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Original Article

Modelling tourist departures in the European Union using a threshold cointegration approach

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Abstract:
The aim of the article is to discuss and demonstrate the problem of nonlinearity in tourism trips in the European Union. Tourism is a growing branch of economy but it is very sensitive for any instabilities of economic and non-economic nature. These can cause a nonlinear structure of the time series which has serious consequences for econometric modelling. An irregular course of the process over time may not be a sufficient reason to use the simplest linear models. Therefore, this paper applies a series of tests and models to describe phenomena with non-linear or partly linear structures. The main class of the analysed econometric models is threshold models. For the purpose of identification of non-linear character of dependency for tourist departures and arrivals in the European Union, the following tests were used: Enders and Siklos test, a modification of Kapetanio set al. test, a newly proposed test for threshold cointegration, Tsay test and Hansen and Seo test. After testing for nonlinearity the forecasts of tourist departures were computed. As the results of testing indicated a stationary threshold structure or a linear cointegration two models were used in prediction, i.e. a stationary threshold model and a linear error correction model (ECM).A comparison of forecasting errors indicates that all forecasts are accepted, but ECM gave the smallest values of errors. The forecast can be utilized in economic practice by tourist industry.
Key Words: Threshold cointegration, econometric model, forecasting, tourism industry

Introduction

The aim of the study is to discuss the tools of testing for non-linear econometric models and to implement them in tourism departures analysis. It is assumed that tourist departures and arrivals are mutually dependent. Further it is assumed that nonlinearity results from changes in structure. The current COVID19 pandemic is a good example of such a change. Due to lack of data the impact of the pandemic on tourist trips will not be taken into account in the empirical part of the study. However tourism industry is vulnerable for structural breaks. As it was shown by Cró and Martins (2017) both economic and noneconomic shock influenced tourism trips in 25 European countries as well as Madera Island. Gałecki (2020) showed that economic recession in 2008-2009 as well as Eurozone crisis in 2013 significantly affected flows of tourists to and from the European Union. Presence of structural breaks makes the use of linear econometrics tools not very accurate to reflect the structure of the studied phenomenon. For this purpose, the article discusses tests verifying possibility of using threshold models. The starting point of the analysis is a definition of stationarity of the time series. If tourist departures and arrivals are non-stationary then the problem of cointegration, i.e. a long-run dependence is considered in two forms: a linear and threshold-based non-linear one. If non-linearity is confirmed by statistical tests than two types of econometric models can be used, these are threshold models with cointegration i.e. threshold error correction model (TECM, TVECM) or stationary threshold models. These models not only capture nonlinearities resulted from structural breaks but also can help in more accurate forecasting. Thus, forecasts for tourist departures in the European Union are prepared to decide whether linear or non-linear models better fit the changes in future. For the sake of accuracy of the forecasts, the available time series for annual data from 1995 to 2018 were limited by the last 3 observations. The novelty of the paper lies in the fact that a sequence of advanced tests for nonlinearity were applied to tourism departures and arrivals resulting with deep recognition of the structure of these processes as well as relationship between them.

Material & methods

Gałecki (2020) showed that structural breaks are included into the series representing tourist arrivals and departures in the European Union. This is a starting point to check whether they are cointegrated. The term cointegration assumes a long run relationship between at least two time series which are independent from time (Engle and Granger, 1987) and it is a subject of statistical testing (Dickey and Fuller, 1979; Engle and Granger, 1987, Johansen, 1988). The time series should be integrated of the same order. In this part we consider fairly advanced form of cointegration, i.e. threshold cointegration.

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In order to test for threshold cointegration with the use of Enders and Siklos test (2001) we start from the linear long-term dependence in the form proposed by Engle and Granger (1987):

$$Y_t = \alpha_0 + \sum_{j=1}^{k} \alpha_j X_{jt} + u_t, \quad (1)$$

where: Y_t, X_{1t}, X_{2t}, …, $X_{kt} \sim I(1)$. Stationarity of the adjustment process, represented by residuals from equation (1), is studied with the use of the following form:

$$\Delta u_t = I_t \rho_1 u_{t-1} + (1 - I_t)\rho_2 u_{t-1} + \sum_{i=1}^{p} \beta_i u_{t-i} + \varepsilon_t \quad (2)$$

