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COINTEGRATING THE LONG-RUN RELATIONSHIP OF ECONOMIC VARIABLES

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Abstract: *The economic non-stationary time series often have long-run relationships. The cointegration relationship of time variables describes the continuous adaptation to their equilibrium in the long-run. This paper presents the ways of analysing and modelling the cointegration of time series. The Error Correction Model, as a main tool, and the Engle-Granger method are used to estimate the cointegration in the case of the long-run relationship between the quarterly GDP and the Final Consumption in Romania during the period 1995 – 2019. The practical importance of applying the cointegrating model consists in knowing the effect of GDP in the long term.*

Key words: *non-stationarity, cointegrating equation, Error Correction Model (ECM), Engle-Granger method.*

1. Introduction

The market economy forces show an equilibrium relationship between some economic series. The linear combination of the envisaged economic variables should have a constant mean, to which often to return for describing an equilibrium relationship. The long-run auto-dependence of the observations of a time variable can be explained by the nature of its dynamics; this series is non-stationary. Using such variables in regressions may conduct to spurious regressions, first identified by Granger and Newbold in 1974.

The stationary series have constant mean, constant variance and constant autocovariances for each lag. A strictly stationary process with finite second moments is automatically covariance stationary. An upward trend of the mean of a time series in levels is a violation of the covariance stationarity (Diebold, 2017, 2019). For a time series which is a stationary process, the effects of shocks found in errors are reducing in time (Kemp, 2012).

For the non-stationary processes, the effects of shocks remain over time, and the persistence of shocks will be infinite. A non-stationary time series having *a deterministic linear trend* (trend-stationary process) can become stationary by the de-trending

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operation (Brooks, 2008). The non-stationary time series may have *a stochastic trend* (difference-stationary process). The *random walk* is the simplest case of non-stationary process; it is *highly persistent*, eqn. (1):

$$\begin{aligned} y_t &= y_{t-1} + e_t \\ y_t &= y_{t-1} + e_t = y_{t-2} + e_{t-1} + e_t = \ldots = y_0 + (e_1 + \ldots + e_{t-1} + e_t) \end{aligned} \tag{1}$$

where e_t are the errors i.i.d. (*independently identically distributed* - meaning that the probability distribution does not depend on the past values and $Cov(e_t, e_{t-1}) = 0$ with mean 0 and constant variance σ^2. The mean of the process is $E(y_t) = y_0$, when y_0 is fixed, and the variance depends on time $Var(y_t) = t \times \sigma^2$.

The highly persistent behaviour has long lasting effects caused by every change, and is different from the trend behaviour. A highly persistent process may also have a trend. *A random walk process with drift*, eqn. (2):

$$y_t = a_0 + y_{t-1} + e_t \tag{2}$$

becomes $y_t = y_0 + ta_0 + (e_1 + \ldots + e_{t-1} + e_t)$ and it has the mean expected value of the process $\{y_t\}$being $E(y_t) = y_0 + ta_0$, and the variance $Var(y_t) = t \times \sigma^2$.

If the time series has a *unit root*, it is *integrated of order 1*, I(1), and the first differences of the process $\{y_t\}$ are weakly dependent, in eqn. (3):

$$\Delta y_t = y_t - y_{t-}1 = a_0 + e_t = u_t \,, \tag{3}$$

and u_t is weakly dependent.

Both trend-stationary and difference-stationary processes are “trending” over time.

The first difference series of the trend-stationary series can remove the non-stationarity and finding a MA(1) structure into the errors (Brooks, 2008, p. 323-325). The presence of a unit root in the residuals means that the effects of a shock persists forever, making it difficult to separate the long-run growth from the other cyclical fluctuations to be separately studied (Favero, 2014). Nelson and Plosser were pioneers of these issues and after their work many tests were proposed to differentiate between the stochastic and the deterministic trends (Favero, 2014).

Examining the time series for a highly persistent but stationary process should be undertaken with approaches other than its autocorrelation function or partial autocorrelation function, which decay to zero. The Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests are used to check the existence of the unit root of the time series.

