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Is Real Gross Domestic Product (GDP) Series Stationary in EU Countries? Evidence from the RALS-CIPS Test

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Abstract

The purpose of this study is to propose a new residual-based unit root test and then apply it to examine the stationarity of gross domestic product (GDP) for EU membership countries. For this purpose, the CIPS test proposed by Pesaran (2007) has been extended to a structure that takes into account the knowledge of the non-normally distributed residuals. For this, the residual augmented least squares (RALS) estimators proposed by Im and Schmidt (2008) were included in the CIPS test. The second and third moments of the error terms are added to the cross-sectionally augmented ADF (CADF) regression that constitutes the CIPS test process. When calibrated under the behavior of the residues non-normally distributed residuals during the data generation process, it is seen that the panel unit root test specific to the series in which the residuals are not normally distributed has higher power and more appropriate size than CIPS test. According to the results of empirical analysis, it was concluded that the CIPS test was stationary only at the 10% level, while according to the RALS-CIPS test it was concluded that it was stationary at the 1% significance level. It can be interpreted that the RALS-CIPS test is stronger because it used additional information consisting of residual moments. The test offers a simple way to have good size and power properties for non-normal errors.

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1. Introduction

Since the Nelson and Plosser (1982), various studies have been conducted to investigate the stationarity of important macroeconomic variables. Determining whether the shocks for real output levels, one of the macroeconomic variables, are temporary or permanent is one of these studies. This test is important for making inferences such as policy making, modeling, and forecasting. Therefore, real gross domestic product per capita is an important indicator of economic activities and is generally used by decision makers to plan economic policy.

The Gross Domestic Product (GDP) of a country is defined as the monetary value of all final goods and services produced in a year by all production factors within the borders of that country. That is, it represents the total statistics of all economic activities. It can be decided whether the performance of the economy is good or not through GDP (Dritsaki, 2015). Real gross domestic product per capita shows the production power free from inflationary effects. Therefore, the way to measure economic growth is to look at the macroeconomic variable of real GDP per capita (Fırat, 2016).

Besides being of great importance for policy makers, this issue also attracts the attention of researchers conducting empirical studies. Nelson and Plosser (1982) state that the unit root in real output is inconsistent with the idea that business cycles are stationary fluctuations around a deterministic trend. Despite the empirical evidence of the stationarity of real GDP in developing countries, it suggests that shocks to real output have permanent effects on the system (Shen et al., 2013).

The purpose of Keynesian business cycle models is to implement macroeconomic policies, such as fiscal policies, to offset the revenue fluctuations of governments. Real GDP fluctuations have temporary deviations from the trend. Therefore, the neo-classical macroeconomic suggests that there is no need to implement monetary and fiscal policies to cope with the GDP shocks as GDP fluctuations adjusts in the long run (Chang et al., 2014).

Temporary macroeconomic fluctuations around a deterministic trend mean that monetary and fiscal shocks have temporary effects on the economy. On the other hand, permanent output shocks indicate that if the fluctuations in production are caused by disruptions that have permanent effects on output such as technology shocks and monetary and financial shocks, the long-term output will be uncontrolled (Guloglu and Ivrendi, 2010). That is, if a series receives any shock or policy intervention, then it cannot return to the average and moves away from the average (Murthy and Anoruo, 2009). Conversely, if real GDP per capita follows a stationary path, shocks will have temporary effects. In this case, it is sufficient to trust the market and the economy will return to its natural path soon without any direct or indirect intervention.

The linear unit root test methodology assumes that the real gross domestic product level process moving towards equilibrium despite the deviation state is linear and the adjustment rate is constant. In this respect, linear unit root tests are important tools for determining whether the economic series follow a consistent way or not. But power is also an important factor in unit root tests. A suitable way to increase power while testing the unit root might be to use the panel data structure (Shen et al. 2013).