where:

$$I_t = \begin{cases} 1 \ if & u_{t-1} \geq \hat{\gamma} \\ 0 \ if & u_{t-1} < \hat{\gamma} \end{cases} \quad (3)$$

in the case of SETAR type adjustment process and

$$I_t = \begin{cases} 1 \ if & \Delta u_{t-1} \geq \hat{\gamma} \\ 0 \ if & \Delta u_{t-1} < \hat{\gamma} \end{cases} \quad (4)$$

if the adjustment process is of M-TAR type, $\hat{\gamma} = 0$. Testing threshold cointegration involves verification of two hypotheses (H_0^1 i H_0^2). The first set of hypotheses (null and alternative hypothesis) takes the following form:

$H_0^1: \rho_1 = \rho_2 = 0$

$H_1^1: \exists \rho_i \neq 0, i = 1,2$

If the cointegration has been confirmed (H_0^1 has been rejected), during the second step we verify whether there is asymmetry in adjustment to long-term equilibrium, which confirms a threshold cointegration. We analyze the following set of hypotheses:

$H_0^2: \rho_1 - \rho_2 = 0$

$H_1^2: \rho_1 - \rho_2 \neq 0$

Hypothesis H_0^2 assumes no asymmetry in adjustment to long-term equilibrium. For H_1^1in the case of one-equation model, three variants are possible:

1. Non-linear residual process, including partial cointegration: H_0^2 is rejected and conditions from H_1^2 occur

$$H_1^2 = \begin{cases} \rho_1 < 0 \ and \ \rho_2 \geq 0 \\ or \\ \rho_1 \geq 0 \ and \ \rho_2 < 0 \end{cases}$$

$$H_1^2 = \begin{cases} \rho_1 > 0 \ and \ \rho_2 \geq 0 \\ or \\ \rho_1 \geq 0 \ and \ \rho_2 > 0 \end{cases}$$

2. Linear cointegration: non-rejecting H_0^2

$H_0^2: \rho_1 - \rho_2 = 0$

3. Threshold cointegration: H_0^2 is rejected and conditions from H_1^2 occur

$H_1^2 = \{\rho_1 < 0 \ i \ \rho_2 < 0\}$

In order to verify the hypotheses, we calculate the value of F statistics in the following form:

$$F = \frac{(SSR_1 - SSR_0)}{SSR_0} \ x \ \frac{n-k}{q}, \quad (5)$$

where: SSR_1 – a sum of squares of residuals from the restricted model, SSR_0 – a sum of squares of residuals from a non-restricted model, n- the number of observations used for estimation of the model's parameters, k – the number of estimated parameters in a non-restricted model, q – the number of restrictions, first degrees of freedom, n - k – second degrees of freedom.

Another method of testing for threshold cointegration is using a threshold error correction model (TECM) in the form:

$$\Delta Y_t = I_t \rho_1 u_{t-1} + (1 - I_t)\rho_2 u_{t-1} + \sum_{s=1}^{p} \beta_s \Delta Y_{t-s} + \sum_{i=0}^{k} \alpha_i \Delta X_{it} + \sum_{j=1}^{q} \sum_{i=1}^{k} \gamma_j \Delta X_{it-j} + \varepsilon_t \quad (6)$$

Regression (6) is a modification made by Bruzda (2007) of the approach proposed by Kapetanioset al. (2006). Lags in variable Y_t and variables $X_{it}$are established to ensure the white-noise nature of the residual process. The indicator function $I_t$is in the form (3) and (4) for threshold variables u_{t-1} i Δu_{t-1}, respectively. The value of threshold variable $\hat{\gamma}$can be established (typically zero) or be estimated using Chan method (Chan at al. 1985):

$$-\infty < \hat{\gamma} < \infty \,;\, \hat{\gamma} = arg\min_{\gamma} AIC(\gamma) \tag{7}$$

Additionally, the set of threshold variables has been extended by vector Z_t.