The VAR models are appropriate for modelling I(0) data, for example growth rates of macroeconomic time series. Often the levels of time series variables, being I(1), describe the equilibrium relationships existing in the economic theory (Zivot and Wang, 2003).

2. Methodology and Data

The main objective of this study is to see if the quarterly GDP and Final Consumption are cointegrated series and so if they have a long-run relationship. We continue to estimate their long-run relationship using the Error Correction Model.

2.1. Error correction model - a tool to describe the cointegrating relationship

Although in the short term the variables may present some deviations from their common tendency, in the long-run they return to converge. This long-run equilibrium relationship of variables can be defined by a *cointegrating relationship*. The *cointegrating equation* describes this stationary linear combination of the non-stationary variables.

If the time series are non-stationary, I(1), an approach is to use their first differences for any following univariate modelling process, in order to build ARMA models (Brooks, 2008). But the first difference models have no long-run solution, in eqn. (4):

$$\Delta y_t = \Delta x_t + u_t\,, \tag{4}$$

The error correction model, also known as *the equilibrium correction model* is defined in eq. (5) (Brooks, 2008), based on the first differences of y_t and x_t and also the lagged values of the cointegrated variables:

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \tau x_{t-1}) + u_t\,. \tag{5}$$

If the two variables y_t and x_t are I(1) and their combination $(y_{t-1} - \tau x_{t-1})$ is an I(0), the OLS procedure is valid for the model from eqn. (2).

The term $(y_{t-1} - \tau x_{t-1})$ is an error term, called the *cointegrating term*, and τ - the *cointegrating coefficient* describes the long-run relationship between the two variables. The cointegrating term, called the *error correction term*, gradually corrects the deviations from the long-run equilibrium through a series of partial short-run adjustments. The proportion β_{12} of the error recorded for the period *t - 1* is considered to correct the path at present period *t*, and it is known as *the speed of adjustment to the equilibrium*.

The *cointegrating vector* is $[1, -\hat{\tau}]$ and any of its linear transformation will also be a cointegrating vector. An intercept may appear in the cointegrating term $(y_{t-1} - \alpha - \tau x_{t-1})$ or in the model (eqn. 6) or in both situations (Brooks, 2008).

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \tau\, x_{t-1}) + u_t \tag{6}$$

The number of cointegrating vectors is one less than the number of variables. When analysing the long-run relationship between two variables, only one cointegrating vector should be, meaning that the two variables may move away from the long-run average in the short-run, but they will converge to the equilibrium in a longer period of time.

When adding more explanatory variables in eqn. (2), *the Granger theorem* says that the I(1) variables $y_t, x_{1t}, x_{2t}, ...x_{kt}$ are cointegrated if the error term of u_t is I(0); otherwise u_t is non-stationary and the variables are not cointegrated.

No matter the number of explanatory variables, using the OLS regression, a single cointegrating relationship can be found. There can be *r* cointegrating relationships, $r < k$, where *k* is the number of the variables. Using the Johansen's system cointegration approach we can determine all *r multiple cointegrating relationships*.

2.2. Estimation of the cointegrating relationship with Engle-Granger Method

There are more methods for parameter estimation in cointegrated systems: Engle-Granger and Johansen methods.

After checking the variables to be I(1), the Engle-Granger 2-step method supposes estimation of the cointegrating regression with OLS, and testing the stationarity of residuals. If the residuals are stationary, I(0), the method is continuing with the 2nd step; otherwise the residuals are I(1) and the model estimation will continue with the first differences, because there is no long-run relationship.

For Engle-Granger test, when accepting H_0, there is no cointegration of series, having no long-run solution. The lack of cointegration implies the inexistence of a long-run relationship.

The 2nd step is the estimation of the *error correction model* in eqn. (7), using the residuals obtained in 1st step, as a variable in the model, $\hat{u}_{t-1}$, because they represent *the error correction term*.

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2 \hat{u}_{t-1} + v_t \text{, where } \hat{u}_{t-1} = y_{t-1} - \hat{\tau} x_{t-1} \quad (7)$$

The Johansen cointegrating test is recommended when using more than two variables.

