the A(1) can be considered as a suitable description of time series covering imports of all wood products imported after enforcing EUTR. The P-value connected with the Ljung and Box test statistic (14) implies that the linear detrending did not completely lead to a stationary time series. In contrast to that the residuals can be regarded as white noise with no further information, which would suggest that another, more complex model may be advisable. The estimate for AR(2) (not included in Table 7) was nonsignificant and the information criteria (AIC = 28.62, SBC = 33.84) higher than those for AR(1) model.

Table 7: Parameters and statistics of the AR(1) model from March 2013 to August 2016 after EUTR was enforced

Parameter	Estimate/ Statistics	Standard error	95 % CI	P-value
Back shift operator	$1 - 0.4585B^1$	-	-	-
Mean μ	-0.0075	0.09021	(-0.1843, 0.1693)	0.9333
AR(1)	0.4585	0.14194	(0.1803, 0.7367)	0.0012
Constant α	-0.0041	-	-	-
Number of parameters k	2	-	-	-
Time series length N	42	-	-	-
Q_6: time series	13.70	-	-	0.0331
Q_6: residuals	6.94	-	-	0.2248
Likelihood function ln(L)	-11.3153	-	-	-
AIC(k)	26.6307	-	-	-
SBC(k)	30.1060	-	-	-

Source: own analyses

The equation based on the estimates of Table 7 is

$$\begin{aligned} X_t &= -0.0075(1 - 0.4585) + 0.4585X_{t-1} \\ X_t &= -0.0041 + 0.4585X_{t-1} \end{aligned} \tag{17}$$

March 2013, when EUTR came into effect, can be thought of as an intervening event, and although the separate analyses performed did not (so far) show any effect, it is worth considering both time series together, i.e., from September 2009 to August 2016, by fitting an intervention model. As the EUTR and its influence can be assumed as persisting from March 2013 on, a continuing intervention model may be the right one to capture the effect of EUTR. Prestemon (2009) employed the intervention analysis to investigate the impact of legally regulated chemical wood treatment on timber prices. A general approach of the intervention models is given by Harvey (1998). The simplest model accounting for continuing intervention is based on an additional variable that flags the time series with the value 0 before the intervening event, and afterwards with 1.

Table 8: Parameters and statistics of intervention model covering the time series in Fig. 3 from September 2009 to August 2016

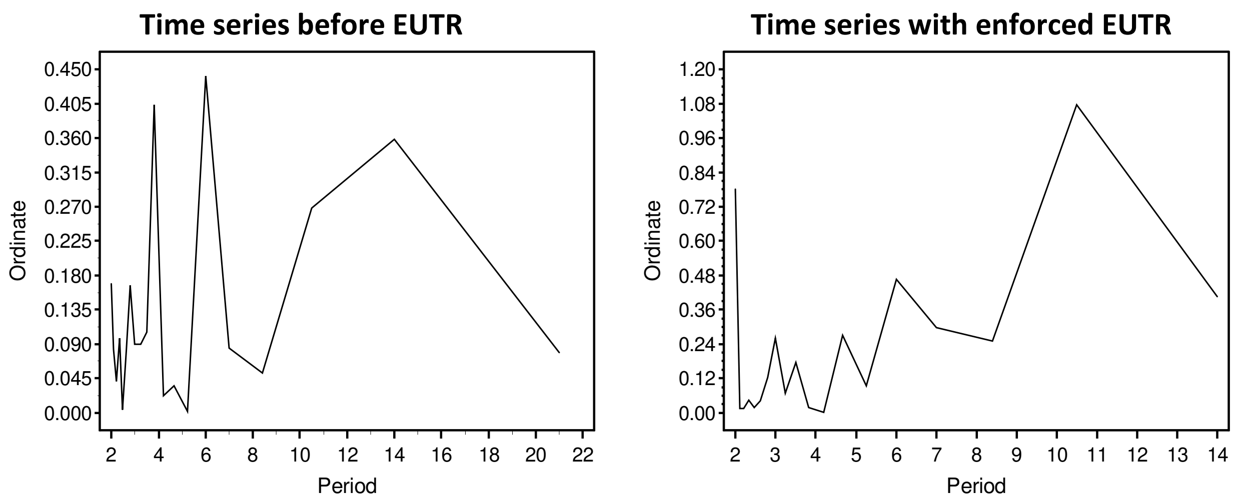
Parameter	Estimate/ Statistics	Standard error	95 % CL	P-value
Back shift operator	$1 - 0.5317B^1$	-	-	-
Mean μ	3.8588	0.09857	(3.6656, 4.0520)	< 0.0001
AR(1)	0.5317	0.09355	(0.3483, 0.7151)	< 0.0001
EUTR	0.8164	0.13567	(0.5505, 1.0823)	< 0.0001
Constant α	1.8070	-	-	-
Number of parameters k	3	-	-	-
Time series length N	84	-	-	-
Q_6: time series	1820.87	-	-	< 0.0001
Q_6: residuals	5.36	-	-	0.3739

Source: own analyses

Formally, the narrow 95 % interval estimate for the parameter EUTR in Table 8 indicates that an effect of EUTR on imports for the examined time series cannot be excluded but by no means envisaged in terms of causality. Also significant is the effect of the autoregressive parameter for AR(1). Together with other information presented in Table 8 nothing could argue strongly against the acceptance of this model.

Since the time representation of a time series does not reveal all its aspects, especially possible periodic behaviour, the time series in Fig. 3 were also investigated in frequency domain. These analyses encompassed the inference from the periodogram, excluding spectral analysis, which would have required a theory not available here. The periodograms in Fig. 4 show some different peaks.

Figure 4: Periodogramms of the time series depicted in Fig. 3



Source: own illustrations

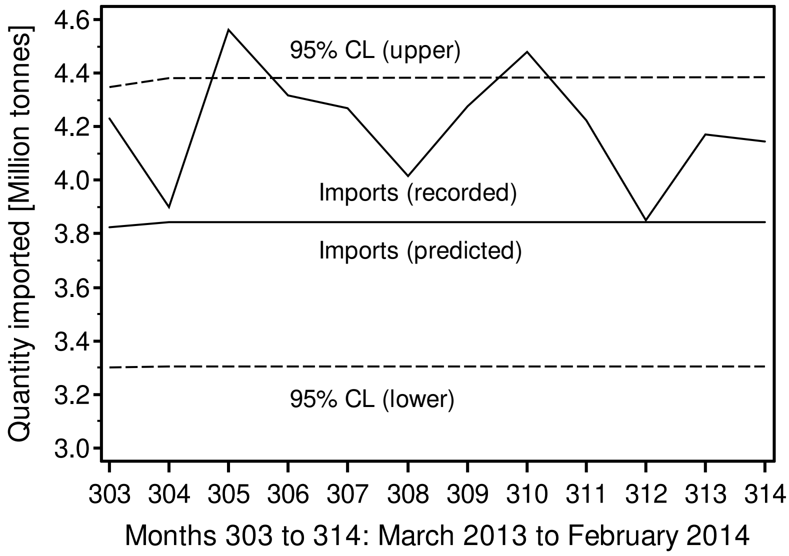
In the periodogram based on the time series before EUTR, a peak can be found at period 6, and the periodogram for the time series after enforcing EUTR shows a high ordinate between 10 and 11 months. As both time series comprise only 42 months, one is reluctant to see these periodicities as being inherent in the development of imports of wood products declared by EU countries. The uncertainty about cycles possibly 'hidden' in time series can be verified by a test based on the following statistic (for variables' meaning see (11) in Chapter 3.2)

$$\xi_M = (M-1) \cdot \max_{1 \le i \le M} I(\lambda_i) \cdot \left[\sum_{i=1}^{M} I(\lambda_i)\right]^{-1} M = \frac{N}{2}\ if\ N\ is\ even, M = \frac{N-1}{2}\ if\ N\ is\ odd \qquad (18)$$

which is the ratio of the largest periodogram ordinate to the sum of all ordinates calculated at the individual frequencies (Brockwell and Davis 2006, p. 339). Fuller (1996) studied the theoretical distribution of this statistic and tabulated the theoretical values of ξ_M for the number M of ordinates between 2 and 1000 for the common significance levels $\alpha = 0.01$, 0.05 and 0.1. Accordingly, if the statistic from (18) is larger than the critical values gained from theoretical distribution of ξ_M the null hypothesis is likely to be rejected. The largest ordinate in the periodogram in the left panel of Fig. 4 is $\lambda = 0.4414$. This corresponds with a frequency of 1.0472 and a cycle of $2\pi/1.0472 \approx 6$ months. The time series with imports subjected to EUTR indicates a marked period of about $2\pi/0.5984 \approx 10.5$ months. The values of the statistic (18) are $\xi_{21} = 3.0613$ and $\xi_{21} = 4.3539$ respectively. As these statistics do not exceed the corresponding quantile 6.666 for the ξ_m distribution at P = 0.01 (Fuller 1996, p. 364) it is unlikely that the cycles indicated in periodograms of Fig. 4 really exist. Together with the similarity of the periodograms and no statistical evidence for periodicities the only conclusion is that the enforcement of EUTR did not produce cyclic signals in import time series, nor did it destroy or disturb the existing signals.