$$Z_t = (Y_t, X_{it})', X_{it} = (X_{1t}, X_{2t}, \dots, X_{kt})'$$

The indicator function $I_t$thus takes the following form:

$$I_t = \begin{cases} 1 \; if & Z_{t-i} \geq \hat{\gamma} \\ 0 \; if & Z_{t-i} < \hat{\gamma} \end{cases} \quad or \quad I_t = \begin{cases} 1 \; if & \Delta Z_{t-i} \geq \hat{\gamma} \\ 0 \; if & \Delta Z_{t-i} < \hat{\gamma} \end{cases} \tag{8}$$

$$-\infty < \hat{\gamma} < \infty \,;\, \hat{\gamma} = arg\min_{\gamma} AIC(\gamma)$$

The threshold error correction model (6) differs in two regimes merely by the error correction component (ΔpECM(t-1) – the error correction component for a threshold variable greater than or equal to $\hat{\gamma}$ and ΔnECM(t-1) – the error correction component for a threshold variable lower than $\hat{\gamma}$). The test hypotheses and F statistics are the same as inEnders and Siklos test. Equations (6) can be extended in such a way that each variable depends on the value of threshold variable. The threshold error correction model will then take the form (9) (Osińska et al. (2019)):

$$\Delta Y_t = I_t \rho_1 u_{t-1} + (1 - I_t)\rho_2 u_{t-1} + \sum_{s=1}^{p} I_t \beta_{s1} \Delta Y_{t-s} + \sum_{s=1}^{r} (1 - I_t)\, \beta_{s2} \Delta Y_{t-s} + \sum_{i=0}^{k} I_t \alpha_{i1} \Delta X_{i1,t} + \sum_{i=0}^{k} (1 - I_t) \alpha_{i2} \Delta X_{i2,t} + \sum_{j=1}^{q} \sum_{i=1}^{k} I_t \gamma_{i+j-1,1} \Delta X_{i1,t-j} + \sum_{j=1}^{w} \sum_{i=1}^{k} (1 - I_t) \gamma_{i+j-1,2} \Delta X_{i2,t-j} + \varepsilon_t \tag{9}$$

where: I_t is defined by formulas: (3) or (4) or (8).
Three tests for threshold cointegration presented so far are based on the difference in the estimation of parameters with error correction components being in a proper regime. The second group of test for threshold cointegration is Tsay test (1998), which is based on a covariance matrix of the residual process. Tsay test indicates whether a variable is generated by a linear or non-linear process. The null hypothesis assumes that Y_t is a multi-dimensional linear process in comparison to the alternative hypothesis, which assumes thatY_t is described by a multi-dimensional threshold model. It is described by equation (10):

$$Y_t = c_j + \sum_{i=1}^{p} \varphi_i^{(j)} Y_{t-i} + \sum_{i=1}^{q} \beta_i^{(j)} X_{t-i} + \varepsilon_t^{(j)} \;\; if \; r_{j-1} < Z_{t-d} \leq r_j \tag{10}$$

where:j = 1, …, s,t = 1, …, n, c_j–a vector of constant,Y_t - k-dimensional time series, $Y_t = (Y_{1t}, \dots, Y_{kt})'$,$X_t$ - v-dimensional exogenous variables , $X_t = (X_{1t}, \dots, X_{vt})'$,$Z_{t-d}$ -threshold variable with delay parameter d, $-\infty = r_0 < r_1 < \dots < r_{s-1} < r_s = \infty$; p and $q$are nonnegative integers.

The residual process $\varepsilon_t^{(j)} = \Sigma_i^{1/2} a_t$ contains innovations. Matrix $\Sigma_i^{1/2}$ is symmetrical and positively defined. Matrix a_t consists of non-correlated random vectors which have the mean value is zero and an identity covariance matrix. Threshold variable Z_t is stationary and described by continuous distribution. Model (10) contains s regimes and only for $s > 1$ is it a threshold model. Threshold variable Z_{t-d} divides the linear dependence between variables into dependence which is linear in sectors. Concerning the threshold variable, it is assumed to be known, but its delay, number of regimes and threshold values are unknown.
Let us simplify the notation of model (10) to the form(11):

$$Y'_t = x'_t\Phi + \varepsilon'_t\,,\ t = h+1, \dots, n \tag{11}$$

where:*h*= *max(p, q, d);* $x'_t = (1, Y'_{t-1}, \dots, Y'_{t-p}, X'_{t-1}, \dots, X'_{t-q}$ is a (*pk* + *qv* + *1*) – dimensional regressor,Φ – is the parameter matrix.
The starting point for Tsay test is ordering of observations according to the growing values of the threshold variable.