3. Results - The Long-Run Relationship between Quarterly GDP and Final Consumption in Romania during 1995 – 2020

3.1. The Quarterly GDP and final consumption during 1995 Q1 – 2020 Q2

The chart from Figure 1 shows the similarities between the evolutions of the two quarterly time series over time.

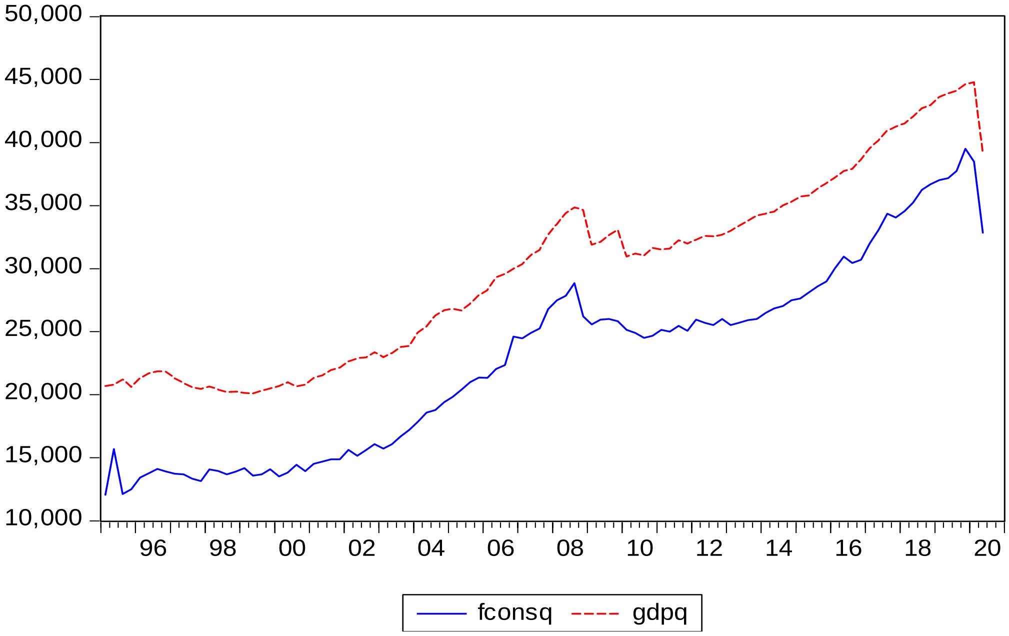

Fig. 1. *The "moving together" over time of quarterly GDP and Final Consumption in Romania during 1995 Q1 – 2020 Q2*