Leaving the frequency domain, it is worth examining whether the enforcement of EUTR in March 2013 can be regarded as a turning point in terms of the quantities imported. To answer this question the model AR(1), with parameters summarized in Table 6, was employed to predict the imports 12 months ahead of the time period with EUTR already in effect. As shown in Fig. 5, the predicted imports lie below the recorded imports, giving rise to the conclusion that the imports experienced an increase from March 2013 onwards.

Figure 5: Actual imports of all wood products after EUTR compared with imports predicted by AR(1) model based on imports comprising 42 previous months (September 2009 to February 2013)

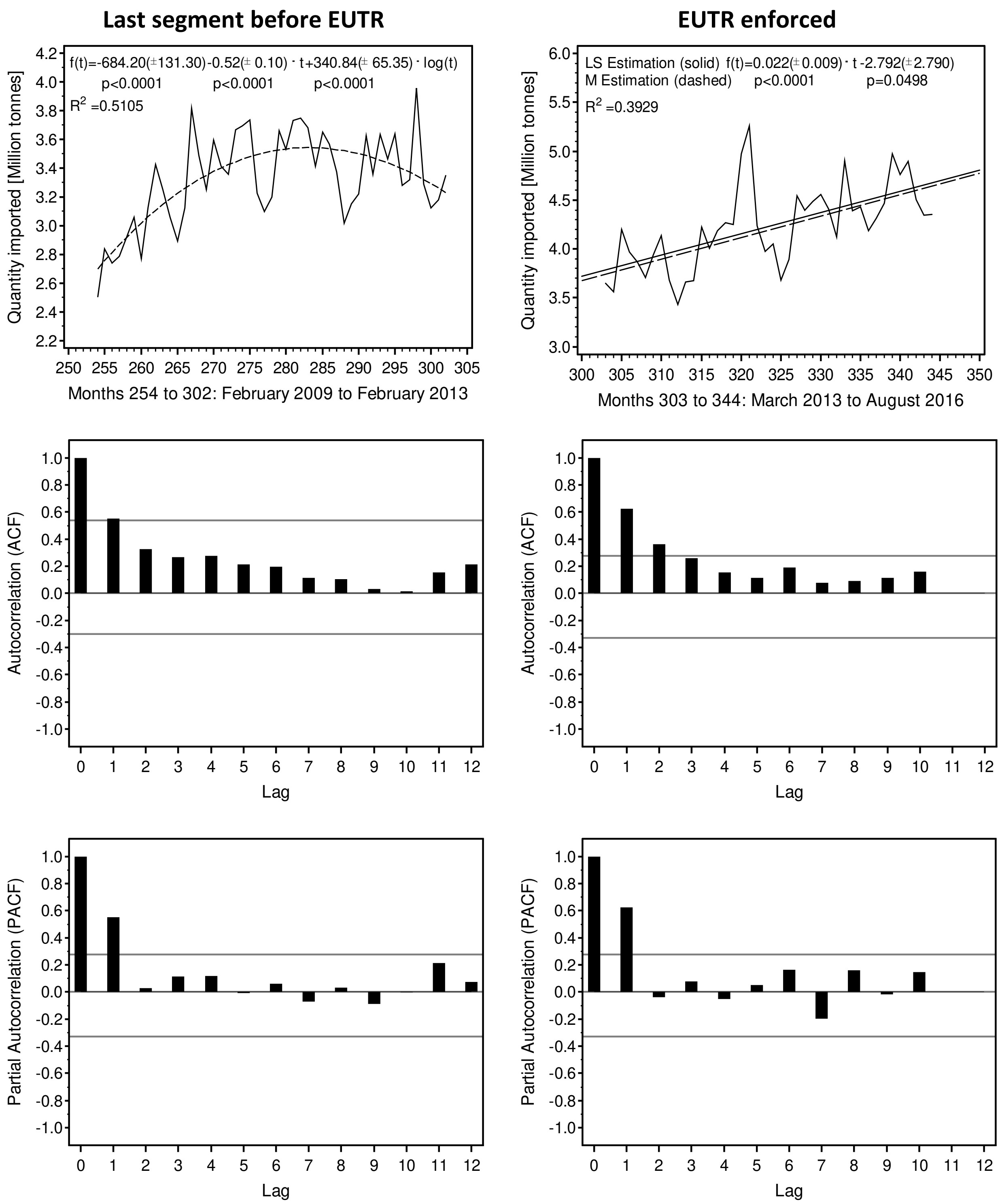


Source: own illustrations

Time series B: only non-tropical wood products

The time series presented in Fig. 6 comprises imports of non-tropical wood products. As the EUTR covers most wood products, the time series shown in Fig. 6 does not differ much from the time series encompassing all EUTR imports (Fig. 3). However, a closer look at the first plot in Fig. 6 reveals a more pronounced trend that could be smoothed by addition of linear and logarithmic term. This manifests itself with a higher coefficient of determination explaining about 51 % of long term variation compared with only 13 % explained by the parabola in Fig. 3. Consequently, the ACF and PACF decay more slowly in Fig. 6 than graphs depicted in Fig. 3. Apart from these differences, the autocorrelation functions showed in both figures cut off at $\tau = 1$, which justifies the autoregressive A(1) model.

Figure 6: EU imports of non-tropical wood products (time series B) showing two penultimate segments of the whole time series with their ACF and PACF (standard error of estimates in parenthesis)



Source: own illustrations

Statistics summarized in Table 9 confirm the appropriateness of AR(1) for the time series shown in the left panel of Fig. 6. In particular, the probability that the data could follow a white noise process is very small and the high probability connected with the statistic Q_6 for residuals indicates that the AR(1) model captures the most information contained in this time series.

Table 9: Parameters and statistics of AR(1) model from February 2009 to February 2013 for EU imports of non-tropical wood products

Parameter	**Estimate/ Statistics**	**Standard error**	**95 % CI**	**P-value**
Back shift operator	$1 - 0.62412B^1$	-	-	-
Mean μ	3.30104	0.09596	(3.1130, 3.4891)	< 0.0001
AR(1)	0.62412	0.11200	(0.4046, 0.8436)	< 0.0001
Constant α	1.2408	-	-	-
Number of parameters k	2	-	-	-
Time series length N	49	-	-	-
Q_6: time series	34.62	-	-	< 0.0001
Q_6: residuals	2.40	-	-	0.7921
Likelihood function ln(L)	-3.1848	-	-	-
AIC(k)	10.3695	-	-	-
SBC(k)	14.1532	-	-	-

Source: own analyses

As evident from Fig. 6 after enforcement of EUTR the imports of non-tropical wood products show a linear trend resembling the development of all imports depicted in Fig. 3. The pattern of ACF and PACF of the time series with EUTR enforcement are similar to previous ACF and PACF (Fig. 6) so that the AR(1) appears to be appropriate, and it can be concluded that in terms of autocorrelation, the structure of the time series before and after EUTR do not differ. This finding gained from visual check of autocorrelations confirms the statistics presented in Table 9.

Table 10: Parameters and statistics of the AR(1) model from March 2013 to August 2016 after EUTR was enforced

Parameter	Estimate/ Statistics	Standard error	95 % CI	P-value
Back shift operator	$1 - 0.63771B^1$	-	-	-
Mean μ	4.20917	0.13469	(3.9452, 4.4732)	< 0.0001
AR(1)	0.63771	0.11942	(0.4036, 0.8718)	< 0.0001
Constant α	1.52494	-	-	-
Number of parameters k	2	-	-	-
Time series length N	42	-	-	-
Q_6: time series	30.49	-	-	< 0.0001
Q_6: residuals	4.46	-	-	0.4859
Likelihood function ln(L)	-12.4186	-	-	-
AIC(k)	28.8372	-	-	-
SBC(k)	32.3125	-	-	-

Source: own analyses

Moreover, when comparing the time series before and after EUTR, the notable finding is that the estimates for AR(1) 0.6241 and 0.6377 in Tables 9 and 10 lie within the 95 % confidence limits of

both models, confirming once again that EUTR had no impact on the autocorrelation structure of imports covering non tropical woods.
Whilst the autocorrelation structure expressed by ACF, PACF and confirmed by model parameters given in Tables 9 and 10 must be assumed the same, the influence of the dummy variable EUTR = 0/1, marking EUTR enforcement, is significant (Table 11).