$$Y'_{t(i)+d} = x'_{t(i)+d}\Phi + \varepsilon'_{t(i)+d}\,,\ i = 1, \dots, n-h \tag{12}$$

where: *t(i)* is the time index of *z(i)*, *z(i)* is the *i*th smallest element of S,S is the threshold variable from regression (10), $S = \{Z_{h+1-d}, \dots, Z_{n-d}\}$
If Y_t is a linear process, then the recursive least squares method for regression (12) is unbiased. In consequence, the residual process which mean a forecast error in a regime above the threshold variable isthe white noise. The residuals are not correlated with independent regressors$x'_{t(i)+d}$. On the other hand, if, Y_t is a non-linear process described by the threshold model, then the residual process will not be white noise. As the consequence, the residuals from the equation (12)are correlated with independent regressors and the least squaresestimatoris biased.
Let $\hat{\Phi}_m$denote the least squares estimate of $\Phi$from equation (12) with *i = 1, ... m.* It means the estimate of arranged regression (12) using data points ordered according to the *m* smallest values of Z_{t-d}.
Let's continue

$$\hat{e}_{t(m+1)+d} = Y_{t(m+1)+d} - \hat{\Phi}'_m x_{t(m+1)+d} \tag{13}$$

be the predictive residual and

$$\hat{\eta}_{t(m+1)+d} = \frac{\hat{e}_{t(m+1)+d}}{[1 + x'_{t(m+1)+d} V_m x_{t(m+1)+d}]^{1/2}} \tag{14}$$

where

$$V_m = [\sum_{i=1}^{m} x_{t(i)+d} x'_{t(i)+d}]^{-1}$$

are standardized predictive residuals of regression (12). The residuals can be efficiently calculated by the recursive least squares algorithm. Next, consider the regression

$$\hat{\eta}'_{t(l)+d} = x'_{t(l)+d}\Psi + \mathrm{w}'_{t(l)+d}\,, \mathrm{l} = \mathrm{m}_0 + 1, \dots, \mathrm{n} - \mathrm{h} \tag{15}$$

where m_0 means the starting point of the recursive least squares estimation.
The hypotheses refer equation (15):
$H_0: \Psi = 0$
$H_1: \Psi \neq 0$
Tsay used the test statistic:

$$C(d) = [n - h - m_0 - (kp + vq + 1)]\{\ln[det(S_0)] - \ln[\det(S_1)]\}, \tag{16}$$

where: $\det(S_i)$ indicates the determinant of the matrix S_i, the delay *d*means that the test statistics depends on the threshold variable Z_{t-d} and

$$S_0 = [\frac{1}{n-h-m_0}] \sum_{l=m_0+1}^{n-h} \hat{\eta}_{t(l)+d}\hat{\eta}'_{t(l)+d}$$

and

$$S_1 = [\frac{1}{n-h-m_0}] \sum_{l=m_0+1}^{n-h} \hat{w}_{t(l)+d}\hat{w}'_{t(l)+d}$$

where $\widehat{w}_t$ is the least squares residuals vector of regression (15). If the null hypothesis is true and some regularity conditions are met, *C(d)* is asymptotically the chi-squared random variable with k(pk + qv + 1) degrees of freedom.

A test which combines the approach of using the difference between parameters in regimes and the properties of the residual process is Hansen and Seo test (2002). The authors proposed a test for threshold cointegration, in which the test statistics are dependent on the covariance structure of the analysed processes and have an asymptotic distribution. Determining the p-value is conducted using the bootstrap procedure. The starting point for the test is a linear vector error correction model (VECM) for *p* first differences of endogenous processes with *l* delays. Each process is assumed to be integrated to the first degree. there is only one cointegrating vector in the model. A linear VECM model is written in the following form:

$$\Delta x_t = A' X_{t-1}(\beta) + u_t \tag{17}$$

where:

$$X_{t-1} = \begin{pmatrix} 1 \\ w_{t-1}(\beta) \\ \Delta x_{t-1} \\ \Delta x_{t-2} \\ \dots \\ \Delta x_{t-l} \end{pmatrix}$$