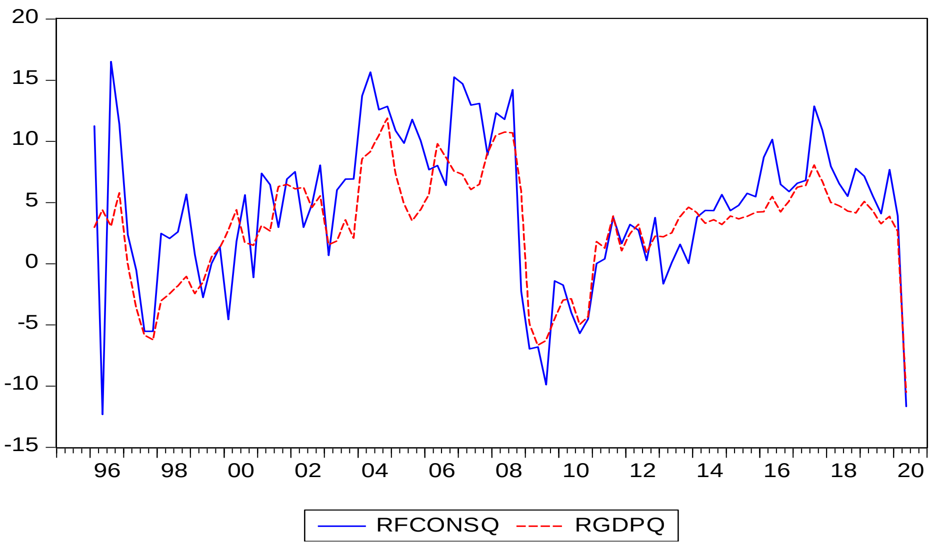

Fig. 2. *The growth rates (y-o-y) of GDPQ and FCONSQ during 1995 Q1 – 2020 Q2*

As seen in Figure 2, the changes of the quarterly Final Consumption (FCONSQ) are more volatile than the changes of the quarterly GDP (GDPQ). During the world crisis from 2008, the decline in FCONSQ started one quarter earlier than the decline of GDPQ. The FCONSQ recorded the first negative rate in the Q4 2008 (-2.25%), compared with GDPQ which recorded the negative dynamic rate in Q1 2009 (-4.88%). The lowest change rate of the quarterly Final Consumption (FCONSQ) along the crisis was in Q3 2009 (-9.89%), which can be seen in Figure 2, but these negative rates lasted for nine successive quarters, until 2010 Q4. The negative dynamic rates of GDPQ lasted eight quarters. We identify the lag 1 between the two variables.

3.2. Testing the causality and the non-stationarity of quarterly GDP and final consumption

The pairwise *Granger Causality* test shows whether an endogenous variable can be treated as exogenous. For the two equations of a VAR, the Wald statistics show the joint significance of each variable of the other lagged endogenous variable in that equation.

The variable GDPQ with its lagged values can be exogenous for the dependent variable FCONSQ. Also the variable FCONSQ with its lagged values can be exogenous for the dependent variable GDPQ, as it can be seen below in Table 1.

Considering 1 lag and then 2 lags, we reject H_0 for both variables in the equations of a VAR and we conclude that GDPQ is a Granger cause for FCONSQ, and FCONSQ is a Granger cause for GDPQ.

Table 1

Testing the causality of the variables GDPQ and FCONSQ

Pairwise Granger Causality Tests
Sample: 1995Q1 2019Q4
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
GDPQ does not Granger-cause FCONSQ	99	17.3013	7.E-05
FCONSQ does not Granger-cause GDPQ		6.81134	0.0105

Pairwise Granger Causality Tests
Sample: 1995Q1 2019Q4
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
FCONSQ does not Granger-cause GDPQ	98	8.79539	0.0003
GDPQ does not Granger-cause FCONSQ		3.93931	0.0228

The Dickey-Fuller tests for both series of the quarterly GDP (GDPQ) and the Final Consumption (FCONSQ) conduct us to accept H_0, because *t Student ratios* from Table 2 are higher than all the *critical values* established by Dickey and Fuller, meaning that both series have unit roots. The identified *lag length* is 0.

Table 2

Dickey-Fuller tests for GDPQ and FCONSQ

Null Hypothesis: FCONSQ has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		2.489749
Test critical values:	1% level	-2.588292
	5% level	-1.944072
	10% level	-1.614616

*MacKinnon (1996)

Null Hypothesis: GDPQ has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic
Elliott-Rothenberg-Stock DF-GLS test statistic		3.816381
Test critical values:	1% level	-2.588292
	5% level	-1.944072
	10% level	-1.614616

*MacKinnon (1996)

The conclusion is the same when applying the Augmented Dickey-Fuller for both series with intercept. For the series of FCONSQ and GDPQ we accept H_0 of non-stationarity.

The group of the two variables is tested for the existence of a common unit root. Using the Group unit root test, more tests are in the Summary of: *t* of Levin, Lin & Chu, the *W-stat* of Im, Pesaran and Shin and the *Fisher based tests* of ADF and PP - in Table 3; we cannot reject H_0. Based on Table 3, we conclude that the two variables of the group are individual unit root processes and also have a long-run relationship. A similar conclusion is available when using the annual data of GDP and Final Consumption, during 1995-2019.

Table 3

Testing the existence of individual and a common unit roots within the group

Group unit root test: Summary
Series: FCONSQ, GDPQ
Sample: 1995Q1 2019Q4
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	3.41516	0.9997	2	198
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	4.79135	1.0000	2	198
ADF - Fisher Chi-square	0.00731	1.0000	2	198
PP - Fisher Chi-square	0.00830	1.0000	2	198

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

The quarterly variables are integrated of order one, I(1). Looking at the Figure 1 and Figure 2, we also expect them to be cointegrated and have a long-run relationship.