Table 11: Parameters and statistics of intervention model covering the time series in Fig. 6 from February 2009 to August 2016

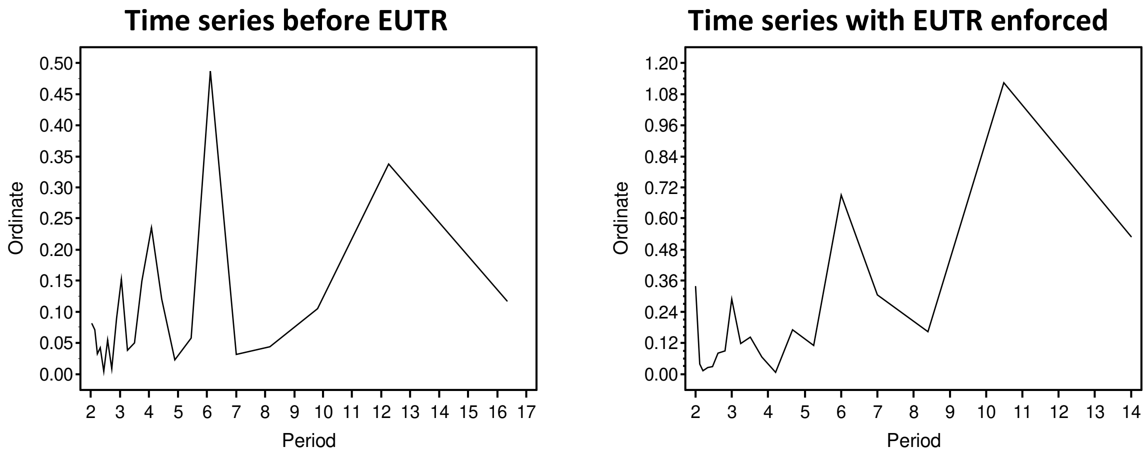
Parameter	Estimate/ Statistics	Standard error	95 % CI	P-value
Back shift operator	$1 - 0.62844$	-	-	-
Mean μ	3.34642	0.10806	(3.1346, 3.5582)	< 0.0001
AR(1)	0.62844	0.08280	(0.4661, 0.7907)	< 0.0001
EUTR	0.83009	0.15158	(0.5330, 1.1272)	< 0.0001
Constant α	1.24339	-	-	-
Number of parameters k	3	-	-	-
Time series length N	91	-	-	-
Q_6: time series	1803.83	-	-	< 0.0001
Q_6: residuals	4.13	-	-	0.5308

Source: own analyses

The significance of EUTR in connection with non-overlapping confidence intervals for μ included in Tables 10 and 11 justify the conclusion that EUTR can be considered as an (continuing) 'intervention' event. It caused an elevated level of imports from March 2013 onwards.

As in case of all imports the analysis of the time series before and after enforcement of EUTR in frequency domain does not reveal differences. The periodograms presented in Fig. 7 show peaks around periods 6 and 12 months, which may imply half-yearly and yearly cycles of imports.

Figure 7: Periodogramms of the time series showed in Fig. 6

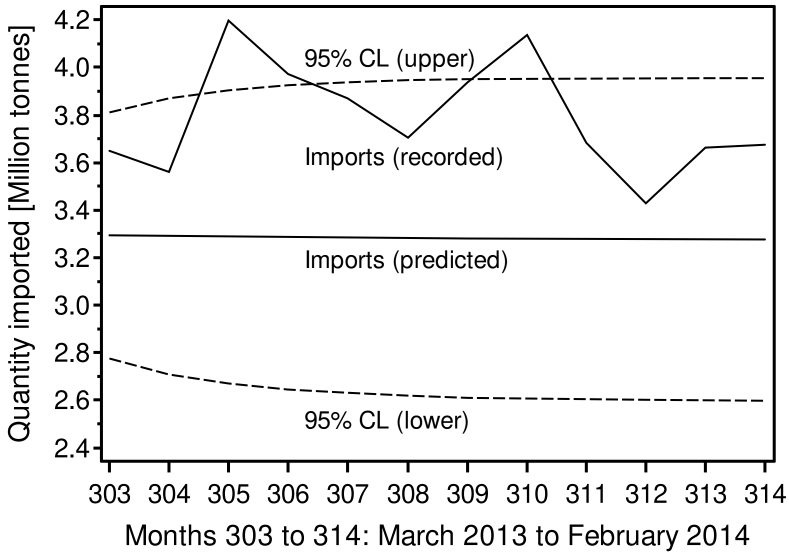


Source: own illustrations

Although such cycles appear plausible, caution must be exercised in particular when interpreting periodograms because the peaks are not significant when formally tested. The highest peak of the periodogram on the left-hand side of Fig. 7 corresponding with a period of 6 months is based on 49 months which yields $\xi_{24} = 4.7740$ from test statistic (18). For the time series with EUTR enforced, the largest ordinate of the periodogram is at period 10.5 months producing $\xi_{20} = 5.2003$. In both cases these statistics lie below the percentage points of 6.883 (M = 24) and 6.594 (M = 20) from theoretical distribution given by Fuller (1996, p. 364).

As no differences were found in AR(1) based on time series before and after EUTR, the autoregressive model derived from the import data between February 2009 and February 2013 is used to predict the imports of non-tropical woods 12 months forward.

Figure 8: Actual imports of non-tropical wood products after EUTR compared with imports predicted by AR(1) model based on imports comprising 49 months (February 2009 to February 2013)



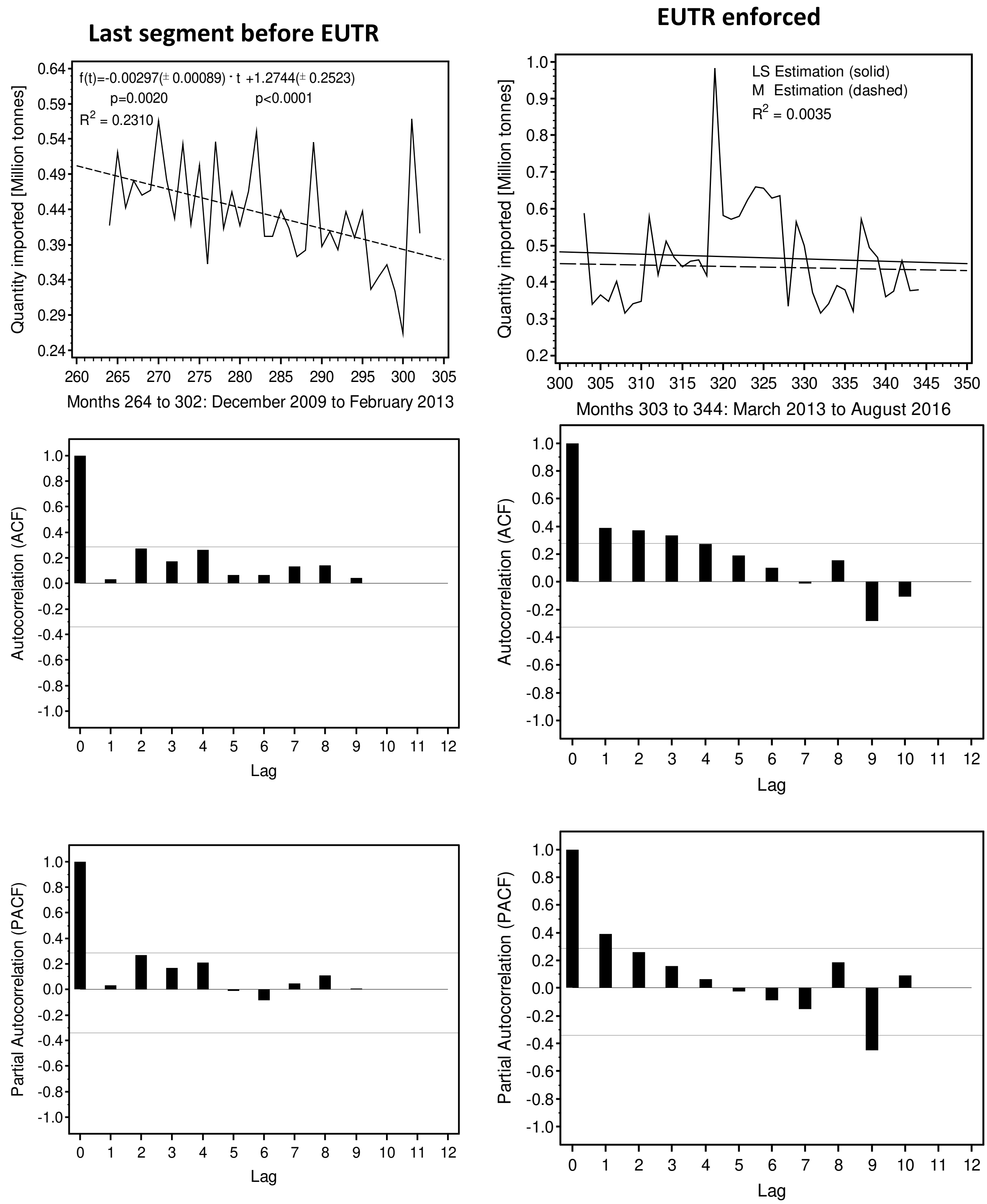
Source: own illustrations

From the analyses performed so far, the AR(1) model derived from the time series before EUTR came into effect is likely to fail if used for predicting the import values for months with EUTR in effect. As with all wood products (Fig. 5) the actual imports of non-tropical woods lie over the predicted quantities (Fig. 8).