x_t – *p* – dimensions vector of processes I(1)
$w_t(\beta) = \beta' x_t$ – cointegrating vector -I(0)
$X_{t-1}(\beta)$ – vector of independent variables measuring *k* x *1*
A – matrix of parameter measuring *k* x *p*
k = pl + 2
$\sum = E(u_t u_t')$ – covariance matrix for residual processes.
The vector of residuals processes takes the following form:

$$\tilde{u}_t = \Delta x_t - \tilde{A}' X_{t-1}(\widetilde{\beta}) \tag{18}$$

Parameters $(\beta, A, \sum)$ are estimated using the maximum likelihood method, in order for the residuals processes u_t to be Gaussian white noise. If *p = 2*, one normalizing restriction should be placed on β matrix in the form of comparing one of the matrix elements to one. For *p > 2* a normalizing restriction should be placed on the variables within the cointegrating vector, preferably those who adapt themselves to long-term equilibrium. Placing restrictions is necessary, in order for the model to be identified.

Let us transform model (17) into a two-regime model with threshold cointegration, described by equation:

$$\Delta x_t = \begin{cases} A_1' X_{t-1}(\beta) + u_t, if \ w_{t-1}(\beta) \le \gamma \\ A_2' X_{t-1}(\beta) + u_t, if \ w_{t-1}(\beta) > \gamma \end{cases} \tag{19}$$

or equivalently

$$\Delta x_t = A_1' X_{t-1}(\beta) d_{1t}(\beta,\gamma) + A_2' X_{t-1}(\beta) d_{2t}(\beta,\gamma) + u_t \tag{20}$$

where:

$$d_{1t}(\beta,\gamma) = l(w_{t-1}(\beta) \le \gamma)$$
$$d_{2t}(\beta,\gamma) = l(w_{t-1}(\beta) > \gamma)$$

l(.) – indicator function.

Switching between equations within regimes depend on the cointegrating vector (the error correction component does not, however, have to be a threshold variable). The matrixes of A_1 and A_2 coefficients define the dynamics in regimes, both long- and short-term.

The null hypothesis takes the following form:
$H_0: A_1 = A_2$
$H_1: A_1 \neq A_2$

In the null hypothesis a linear model with cointegration is assumed, whereas the alternative assumes a threshold model with cointegration. Let us assume that parameters ($\beta \ i \ \gamma$) are known and constant. The model which is in accordance with H_0 takes the form of:

$$\Delta x_t = A'X_{t-1}(\beta) + u_t, \quad (21)$$

whereas the model in accordance with H_1 will be written as:

$$\Delta x_t = A_1'X_{t-1}(\beta)d_{1t}(\beta,\gamma) + A_2'X_{t-1}(\beta)d_{2t}(\beta,\gamma) + u_t \quad (22)$$

By

$$X_1(\beta,\gamma) = X_{t-1}(\beta)d_{1t}(\beta,\gamma)$$

the observation of independent variables in a regime below the threshold variable was defined, whereas

$$X_2(\beta,\gamma) = X_{t-1}(\beta)d_{2t}(\beta,\gamma)$$

describes the matrix of observations of independent variables in a regime above the threshold variable.
During the next step Kronecker products were set for the matrixes of independent variables in a growing order, according to the threshold variable and the vector of residuals from the linear VECM model.

$$\xi_1(\beta,\gamma) = \tilde{u}_t \otimes X_{t-1}(\beta)d_{1t}(\beta,\gamma)$$
$$\xi_2(\beta,\gamma) = \tilde{u}_t \otimes X_{t-1}(\beta)d_{2t}(\beta,\gamma) \quad (23)$$

where:$\tilde{u}_t$ – vector of residuals from the linear VECM model.
By $M_1(\beta,\gamma)$ i $M_2(\beta,\gamma)$ the matrixes created in the following manner were denoted:

$$M_1(\beta,\gamma) = I_p \otimes X_1(\beta,\gamma)'X_1(\beta,\gamma)$$
$$M_2(\beta,\gamma) = I_p \otimes X_2(\beta,\gamma)'X_2(\beta,\gamma) \quad (24)$$

where:I_p – identity matrix dimensions *p x p*.
Next, matrixes$\Omega_1(\beta,\gamma)$ and $\Omega_2(\beta,\gamma)$ were set: (25)

$$\Omega_1(\beta,\gamma) = \xi_1(\beta,\gamma)'\xi_1(\beta,\gamma)$$
$$\Omega_2(\beta,\gamma) = \xi_2(\beta,\gamma)'\xi_2(\beta,\gamma)$$