3.3. The equilibrium relationship of GDP and final consumption during 1995-2019

The Johansen cointegration test can be used for the group object which consists of the two variables FCONSQ and GDPQ. The Johansen test identifies the model and the number of cointegrating relations.

The three information criteria indicate the number of cointegrating relations and the lowest value of the Schwarz criterion indicates the existence of one cointegrating linear relation with intercept and no trend. After identifying the type of cointegrating relation, we take again Johansen cointegration test to find the cointegrating equation, in Table 4.

Trace test and Maximum Eigenvalue test indicate 1 cointegrating equation at the 5% level of significance. The conclusion of the Johansen cointegration test is that there is one cointegrating relationship between FCONSQ and GDPQ.

Johansen Cointegration test for the group object Table 4

Sample (adjusted): 1995Q2 2019Q4
Included observations: 99 after adjustments
Trend assumption: Linear deterministic trend
Series: FCONSQ GDPQ
Lags interval (in first differences): No lags

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.308061	40.20259	15.49471	0.0000
At most 1	0.037123	3.745081	3.841466	0.0530

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.308061	36.45751	14.26460	0.0000
At most 1	0.037123	3.745081	3.841466	0.0530

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

FCONSQ	GDPQ
-0.001421	0.001426
9.78E-07	0.000138

Unrestricted Adjustment Coefficients (alpha):

D(FCONSQ)	296.4502	111.3438
D(GDPQ)	-130.7397	88.41061

1 Cointegrating Equation(s): Log likelihood -1534.981

Normalized cointegrating coefficients (standard error in parentheses)

FCONSQ	GDPQ
1.000000	-1.003578
	(0.01493)

Adjustment coefficients (standard error in parentheses)

D(FCONSQ)	-0.421303
	(0.10518)
D(GDPQ)	0.185802
	(0.07200)

In Table 4, we have the adjustment coefficients of -0.4213 for the dependent variable D(FCONSQ) and 0.1858 for the equation of D(GDPQ) and the long-run cointegrating coefficient of 1.0036 for FCONSQ on GDPQ. The same results are found with the cointegrating equation with 0 lags, identified with VECM, in Table 6, in the section 3.4.

Using the Engle-Granger 2-step method to test the cointegrating supposes that the variables are I(1), as we have already seen in Table 2 and Table 3, then to estimate the cointegrating regression with OLS, and check the stationarity of residuals.

When using the Cointegrating equation, the Engle-Granger test is automatically applied on the residuals of the estimated model FCONSQ = C(1)*GDPQ + C(2), in Table 5.

Table 5

Engle-Granger method for the cointegrating of FCONSQ and GDPQ

Dependent Variable: FCONSQ
Method: Fully Modified Least Squares (FMOLS)
Sample (adjusted): 1995Q2 2019Q4
Included observations: 99 after adjustments
Cointegrating equation deterministics: C
Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth =4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPQ	1.007698	0.014741	68.36168	0.0000
C	-7177.504	449.5937	-15.96442	0.0000

R-squared	0.990742	Mean dependent var	22659.13
Adjusted R-squared	0.990646	S.D. dependent var	7391.649
S.E. of regression	714.8792	Sum squared resid	49572066
Long-run variance	1139097.		

Cointegration Test - Engle-Granger
Equation: UNTITLED
Specification: FCONSQ GDPQ C
Cointegrating equation deterministics: C
Null hypothesis: Series are not cointegrated
Automatic lag specification (lag=0 based on Schwarz Info Criterion, maxlag=12)

	Value	Prob.*
Engle-Granger tau-statistic	-6.520641	0.0000
Engle-Granger z-statistic	-60.33880	0.0000

*MacKinnon (1996) p-values.

Engle-Granger Test Equation:
Dependent Variable: D(RESID)
Method: Least Squares
Sample (adjusted): 1995Q2 2019Q4
Included observations: 99 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID(-1)	-0.609483	0.093470	-6.520641	0.0000

The Engle-Granger test of cointegration, in Table 5, shows that H_0 is rejected and the residuals are stationary, i.e. I(0), meaning that the series FCONSQ and GDPQ are cointegrated; they have a long-run relationship. The cointegration regression with the representation COINTREG FCONSQ GDPQ, with substituted coefficients is: FCONSQ=1.0077*GDPQ-7177.504.