Time series C: only tropical wood products

In contrast to all imports and imports with non-tropical wood products, the trend of tropical wood products imported by EU countries fell linearly between December 2009 and February 2013. The ACF and PACF cut off at τ = 1 and went up afterwards (Fig. 9). This is quite different from ACF and PACF patterns of imports covering all wood products or products with tropical woods excluded, for which AR(1) models appeared to be adequate (Fig. 3 and 6).

Figure 9: EU imports of tropical wood products showing two penultimate segments of the whole time series with their ACF and PACF



Source: own illustrations

The AR(1) model employed to fit imports of tropical wood products resulted in an insignificant autoregressive estimate of 0.03124, with the 85 % probability of being zero. Instead, the ARMA(1, 1) model (see B-16 and B-17 in Appendix B) proved to be appropriate for describing the imports of tropical wood products before EUTR went into effect.

Table 12: Parameters and statistics of ARMA (1, 1) model covering the time series in Fig. 9 from December 2009 to February 2013

Parameter	Estimate/ Statistics	Standard error	95% CI	P-value
AR back shift operator	$1 - 0.92809B^1$	-	-	-
MA back shift operator	$1 - 0.81366B^1$	-	-	-
Mean μ	0.43335	0.03326	(0.3682, 0.4985)	< 0.0001
AR(1)	0.92809	0.22941	(0.4785, 1.3777)	< 0.0001
MA(1)	0.81366	0.33094	(0.1650, 1.4623)	0.0139
Constant α	0.03116	-	-	-
Number of parameters k	3	-	-	-
Time series length N	39	-	-	-
Q_6: time series	8.09	-	-	0.2313
Q_6: residuals	3.24	-	-	0.5186

Source: own analyses

The adequateness of the ARMA(1,1) model confirms the relatively high probability that the residuals are likely to follow a white noise process and the significance of the autoregressive AR(1) and the moving average parameter MA(1) (Table 12). Also relevant is the simplicity of this model since for the description of imports first orders proved to be sufficient for both the autoregressive and moving average factor. The equation of the ARMA(1, 1) model defined in B-17 as $\varphi(B)X_t = \theta(B)\varepsilon_t$ written with parameters presented in Table 12 is

$$(1 - 0.92809B^1) \cdot X_t = (1 - 0.81366B^1) \cdot \varepsilon_t.$$

Adding the constant α, accounting for the back shift factors, and rearranging terms, the above equation gets the formula

$$X_t = 0.03116 + 0.92809 \cdot X_{t-1} + \varepsilon_t - 0.81366 \cdot \varepsilon_{t-1}.$$

A lack of trend is evident from the time series showing imports of tropical wood products by EU after imposing EUTR. The peak in July 2014 (month number 319) was identified as being caused by unusually high imports declared by the Netherlands from Malaysia (Fig. 9).

The ARMA(1, 1) model, found as suitable for fitting data before EUTR, shows the lower boundary of the 95 % CL for MA(1) as being only slightly different from zero, which indicates that the moving average factor for time series with EUTR in effect may be dispensed with (Table 13). Apart from this, the ACF and PACF on the right side of Fig. 9 cut off and decay for time series with EUTR in effect indicating an AR(1) model. In contrast to that the ACF and PACF before EUTR are negligible at τ = 1 becoming visible first for the lags 2, 3 and 4. The differences between AIC and SBC for the competing models (Table 13) are extremely small as if they could be used to decide which of the models is superior. Regarded together, and bearing in mind the principle of simplicity and parsimony, the AR(1) model should be preferred.

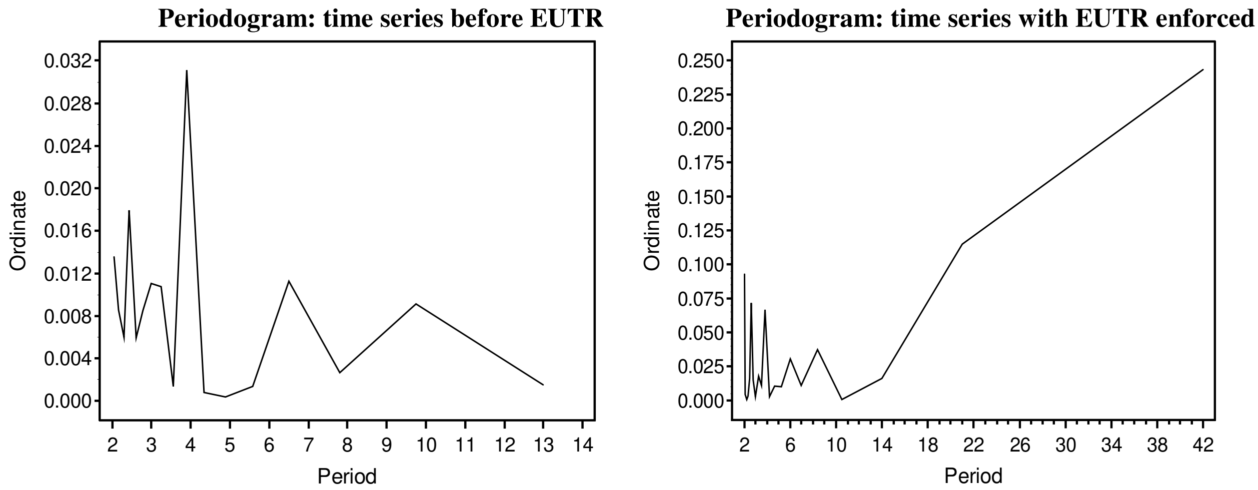
Table 13: Competing AR(1) and ARMA(1, 1) models from March 2013 to August 2016 after enforcement of the EUTR (in parentheses 95 % CI)

Parameter	Model AR(1)	Model ARMA(1, 1)
AR back shift operator	$1 - 0.38972$	$1 - 0.82214B^1$
MA back shift operator	-	$1 - 0.53100B^1$
Estimated mean μ	0.46690 (0.4060, 0.5278)	0.46060 (0.3702, 0.5510)
AR(1) estimate	0.38972 (0.1042, 0.6752)	0.82215 (0.4733, 1.1710)
MA(1) estimate	-	0.53100 (0.0087, 1.0533)
P-values	μ : <.0001, AR(1): 0.0075	μ : < 0.0001, AR(1): < 0.0001, MA(1): 0.0463
Constant estimate α	0.2849	0.0819
Number of parameters k	2	3
Length of the time series N	42	42
Q_6: white noise time series	24.28	24.28
P-value: time series	0.0005	0.0005
Q_6: white noise residuals	4.53	1.02
P-value: residuals	0.4756	0.9068
Likelihood function ln(L)	28.7326	30.4335
AIC(k)	-53.4653	-54.8671
SBC(k)	-49.9899	-49.6541

Source: own analyses

As with the previous time series covering imports of all wood products, and imports with tropical woods excluded, the time series plotted in Fig. 9 were labelled with the additional variable EUTR=0/1. As said above EUTR=0 marks the time series segment before EUTR was enforced and EUTR=1 time series with EUTR in effect. In contrast to the time series in Fig. 3 and 6 there was no statistical evidence (95 % CL for EUTR: [-0.0278, 0.1004]) that EUTR may exert an immediate impact on tropical woods imported by EU countries from March 2013 onwards. The analyses of tropical woods imported by EU countries in frequency domain produced periodograms are shown in Fig. 10.