Based on matrixes $M_1(\beta,\gamma), M_2(\beta,\gamma)$ and $\Omega_1(\beta,\gamma)$ and $\Omega_2(\beta,\gamma)$ the Eicker – White covariance matrix estimator $\hat{V}_1(\beta,\gamma)$ and $\hat{V}_2(\beta,\gamma)$ was established for the estimation vectors of parameters $\hat{A}_1(\beta,\gamma)$ and $\hat{A}_2(\beta,\gamma)$:

$$\hat{V}_1(\beta,\gamma) = M_1(\beta,\gamma)^{-1}\Omega_1(\beta,\gamma)M_1(\beta,\gamma)^{-1}$$
$$\hat{V}_2(\beta,\gamma) = M_2(\beta,\gamma)^{-1}\Omega_2(\beta,\gamma)M_2(\beta,\gamma)^{-1} \quad (26)$$

Setting the statistics

$$LM(\beta,\gamma) = vec(\hat{A}_1(\beta,\gamma) - \hat{A}_2(\beta,\gamma))' (\hat{V}_1(\beta,\gamma) - \hat{V}_2(\beta,\gamma))^{-1} vec(\hat{A}_1(\beta,\gamma) - \hat{A}_2(\beta,\gamma))' \quad (27)$$

takes place on condition that parameters β and γ are known (for example, from the theory of economy) or estimated (one-equation models only). Otherwise, the test statistics take the following form:

$$supLM = sup_{\gamma_L \leq \gamma \leq \gamma_U} LM(\tilde{\beta}, \gamma) \quad (28)$$

The obtained LM statistic is resistant for hederoskedasticity. Both LM and SupLM statistics do not have stabilized distribution with critical values. In order to verify the null hypothesis, a bootstrap p-valuewas set as the percentage of simulated LM statistics which exceeded the actual statistic. The bootstrap may be constructed by taking random residuals within regimes or taking random observations of independent variables within regimes. The choice of LM statistics was motivated by the possibility of implementing it into the bootstrap.Gosińska et al. (2020) proposed a modification of Hansen and Seo test in the case of presence the deterministic term in the cointegrating space.

To check the time series for threshold cointegration two variables, i.e. tourist departures -Dep_t and tourist arrivals - Arr_t in the European Union were considered. It is assumed that they are related in the long run. The data comes from the World Bank database and are presented in millions of people. These are annual data from 1995-2018. Final criterion of model comparison is forecasting accuracy. The forecast of tourist trips in the EU was therefore calculated for the period 2016-2018. Relative forecast errors are calculated and compared.

Results

To start the empirical analysis standard unit roots tests were performed, i.e.ADF (Dickey and Fuller, 1979), KPPS (Kwiatkowski, Phillips, Schmidt and Shin, 1992) and PP tests (Phillips and Perron, 1988). The results indicate that both variables $Arr_t$and $Dep_t$are I(1) which is the basic condition for cointegration. The variables in the first differences, i.e. ΔArr_t and ΔDep_t are stationary (I(0)). The results are available from authors for request.The long term equation was estimated using OLS method. The results show that it is in line with Kvedaras(2003), who allows lagged variables to enter the long run equation in the presence of autocorrelation.

Tab. 1. Cointegrating equation. Dependent variable - Dep_t

Variable	Coefficient	Standard error	t-Student	p-value
const	6,5135	15,5677	0,418	0,6809
Arr_{t-2}	0,78183	0,047972	16,3	8,24E-12
R squared	0,9398	DW	1,17	S(e)=8,84

Source: Own elaboration.

As the ECM_t exhibits stationarity we decided to follow the procedure described in the previous section. The simplest form of testing is performed using Enders and Siklos test. The results are presented in Tab. 2.

Tab. 2. Results of theEnders and Siklos test

Threshold variable	F-Statistic	p-value H_0^1	F-Statistic	p-value H_0^2	Decision
ECM(t-1) = 0	3,650	0,049	0,0004	0,985	Linear ECM
ΔECM(t-1) = 0	4,053	0,039	0,868	0,366	Linear ECM

Source: Own elaboration.