We accept the cointegration of variables and we can estimate *the error correction model*.

3.4. Modelling the cointegrating relationship with Error Correction Model (ECM)

With the Engle-Granger method and Johansen Cointegration tests, a single cointegrating relationship was identified since there are two variables to consider: GDPQ and FCONSQ.

Taking the Error Correction Model in estimating VAR, with 0 lags because the Cointegrating Rank test (Trace) identified the existence of one cointegrating relationship at lag 0, under these conditions we obtain the cointegrating equation in Table 6:

Table 6

VECM for FCONSQ and GDPQ with 0 lags

Vector Error Correction Estimates
Sample (adjusted): 1995Q2 2019Q4
Included observations: 99 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
FCONSQ(-1)	1.000000	
GDPQ(-1)	-1.003578	
	(0.01493)	
	[-67.2097]	
C	7100.623	
Error Correction:	**D(FCONSQ)**	**D(GDPQ)**
CointEq1	-0.421303	0.185802
	(0.10518)	(0.07200)
	[-4.00540]	[2.58070]
C	277.2354	241.9909
	(74.0127)	(50.6606)
	[3.74578]	[4.77671]

VAR Model - Substituted Coefficients:
===============================
D(FCONSQ) **=** - 0.4213***(FCONSQ(-1) - 1.0036*GDPQ(-1) + 7100.6234)** + 277.2353
D(GDPQ) = 0.1858***(FCONSQ(-1) - 1.0036*GDPQ(-1) + 7100.6234)** + 241.9909

The VECM model presented in Table 6 has the system of equations in eqn. (8).

$$\Delta y_t = \alpha_{11}\left(\beta_{11} y_{t-}1 + \beta_{12} x_{t-1} + \beta_{13}\right) + \gamma_{11}$$

$$\Delta xt = \alpha 21\left(\beta_{11} y_{t-1} + \beta 12 x_{t-1} + \beta_{13}\right) + \gamma_{21} \quad (8)$$

For the equation of FCONSQ, the cointegrating term, called also the error correction term is $\left(y_{t-1} - \left(\tau\, x_{t-}1 - \beta_0\right)\right)$, i. e. ($FCONSQ_{t-1}$ - 1.0036*$GDPQ_{t-1}$ + 7100.6234), being the partial short adjustments to the long-run equilibrium. The *cointegrating coefficient* τ, here β_{12} (eq. 8) describes the long-run relationship between the two variables and it is 1.0036. The speed of adjustment to the equilibrium is the coefficient α_{11}= -0.4213 which shows the proportion of the error of period *t-1* which is considered to correct the path at the present period *t*. So at period *t*, 42.13% of the error at *t-1* is subtracted, in order to be on the long-run equilibrium path.

For the equation of GDPQ, the cointegrating term and the *cointegrating coefficient* are the same. The speed of adjustment to the equilibrium is the coefficient α_{21}= 0.1858 which shows the proportion 18.58% of the error of period *t-1* to be added in order to correct the path at the present period *t*.

4. Conclusions

The economic theory describes the equilibrium relationships of time series in levels that are non-stationary, I(1), based on the concept of cointegration. The cointegration gives sense to the regression and VAR models for variables which are I(1).

When the explanatory variables in a regression analysis are I(1) and they are not cointegrated, then there is a spurious regression with the results which do not hold. The regressions with I(1) variables make sense only when these series are cointegrated.

The Final Consumption is more volatile than the GDP; the growth rates (y-o-y) of GDPQ and FCONSQ during 1995 Q1 – 2020 Q2 in Figure 2 show this sensitive behaviour of consumption to the GDP shocks.

This paper proves that the Final Consumption proactively changes before the GDP changes, and the effect of a shock is longer lasting than that over GDP. The consumption behaviour reacts in advance when a crisis dawns and produces changes on the future outputs. The paper emphasizes the importance of studying cointegration when analysing the long–run relationships of economic variables.

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