Figure 10: Periodogramms of the time series showed in Fig. 9



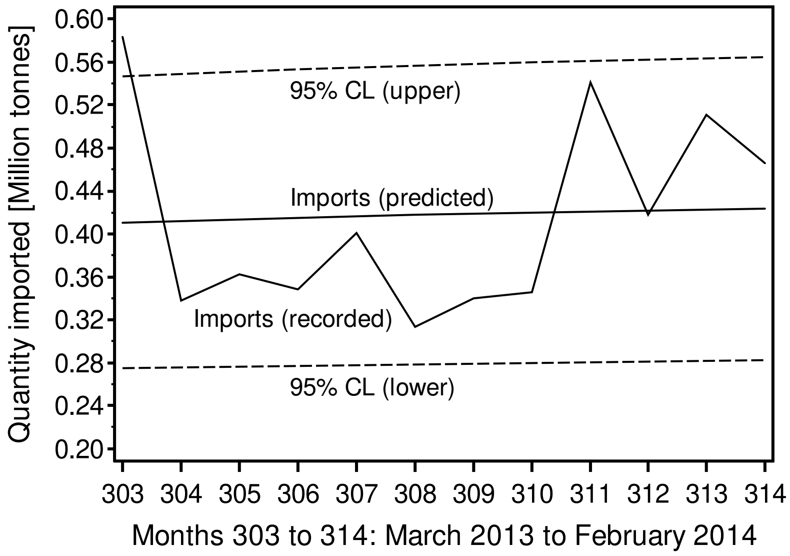
Source: own illustrations

The periodogram based on time series before imposing EUTR is dominated by the period of 4 months which, cautiously interpreted, could mean 4 months periodicity 'hidden' in the development of imports with tropical woods between December 2009 and February 2013. The cycle of 4 month can also be seen when looking at ACF and PACF on the left side of Fig. 9. However, the formal statistical test based on the statistic (18) does not confirm the existence of the 4 month period in imports of tropical woods and wood products: the value $\xi_{20} = 4.072$ calculated from (18) is smaller than 6.883 from theoretical distribution given in Fuller (1996, p. 364).

After enforcing EUTR, the imports stop having a trend. Moreover, in time series plotted in the right panel of Fig. 9, no regular periods can be recognized. This confirms the periodogram with no striking peaks at high frequencies. Practically, it consists only of one wave with a length (period) of 42 months which is the length of the whole time series ranging from March 2013 to August 2016. This 'period' can be regarded as significant since the statistic (18) $\xi_{20} = 7.049$ based on the time series exceeds just the value 6.594 gained from the theoretical distribution (Fuller 1996, p. 364).

In addition to the previous analyses aimed at comparing the imports of tropical wood products and products before and after enforcing EUTR the actual imports for 12 months ranging from March 2013 to February 2014 were compared with the data predicted by ARMA(1, 1) based on import values prior to EUTR (Fig. 11).

Figure 11: Actual imports of tropical wood products after EUTR compared with imports predicted by the AR(1, 1) model based on imports between December 2009 and February 2013



Source: own illustrations

If the predicted and actual data do not differ from each other the conclusion may be allowed that the enforcement of EUTR in March 2013 did not change the quantities of tropical woods imported by EU countries. Obviously, this is the case since imports recorded lie within the bounds marking imports predicted by A(1, 1) (Fig. 11).

5 Discussion and concluding remarks

Deforestation and degradation of forests fostered activities that led to voluntary and legal declarations and agreements aimed at reducing illegal logging and trading with illegally sourced wood products. Since the relationships between countries involved in international trade are complex, i.e., neither absolutely predictable nor completely understood, legal intervention may fail to bring about the changes desired. Moreover, the legal measures taken may cause unintended detrimental side effects or may leave the whole system unchanged. Bearing this in mind, it is important to check whether concrete legislation does show the effects it was designed for. For this reason, many studies have been carried out worldwide trying to assess the impact of legislative measures on the trade of wood products. Among studies on the evaluation of factors influencing timber trade including the impact of legislation the study by Prestemon (2015) is worthy of mention. It investigated the impact of the Lacey Act Amendment of 2008 on wood imports in USA. In general, this study confirms the common trade theory saying that legislative restrictions imposed on imports of illegal sourced wood products would cause a reduced import flow, leading to lowered supply and accordingly increasing prices. A similar study conducted by Luo et al. (2015) examined the question if antidumping duty understood as intervention could impair the international trade. The authors of this study modelled imports regarded as depending on price index and the total expenditure on all imports in a market. The models contained dummy variables denoting countries involved in trade and dummy variables accounting for policy interventions. The results showed that antidumping duty lowers exports from countries with low production costs and force them to enter new markets. In summary, the studies mentioned, especially that of Prestemon (2015), use time series with large numbers of independent variables including metric scaled prices, imports and discrete dummy variables covering the product categories and countries involved in trade. All these variables were put in a complex co-integration intervention model with price and quantity as dependent variables. Although there is no doubt that such models can produce plausible results, the large number of independent variables included (some of them more or less correlated) may cause confounding, hardly interpretable effects.

To prevent European markets from entering wood products from illegal sources the European Union launched in 2003 the Forest Law Enforcement, Governance and Trade (FLEGT) Action Plan. Within FLEGT the EU Timber Regulation (EUTR) came into force in March 2013. Similar to studies mentioned above the impacts of EUTR on trade with wood products have been investigated quantitatively anticipating that the effects of EUTR may have caused reduced imports from producers of wood products to European markets. In this respect the report of Jonsson, Giurca et al. (2015) and the study by Weimar et al. (2015) should be mentioned.

The approach applied and presented in this paper is different. Without rejecting the natural assumption that EUTR (as an intervening legislative measure) could affect trade with wood products in quantitative way, the question pursued here is whether EUTR changed the pattern of time series on imports after it came into effect. The decisive variable is the time that for itself, when taken at discrete points, does not have quantitative character. Thus, the impact of EUTR may have changed the pattern of import time series without affecting the quantities imported. This can be made visible in autocorrelations along a time series, but above all by examining time series in the frequency domain. In comparison to the methods cited above, and problems addressed there, the methods employed here are simple and therefore the danger of confounded results are smaller.

The monthly import time series ranging from January 1988 to August 2016 were found to consist of sections showing different features with respect to stationarity and amplitudes. Some of them were identified as mean stationary and practically flat with small amplitudes. Other plots showed more or less pronounced trends with import values oscillating at high or small amplitudes over trend. These easily observable characteristics supported the assumption that although the origin of the time series is the same, events such as the enlargement of EU by eleven new member states in 2004 may have caused discernible jumps in imports. For these reasons, the time series had to be fragmented and the individual sections investigated separately. For purposes of brevity, detailed analyses were carried out and results reported on only two segments of the time series: the segments before and after the enactment of EUTR. This made it possible to check whether the EUTR, enacted in March 2013 and presumed as intervention event, may have affected the after-time series. The time series before and after the anticipated intervention by EUTR were investigated in the time and frequency domain. To find out whether all wood products respond in the same way to EUTR legislation, the EUROSTAT import data were filtered and separate analyses were conducted for three groups: all wood products, non-tropical wood products and tropical wood products. At the very beginning the long term variation of the time series, before and after EUTR was examined, and in case of a recognizable trend, smoothed by linear or linear logarithmic equation. The trend of imports prior to EUTR for all wood products and imports with non-tropical wood products showed trends with linear and logarithmic terms. The imports of tropical wood products indicated a negative linear trend before the EUTR came into effect in March 2013. Linear positive trends could be observed for all wood products and those with non-tropical wood products in the time series from March 2013 onwards. In contrast, the amount of wood products imported by the EU from countries producing tropical timber remained constant, generating practically stationary time series. Despite some reservations about data reliability, possible influential outliers or model shortcomings, it can be concluded that the imports, after the enforcement of EUTR, experienced a linear increase, or in case of tropical wood products, stagnation after a previous falling trend. The visual inspection of the time series, their autocorrelation and partial autocorrelation functions before and after EUTR as an intervention event, indicated the appropriateness of AR(1), i.e., an autoregressive model of first order.

The ARMA(1, 1) process, adequate for imports of tropical wood products before EUTR, did not describe these imports under EUTR (from March 2013 to August 2016) in a proper manner. For this time period the AR(1) model was found to be suitable. Although under the EUTR the autocorrelation structure of the time series remained unchanged, leading (with exception of tropical wood products) to the same kinds of models, their parameters before and after EUTR are different. This is evident from no overlapping confidence limits for model estimates before and after EUTR. In fact, the AR(1) models based on time series prior to EUTR failed to forecast the imports of wood products after March 2013. The AR(1) model based on time series before EUTR, underestimated the actual imports when used as a prediction model for 12 months from March 2013 on. This change in overall imports can likely be attributable to EUTR as intervention event. In contrast to that the actual imports of tropical wood products lie completely within the confidence bounds of predicted values. In line with the above findings, the models with EUTR assumed to have a continued intervening impact were found significant for all imports of wood products and imports with non-tropical wood products, but not significant for imports of tropical wood products.