Enders and Siklos test (2001) indicates that despite of structural breaks the growth in tourist trips in the EU can be described with a linear cointegration model. It is however initial, because single variables can still be responsible for nonlinear mechanism, not necessarily related with threshold cointegration. It can also be related with a threshold stationary model.

Tab. 3. Results ofthe Kapetanioset al. test modified by Bruzda and the newly proposed test

Threshold variable	Kapetanios et al test results			New test results		
	p-value H_0^1	p-value H_0^2	Decision	p-value H_0^1	p-value H_0^2	Decision
ECM(t-1) = 0	0,123		Linear ECM	0,197		Threshold model
ΔECM(t-1) = 0	0,035	0,101	Threshold model	0,220		Threshold model
Dep(t-3) = 265,513	0,015	0,066	Partial cointegration $pECM_t = 0$	0,019	0,012	Threshold model $pECM_t = 0$
ΔDep(t-2) = 6,494	0,048	0,493	Linear ECM	0,015	0,020	Threshold model
Arr(t-2) = 349,776	0,123		Linear ECM	0,964		Threshold model
ΔArr(t-2) = 10,528	0,072	0,066	Partial cointegration $pECM_t = 0$	0,131		Threshold model $pECM_t = 0$

Source: Own elaboration.

In the case of Kapetanioset al. test (2006) modified by Bruzda (2007) ECM_t and ΔECM_t threshold variables do not confirm non-linear dependence. This is in line with the tests construction as well as with the results provided by Enders and Siklos test. Non-linear dependence (but without cointegration) was confirmed for threshold variablesDep_{t-3}andΔArr_{t-2}, respectively.The newly proposed test for the threshold cointegration (Boehlke et. al. 2018, Osińska,2019) indicates that each of the threshold variables identifies non-linear dependency in the form of a threshold model without cointegration. The main reason for not confirming threshold cointegration may be too few observations in the regimes (usually around 9 observations). Therefore, the overwhelming majority of results point to linear cointegration.

To confirm the results we validated those using different approaches for testing for threshold cointegration, representing by Tsay test as well as Hansen and Seo test. Selected results are presented in Tab. 4.

Tab. 4. Results of the Tsay test and Hansen and Seo test for comparison of the linear model (l.m.) vs. threshold model (t.m.)

	Tsay test			Hansen and Seo test		
Threshold variable	C(d)	p-value H_0	l.m. vs.t.m.	LM	p-value H_0	l.m. vs.t.m.
ECM(t-1) = 0	3,515	0,172	Linear	0,064	0,277	Linear
ΔECM(t-1) = 0	11,210	0,024	Threshold	0,157	0,702	Linear
Dep(t-3) = 265,513	2,873	0,238	Linear	0,268	0,993	Linear
ΔDep(t-2) = 6,494	12,278	0,031	Threshold	0,871	0,999	Linear
Arr(t-2) = 349,776	2,228	0,328	Linear	0,316	0,992	Linear
ΔArr(t-2) = 10,528	11,445	0,001	Threshold	0,284	0,304	Linear

Source: Own elaboration.

The results of Tsay test (1998) in the context of confirming threshold cointegration for each variable indicate dominance of linear cointegration (available on request). However, if we focus on threshold models without cointegration, then for three threshold variables (ΔECM_{t-1}, ΔDep_{t-2}, ΔArr_{t-2}) the null hypothesis of linear dependence is rejected. It is worth noting that a threshold model is identified by stationary threshold variables.On the other hand, Hansen and Seo (2002) test mostly indicates that the null hypothesis of linear dependencecannot be rejected. However, it is worth referring to the design of the Hansen and Seo test and noting that possible non-linear structure may have been distorted by too many zero restrictions on parameters. In the study it is assumed that the full model contained 5 variables without a constant (t, ΔArr_t, ΔArr_{t-1}, ECM_{t-1}, ΔDep_{t-1}) and the estimated parameters were generally zero, except for one and a constant, which could result in low LM statistics.Resulted non-linear models for ΔDep_T and $\Delta Arr_{T,P}$ are presented in Tab. 5.