Although the suitability of the models employed to pursue the objectives of this paper was examined and statistically tested, a substantial and sensible interpretation of the results is difficult. From the perspective of companies acting in sensitive timber markets in public and political focus, an announced policy measure may evoke some uncertainty and thus restrained activities. The final enforcement of a political measure may then be felt as a factor ending the uncertainty in a market and in consequence boosting trade activities. This "wait-and-see" attitude of the importers and markets subjected to EUTR is a possible, but of course a speculative interpretation of the above results.

As regards the analyses carried out in the frequency domain the time series revealed cyclical behaviour. In the periodograms, peaks occurred at months 3, 6 and 12 which could be cautiously interpreted as quarterly, half-yearly or yearly seasonal signals in imports, provided that the significance of these peaks is confirmed by formal test. Nothing peculiar was noted when comparing the periodograms of time series on imports before and after EUTR. Only in the case of imports of tropical wood products values after EUTR they seem to lose their cyclic behaviour at higher frequencies as the largest ordinate of the periodogram is at frequency 0.1496 which corresponds with the period of $2\pi/0.1496 = 42$ months. This 'period' is exactly the number of months comprising the whole time series after EUTR (March 2013 to August 2016). Although a formal test could not reject the significance of the highest periodogram ordinate at this frequency, the statistical inference from periodogram only may be misleading in itself, and inconsistent data may yield spurious results. Improving data reliability and employing analyses based on inferences from multidimensional time series are considered promising for better understanding the factors affecting trade activities, in particular impacts of legislative measures.

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Appendix

Appendix A: Backshift operator and differencing

The backshift operator $\boldsymbol{Bx_t} = \boldsymbol{x_{t-1}}$ produces lagged time series (τ = 1) like

$$\begin{pmatrix} \vdots \\ \boldsymbol{x_1} \\ \boldsymbol{x_2} \\ \boldsymbol{x_3} \\ \boldsymbol{x_4} \\ \vdots \end{pmatrix} = \begin{pmatrix} \vdots \\ \boldsymbol{x_0} \\ \boldsymbol{x_1} \\ \boldsymbol{x_2} \\ \boldsymbol{x_3} \\ \vdots \end{pmatrix}$$

In general the back shift operator $\boldsymbol{B^p x_t} = \boldsymbol{x_{t-p}}$ yields shifted time series as follows

unchanged	p = 0	$B^0 x_t = x_{t-0}$	
backward	p > 0	$B^{+1} x_t = x_{t-1}$	A-1
Forward	P < 0	$B^{-1} x_t = x_{t+1}$	

The repeated use of the backshift operator for differencing of the time series leads to a general expression which is very handy and easy to deal with

First difference

$$\Delta x_t = x_t - x_{t-1}$$
$$\Delta x_t = x_t - Bx_t$$
$$\Delta x_t = (1-B)x_t$$

Second difference

$$\Delta(\Delta x_t) = \Delta^2 x_t = (1-B)(x_t - Bx_t)$$
$$\Delta^2 x_t = (1-B)(1-B)x_t$$

Third difference

$$\Delta(\Delta^2 x_t) = (1-B)(1-B)(x_t - Bx_t)$$
$$\Delta^3 x_t = (1-B)(1-B)(1-B)\, x_t$$

……………………………………………………

Pth - difference

$$\Delta^p x_t = (1-B)^p\, x_t = x_t(1-B)^p \qquad \text{A-2}$$

The backshift operator can also conveniently be used for transforming a no stationary time series, e.g., one exhibiting trend in stationary state by differencing. For a quadratic polynomial is

$$\begin{aligned}
\Delta Y_t &= (a_0 t^0 + a_1 t^1 + a_2 t^2)(1-B) \\
&= a_0 t^0 + a_1 t^1 + a_2 t^2 - a_0 B t^0 - a_1 B t^1 - a_2 B t^2 \\
&= a_0 t^0 + a_1 t^1 + a_2 t^2 - a_0 (t-1)^0 - a_1 (t-1)^1 - a_2 (t-1)^2 \\
&= a_0 t^0 + a_1 t^1 + a_2 t^2 - a_0 - a_1 t + a_1 - a_2 t^2 + 2a_2 t - a_2 \\
&= a_1 + 2a_2 t - a_2 \\
\Delta^2 Y_t &= (a_1 + 2a_2 t - a_2)(1-B) \\
&= a_1 + 2a_2 t - a_2 - a_1 B t^0 - 2a_2 B t + a_2 t^0 \\
&= a_1 + 2a_2 t - a_2 - a_1 (t-1)^0 - 2a_2 (t-1)^1 + a_2 (t-1)^0 \\
&= a_1 + 2a_2 t - a_2 - a_1 - 2a_2 t + 2a_2 + a_2 \\
&= 2a_2
\end{aligned}$$

In one step

$\Delta^2 Y_t = (a_0 t^0 + a_1 t^1 + a_2 t^2)(1 - B)^2$
$\Delta^2 Y_t = (a_0 t^0 + a_1 t^1 + a_2 t^2)(1 - 2B + B^2)$
……………………………………………………………………………
$\Delta^2 Y_t = 2a_2$

Appendix B: Specifying and estimating Autoregressive Model AR(p)

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \varphi_3 X_{t-3} + \cdots + \varphi_p X_{t-p} + \varepsilon_t \quad \text{B-1}$$

Where ε_t is assumed as white noise process with $\mu = 0$ and variance σ_ε^2

$$X_t - \varphi_1 X_{t-1} - \varphi_2 X_{t-2} - \varphi_3 X_{t-3} - \cdots - \varphi_p X_{t-p} = \varepsilon_t, \ ,$$

Using the back shift operator $B^p = X_{t-p}$ defined in **Appendix A** the AR(p) model can be written as

$$\left(B^0 - \varphi_1 B^1 - \varphi_2 B^2 - \varphi_3 B^3 - \cdots - \varphi_p B^p\right) X_t = \varepsilon_t \quad \text{B-2}$$

or in condensed form

$$\varphi(B) X_t = \varepsilon_t \quad \text{B-3}$$

For $\mu \neq 0$ is

$$X_t - \mu = \varphi_1(X_{t-1} - \mu) + \varphi_2(X_{t-2} - \mu) + \cdots + \varphi_p(X_{t-p} - \mu) + \varepsilon_t, \qquad \varphi_p \neq 0$$

$$X_t = \mu + \varphi_1(X_{t-1} - \mu) + \varphi_2(X_{t-2} - \mu) + \cdots + \varphi_p(X_{t-p} - \mu) + \varepsilon_t$$

$$X_t = \mu + \varphi_1 X_{t-1} - \varphi_1 \mu + \varphi_2 X_{t-2} - \varphi_2 \mu + \cdots + \varphi_p X_{t-p} - \varphi_p \mu + \varepsilon_t$$

$$X_t = \mu(1 - \varphi_1 - \varphi_2 - \cdots - \varphi_p) + \ \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t$$

$$X_t = \alpha + \ \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t$$

$$\alpha = \mu(1 - \varphi_1 - \varphi_2 - \cdots - \varphi_p) = \varphi(B)\mu \rightarrow const. \quad \text{B-4}$$

The estimation of the parameters $\boldsymbol{\varphi} = (\varphi_1,\ \varphi_2, \ldots \varphi_p)'$ in AR(p) can be accomplished by different methods. These methods are detailed described in (Brockwell and Davis 2006). In the following only the basic idea of estimating the vector $\boldsymbol{\varphi} = (\varphi_1,\ \varphi_2, \ldots \varphi_p)'$ is outlined. Formally, the autoregressive model

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \varphi_3 X_{t-3} + \cdots + \varphi_p X_{t-p} + \varepsilon_t \quad \text{B-5}$$

can be estimated by minimizing the sum of squares

$$S(\mu, \varphi) = \sum_{t=p+1}^{N} \left[X_t - \mu - \sum_{\tau=1}^{p} \varphi_\tau (X_{t-\tau} - \mu) \right]^2 \quad \text{B-6}$$

Proceeding further, the partial derivatives according to µ and φ would have to be set to zero bringing the solution for the estimates $\widehat{\boldsymbol{\varphi}} = (\widehat{\varphi}_1, \widehat{\varphi}_2\, , \ldots \widehat{\varphi}_p)'$. A more convenient method based direct on sampling autocorrelations and correlations yields the same estimates as B-6 would do. To arrive at the estimates the model B-1 is multiplied by $X_{t-\tau},\ \tau = 0,\ 2,\ 3, \cdots, p$ yielding expectations of the co-variances

$$E[X_t\, X_{t-\tau}] = \varphi_1 E[X_{t-1}\, X_{t-\tau}] + \varphi_2 E[X_{t-2}\, X_{t-\tau}] + \cdots + \varphi_p E[X_{t-p}\, X_{t-\tau}] + E[X_{t-\tau}\varepsilon_t] \qquad \text{B-7}$$