Tab. 5. Threshold models for the variable $\Delta Dep_t$with two different threshold variables

Model I: DependentΔDep_t	Threshold variable: ΔDep_{t-2} = 6,494					
	Regime I $n_1 = 9$			Regime II $n_2 = 8$		
Variable	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
const	-3,362	4,647	0,4965	-21,014	3,915	0,0058
t	1,617	0,736	0,0703	2,045	0,364	0,0049
ΔArr_t	-0,475	0,195	0,0513	0,890	0,072	0,0002
ΔArr_{t-1}				0,587	0,0773	0,0016
Model II: Dependent ΔDep_t	Threshold variable: ΔArr_{t-2} = 10,528					
	Regime I $n_1 = 9$			Regime II $n_2 = 9$		
Variable	Coefficient	Standard error	p-value	Coefficient	Standard error	p-value
const	21,408	7,298	0,0219	4,481	2,179	0,0788
t	-1,856	0,868	0,0699			
ΔArr_t				0,328	0,162	0,0826

Source: Own elaboration.

The forecasts for tourist trips from the EU was built on the basis of 2 models: a threshold model without cointegration, and a linear ECM model.Forecasts are dynamic in nature, i.e. during the forecasting period, forecasted values are used as explanatory delayed variables, not actual observations (Osińska 2007). Table 6presents a summary of the relative ex post forecasting error, which shows the accuracy of the forecasts and the average absolute forecast percentage error (MAPE), which is used to compare forecasts made by different methods (Hyndman and Athanasopoulos, 2018; Wiśniewski, 2020).

Tab. 6. Tourist departures: ex post forecast relative errors and MAPEs[in %]

Year	Model I	Model II	Linear ECM
2016	5,59	2,25	1,61
2017	4,45	3,52	2,18
2018	3,40	5,82	4,26
MAPE	4,48	3,87	2,68

Source: Own elaboration.

The most accurate forecasts come from the linear ECM model. There are tworeasons that account for such a result. First, the error correction component in the forecasting period corrects another forecast by a forecast error from the previous period. Secondly, no structural breaks were identified in the period of forecast.

Discussion

The tests for structural breaks and stationarity of the processes discussed above are known in the literature, as well as the tests identifying threshold cointegration. A new approach was introduced recently in Boehlke at al. (2018) by the test defined in formula (9). In general, majority of tests indicated a linear long term relation between tourist departures and arrivals to the European Union, which is a simpler form than the nonlinear one. On the other hand the tests were able to confirm a stationary non-linear structure (without cointegration) which is related with observed structural breaks (see Gałecki, 2020 for details).Two threshold variables Dep_{t-3} and ΔArr_{t-2}, are confirmed respectively. However to confirm fully a nonlinear structure a larger number of observations is needed. As concerns forecasting of both tourist departures and tourist arrivals the relative forecast errors and MAPE indicate that a linear ECM outperforms the other models, although all results can be considered as acceptable because they are at most equal to 5,82%. Forecasting of variables susceptible to structural breaks should not be done using the simplest methods. Including the non-linear structures into the forecasting models copes better with structural breaks although it requires longer time series. Proper construction of forecasts is important because it can to some extent prepare the tourism industry for possible discontinuities in future.

Conclusions

The paper was aimed to model tourist departures and arrivals to/from the European Union in last 24 years. The reasons were that tourist market in the EU was growing in this time although some structural breaks were detected. These facts motivated us to use a fairly advanced non-linear methodology to find out whether a non-linear relation is appropriate in both long and short run. That is why a wide set of tests for threshold cointegration and for nonlinearity was applied. The tests were supposed to give a clear answer whether we are entitled to assume the linear or non-linear form of the model.Unfortunately, no clear answer has been reached because a linear relation was mostly indicated in the long run however in the short run both linear and nonlinear relations are quite likely. Than two alternative approaches were used for forecasting. Relative forecast errors indicated that a linear error correction model outperforms two nonlinear models, although all forecasts are to be accepted. So the final remark is that having longer time series as well as identifying new structural breaks one should consider a nonlinear model as the alternative for a simplest linear approach. The year 2020 with its unforeseen lockdown will certainly be considered as a structural break in further research on the state of tourist industry.

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