Replacing expectations by co-variances and dividing by $\gamma(0)$ it follows

$$1 = \varphi_1\rho_1 + \varphi_2\rho_2 + \cdots + \varphi_p\rho_p + \frac{\sigma_t^2}{\gamma(0)},\ \ for\ \tau = 0$$

or solved for σ_t^2

$$\sigma_t^2 = \gamma(0)[1 - (\varphi_1\rho_1 + \varphi_2\rho_2 + \cdots + \varphi_p\rho_p)] \qquad \text{B-8}$$

For all lags B-8 leads to
$$\rho_\tau = \varphi_1\rho_{\tau-1} + \varphi_2\rho_{\tau-2} + \cdots + \varphi_p\rho_{\tau-p},\quad \tau = 1, 2, \dots, p \qquad \text{B-9}$$

The last equation written in matrix form is

$$\begin{pmatrix} 1 & \rho_1 \cdots \rho_{p-2} & \rho_{p-1} \\ \rho_1 & 1 \cdots \rho_{p-3} & \rho_{p-2} \\ \cdots & \cdots\cdots\cdots & \cdots \\ \rho_{p-1} & \rho_{p-2} \cdots \rho_1 & 1 \end{pmatrix} \cdot \begin{pmatrix} \varphi_1 \\ \varphi_2 \\ \vdots \\ \varphi_p \end{pmatrix} = \begin{pmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \rho_p \end{pmatrix} = \mathbf{P}_{\boldsymbol{p}}\boldsymbol{\varphi} = \boldsymbol{\rho}_p \qquad \text{B-10}$$

If $|\mathbf{P}_{\boldsymbol{p}}| \neq 0$ the inverse matrix of $\mathbf{P}_{\boldsymbol{p}}$ exists and the estimates of AR(p) called as Yule-Walker estimates (Shumway and Stoffer 2006) follows directly from B-10 as

$$\widehat{\boldsymbol{\varphi}} = \widehat{\mathbf{P}}_{\boldsymbol{p}}^{-1}\widehat{\boldsymbol{\rho}}_{\boldsymbol{p}} \qquad \text{B-11}$$

Inserting B-11 in B-8 yields the estimation for variance

$$\sigma_t^2 = \hat{\gamma}(0)\left[1 - \widehat{\boldsymbol{\rho}}_{\boldsymbol{p}}\widehat{\mathbf{P}}_{\boldsymbol{p}}^{-1}\widehat{\boldsymbol{\rho}}_{\boldsymbol{p}}\right] \qquad \text{B-12}$$

Assuming that the difference $\widehat{\boldsymbol{\varphi}} - \boldsymbol{\varphi}$ (estimates error) is normally distributed with mean zero the asymptotic variance-covariance matrix of the estimates $\widehat{\boldsymbol{\varphi}}$ is

$$1/N\left[1 - (\hat{\rho}_1, \hat{\rho}_2, \cdots, \hat{\rho}_p)' \cdot (\widehat{\varphi}_1, \widehat{\varphi}_2, \cdots, \widehat{\varphi}_p)'\right] \cdot \widehat{\mathbf{P}}_{\boldsymbol{p}}^{-1}$$

$$1/N\left[1 - \left(\hat{\rho}_1\widehat{\varphi}_1 + \hat{\rho}_2\widehat{\varphi}_2 + \cdots + \hat{\rho}_p\widehat{\varphi}_p\right)\right] \cdot \widehat{\mathbf{P}}_{\boldsymbol{p}}^{-1} \qquad \text{B-13}$$

By taking square roots from the diagonal elements of B-13 and multiplying with 1.96 (α = 0.05) the approximate 95 % confidence limits for the estimates of AR(p) can be constructed.

Specifying Moving Average Model MA(q)

Whereas the AR(p) model expresses the observed value of a time series by the linear combination of the past values the moving average model of order q combines in linear way ε_t assumed as white noise

$$X_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_3\varepsilon_{t-3} + \cdots + \theta_q\varepsilon_{t-q} \quad \text{B-14}$$

Using the back shift operator as with B-2 the MA(q) model can be specified as

$$X_t = \left(B^0 + \theta_1 B^1 + \theta_2 B^2 + \theta_3 B^3 + \cdots + \theta_q B^q\right)\varepsilon_t = \theta(B)\,\varepsilon_t \quad \text{B-15}$$

The estimation of $\boldsymbol{\theta} = (\theta_1,\ \theta_2, \dots \theta_q)'$ in MA(q) can be accomplished by the innovation algorithm developed by Brockwell and Davis (1988). The most important details and an example are discussed in (Brockwell and Davis 2006, p. 245-250).

Specifying Autoregressive Moving Average Model ARMA(p, q)

Combining the models AR(p) and MA(q) as specified above, a time series can also be described by ARMA model with p autoregressive and q moving average parameters

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \quad \text{B-16}$$

Assuming $\varphi_p \neq 0$ and $\theta_q \neq 0$ the ARMA(p, q) can be written using B-3 and B-15 as

$$\varphi(B)X_t = \theta(B)\varepsilon_t \quad \text{B-17}$$

The detailed treatment of the statistical properties of this model, including its estimation, is beyond the scope of this paper. A preliminary estimation of $\boldsymbol{\varphi} = (\varphi_1,\ \varphi_2, \dots \varphi_p)'$ and $\boldsymbol{\theta} = (\theta_1,\ \theta_2, \dots \theta_q)'$ starts with a tentative estimation of AR(m) with the parameters $a_1, a_2, a_3 \dots a_m$

$$X_t = a_1 X_{t-1} + a_2 X_{t-2} + a_3 X_{t-3} + \cdots + a_m X_{t-m} + \varepsilon_t \quad \text{B-18}$$

using Durbin-Levinson Algorithm (detailed description in Shumway and Stoffer 2006, p. 113-114). The residuals of B-18 are

$$e_t = X_t - (\hat{a}_1 X_{t-1} + \hat{a}_2 X_{t-2} + \hat{a}_3 X_{t-3} + \cdots + \hat{a}_m X_{t-m}) \quad \text{B-19}$$

As the residuals B-19 are estimates of ε_t the vectors $\boldsymbol{\varphi}$ and $\boldsymbol{\theta}$ in B-16 can be obtained from the least squares condition

$$\sum_{t=1}^{N}\left[X_t - (\varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q})\right]^2 \rightarrow \min_{\varphi,\theta} \quad \text{B-20}$$

Specifying Autoregressive Moving Average Model accounting for trend ARIMA(p, d, q)

The ARMA model with autoregressive and moving average elements of orders p and q defined above can be extended to non-stationary time series i.e. time series showing trend. As shown in **Appendix A** the trend can be removed by repeated differencing of a time series with back shift operator A-2. As this operator can directly be integrated in ARMA(p, q) a model accounting for trend is referred to as ARIMA(p, d, q) where p and q are arguments of ARMA model and d are differences of order d. Employing the operator A-2 and B-17 the ARIMA model can be written as

$$\varphi(B)(1-B)^d X_t = \theta(B)\varepsilon_t \qquad \text{B-21}$$

Appendix C: Time series in frequency domain: introducing a periodogram by regression

The periodogram is important for gaining a deeper insight into the periodic behaviour of a time series. To introduce the periodogram in concise form would require a strong mathematical theory not available here. Instead of that the regression approach described in following will produce as 'by-product' the periodogram and explain in plain way its significance. The postulated regression model (based on Schlittgen and Streitberg 2001) is

$$m(t) = x_t = \beta_0 m_0(t) + \beta_1 m_1(t) + \beta_2 m_2(t) + \cdots + \beta_p m_p(t) \qquad \text{C-1}$$

The least square estimates for the regression coefficients $\beta_0,\ \beta_1,\ \beta_2, \dots, \beta_p$ follow from the condition

$$S = \sum_{t=1}^{N} \left[x_t - \beta_0 m_0(t) - \beta_1 m_1(t) - \beta_2 m_2(t) - \cdots - \beta_p m_p(t)\right]^2 \rightarrow \begin{matrix} min \\ \beta \end{matrix} \qquad \text{C-2}$$

Taking the partial derivatives with respect to $\beta_0,\ \beta_1,\ \beta_2, \dots, \beta_p$ yields

$$\begin{aligned}
\frac{\partial S}{\partial \beta_0} &= 2\sum_{t=1}^{N}\left[x_t - \beta_0 m_0(t) - \beta_1 m_1(t) - \beta_2 m_2(t) - \cdots - \beta_p m_p(t)\right] \cdot m_0(t) \\
\frac{\partial S}{\partial \beta_1} &= 2\sum_{t=1}^{N}\left[x_t - \beta_0 m_0(t) - \beta_1 m_1(t) - \beta_2 m_2(t) - \cdots - \beta_p m_p(t)\right] \cdot m_1(t) \\
\frac{\partial S}{\partial \beta_2} &= 2\sum_{t=1}^{N}\left[x_t - \beta_0 m_0(t) - \beta_1 m_1(t) - \beta_2 m_2(t) - \cdots - \beta_p m_p(t)\right] \cdot m_2(t) \\
&\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\
\frac{\partial S}{\partial \beta_p} &= 2\sum_{t=1}^{N}\left[x_t - \beta_0 m_0(t) - \beta_1 m_1(t) - \beta_2 m_2(t) - \cdots - \beta_p m_p(t)\right] \cdot m_p(t)
\end{aligned} \qquad \text{C-3}$$

Setting to zero, dividing by 2 and multiplying the normal equations are given by

$$\begin{aligned}
&\sum_{t=1}^{N}\left[x_t m_0(t) - \beta_0 m_0^2(t) - \beta_1 m_1(t) m_0(t) - \beta_2 m_2(t) m_0(t) - \cdots - \beta_p m_p(t) m_0(t)\right] = 0 \\
&\sum_{t=1}^{N}\left[x_t m_1(t) - \beta_0 m_0(t) m_1(t) - \beta_1 m_1^2(t) - \beta_2 m_2(t) m_1(t) - \cdots - \beta_p m_p(t) m_1(t)\right] = 0 \\
&\sum_{t=1}^{N}\left[x_t m_2(t) - \beta_0 m_0(t) m_2(t) - \beta_1 m_1(t) m_2(t) - \beta_2 m_2^2(t) - \cdots - \beta_p m_p(t) m_2(t)\right] = 0 \\
&\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\
&\sum_{t=1}^{N}\left[x_t m_p(t) - \beta_0 m_0(t) m_p(t) - \beta_1 m_1(t) m_p(t) - \beta_2 m_2(t) m_p(t) - \cdots - \beta_p m_p^2(t)\right] = 0
\end{aligned} \qquad \text{C-4}$$

The normal equation C-4 and their solution become simply if only orthogonal regressors are allowed

$$\sum_{t=1}^{N} m_i(t)m_j(t) = 0, \qquad i \neq j \tag{C-5}$$

Bloomfield (2000, p. 38) shown that the expression

$$\sum_{t=1}^{N} \cos(2\pi\lambda t)\sin(2\pi\lambda t) = 0 \tag{C-6}$$

satisfies the orthogonality properties C-5. For the full account of the derivation steps (omitted here for space constraints) see (Becher 1999, p. 90-95). The final result from C-2 is

$$S = \sum_{t=1}^{N} \left[x_t^2 - \bar{x}^2 N - 2N\left(C^2(\lambda) + S^2(\lambda)\right)\right] \tag{C-7}$$

where

$$C(\lambda) = \frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})\cos(2\pi\lambda t)$$

C-8

$$S(\lambda) = \frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})\sin(2\pi\lambda t)$$

The expressions C-8 represent the empirical covariance between the centred time series and its periodic variations described by cosine and sine taken at frequency λ. In other words the covariance functions C-8 quantify the periodic components in a time series. As the first two summands in C-7 are constant for a given time series the goodness of fit by the trigonometric functions depends on C-8. This means that the larger the expression $C^2(\lambda) + S^2(\lambda)$ the better a time series can be represented by the linear combination of sine and cosine. As function of the frequency λ the squared sum of C-8 defines the periodogram

$$I(\gamma) = N\left(C^2(\lambda) + S^2(\lambda)\right) \tag{C-9}$$

that is the most important characteristic of time series analysis in frequency domain.

Appendix D: Time series in frequency domain: an approach based on Fourier analysis

The core element of Fourier analysis is the mathematical relationship between the exponential function $f(x) = e^x$ and the periodic functions f(x) = cos(x) and f(x) = sin(x). As all these function and their derivatives are defined for x= 0 they can be expanded to the Taylor series

$$f(x) = f(0)x^0 + \frac{f'(0)}{1!}x^1 + \frac{f''(0)}{2!}x^2 + \frac{f'''(0)}{3!}x^3 + \cdots \qquad \text{D-1}$$

obtaining

$$e^x = 1 + \frac{x}{1!} + \frac{x^2}{2!} + \frac{x^3}{3!} + \frac{x^4}{4!} + \cdots \qquad \text{D-2}$$

$$cos(x) = 1 - \frac{x^2}{2!} + \frac{x^4}{4!} - \frac{x^6}{6!} + \cdots \qquad \text{D-3}$$

$$sin(x) = \frac{x}{1!} - \frac{x^3}{3!} + \frac{x^5}{5!} - \frac{x^7}{7!} + \cdots \qquad \text{D-4}$$

Replacing x by ix in D-2 leads to

$$e^{ix} = 1 + \frac{ix}{1!} + \frac{(ix)^2}{2!} + \frac{(ix)^3}{3!} + \frac{(ix)^4}{4!} + \frac{(ix)^5}{5!} + \frac{(ix)^6}{6!} + \frac{(ix)^7}{7!} + \cdots \qquad \text{D-5}$$

Due to $i^2 = -1$ D-5 can be written as

$$e^{ix} = 1 + \frac{ix}{1!} - \frac{x^2}{2!} - \frac{ix^3}{3!} + \frac{x^4}{4!} + \frac{ix^5}{5!} - \frac{x^6}{6!} - \frac{ix^7}{7!} + \cdots \qquad \text{D-6}$$

or

$$e^{ix} = 1 - \frac{x^2}{2!} + \frac{x^4}{4!} - \frac{x^6}{6!} + \cdots + i\left(\frac{x}{1!} - \frac{x^3}{3!} + \frac{x^5}{5!} - \frac{x^7}{7!} + \cdots\right) \qquad \text{D-7}$$

Together with D-3 and D-4 is

$$e^{ix} = cos(x) + isin(x) \qquad \text{D-8}$$

and correspondingly (replacing x by $-ix$ in D-2)

$$e^{-ix} = cos(x) - isin(x) \qquad \text{D-9}$$

The complex-valued expressions D-8 and D-9 with $i^2 = -1$ known as Euler formulas can now be used for defining the periodogram C-9 as functions of

$$e^{+i2\pi\gamma t} = cos(2\pi\lambda t) + isin(2\pi\lambda t)$$
$$e^{-i2\pi\gamma t} = cos(2\pi\lambda t) - isin(2\pi\lambda t) \qquad \text{D-10}$$

The periodogram C-9 won from regression analysis in Appendix C can be factorized as

$$I(\gamma) = N\big(C^2(\lambda) + S^2(\lambda)\big) = N[(C(\lambda) + iS(\lambda)) \cdot (C(\lambda) - iS(\lambda))] \qquad \text{D-11}$$

Considering C-8 and D-10 the factorized periodogram D-11 becomes

$$I(\lambda) = N\left[\left(\frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})\, e^{+i2\pi\lambda t}\right)\left(\frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x})\, e^{-i2\pi\lambda t}\right)\right] = \frac{1}{N}\left|\sum_{t=1}^{N}(x_t - \bar{x})\, e^{i2\pi\lambda t}\right|^2 \qquad \text{D-12}$$

From the last term in D-12 follows that the for each frequency λ the periodogram $I(\lambda)$ is nothing else but the square of the inner product of the vectors

$$\boldsymbol{x_t} - \boldsymbol{\bar{x}} = (x_1 - \bar{x},\ x_2 - \bar{x},\ x_3 - \bar{x}, \dots, x_N - \bar{x})'$$
$$\boldsymbol{e^{i2\pi\lambda t}} = (e^{i2\pi\lambda 1}, e^{i2\pi\lambda 2}, e^{i2\pi\lambda 3}, \dots, e^{i2\pi\lambda N})' \qquad \text{D-13}$$

Moreover, the elements of the second vector constitute the orthonormal basis in complex vector space satisfying the relation

$$\boldsymbol{e_j'}\boldsymbol{e_k} = \begin{cases} 1, & if\ j = k \\ 0, & if\ j \neq k \end{cases} \qquad \text{D-14}$$

Comparing the approach of Appendix C where periodogram was introduced by means of regression analysis the consideration of the complex valued equations D-10 led to a mathematically neat interpretation of the periodogram as linear combination of $x_t, t = 1, 2, 3, \dots, N$ in the complex orthogonal base.

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