Since the foundation of the European Union, its members have been pursuing many common policies. It aims for an environment where economic activities can be maintained in harmony and balance among EU countries. In addition, the increase in the welfare level for EU countries has been one of the main factors. As it is known from the real economy and literature, one of the important determinants of the increase in welfare is economic growth. It is not possible to talk about an increase in welfare without a steady and permanent economic growth. In this context, it is important to determine whether the GDP series for EU countries is around a positive trend curve and follows a stationary way.

Stationarity tests have an important place in time series and panel data analysis. The assumptions of the classical regression model require the variables to be stationary and the errors to have zero mean and constant variance. If this assumption is not provided, estimates and analyzes made with nonstationary series may give incorrect results. In other words, it is stated that the predictions of the regression output that seem best are not consistent and the results do not have any economic meaning.

Some series may exhibit a fat-tailed distribution that is highly skewed or flat. Similarly, the error term of a regression equation may show skewed distribution from the normal distribution or it may show a flat or pointed distribution compared to the normal distribution. In these cases, ordinary least squares (OLS) estimators are unbiased and consistent, but not efficient. Therefore, unit root tests based on OLS estimates may be affected by the non-normal distribution of the error term. The problems caused by the non-normal distribution of the error term can be eliminated or reduced by the application of some transformations. One of these tests is the unit root test developed with residual augmented least squares (RALS) estimators. These estimators, which were suggested by Im and Schmidt (2008), use the information about the non-normal distribution of residuals and are asymptotically efficient.

RALS tests are based on information specific to errors that are not normally distributed. For this reason, it is believed that RALS tests are significantly more powerful than conventional tests that do not use information about non-normal errors. The RALS procedure can be used in any non-normal situation, including asymmetry and fat-tail distributions (Solarin, 2019). Payne et al. (2017) stated that standard unit root tests are not affected by the presence of non-normal errors, but this does not mean that information about non-normal errors should be ignored and not used.

The RALS method was first extended to the functional form of the estimator under the non-normality of the error term by Im (1996) and then by Im and Schmidt (2008). Then Taylor and Peel (1998) obtained a new unit root test by adding RALS estimators to the DF structure and stated that the RALS-DF unit root test is robust in the distribution of skewed and flat residual terms. Meng (2013) developed the RALS-LM unit root test by adding RALS estimators to the LM unit root test structure proposed by Schmidt and Phillips (1992). Thus, they obtained stronger and more robust test results with non-normal errors and some nonlinear arrangements. Im et al. (2014) included RALS estimators in their ADF regressions. Thus, they have shown that stronger results will be obtained than those of the standard ADF test. Meng et al. (2016) have been developed the RALS-LM test, which allows for trend shifts. They stated that the proposed test results are stronger than those of the LM test. Canpolat (2017) stated that by adding RALS terms to SUR regression models, the model obtained by extending it with a nonlinear structure gives more confidential results.

The rest of the study is structured as follows. The next section consists of econometric methodology. Section III provides Monte Carlo simulation results for the RALS-CIPS test. Section IV discusses the empirical findings, and the final section provides the conclusion.

2. Residual Augmented Least Squares Panel CIPS Unit Root Test

Pesaran (2007) defined a stationary general autoregressive process as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \tag{1}$$

where f_t are common effects that affect units but cannot be observed and $i = 1,2,\ldots,N$ and $t = 1,2,\ldots,T$. In addition, ε_{it} indicates the individual-error. The unit root structure under the null hypothesis is tested. The null hypothesis for all i is as follows:

$$H_0\colon \beta_i = 0$$

An alternative hypothesis is based on the assumption of heterogeneity, and it is as follows:

$$H_1\colon \beta_1 < 0, \beta_2 < 0, \ldots, \beta_{N_0} < 0, \quad N_0 \le N$$

The CADF regression model is as follows:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it} \tag{2}$$

In the case of serial correlation of individual error terms, the test procedure can be easily extended by adding an appropriate number of lagged values to the CADF regression without any change in the distribution of the statistics (Pesaran, 2007):

$$\Delta y_{it} = a_i + b_i + c_i \bar{y}_{t-1} + \sum_{j=0}^{p} d_{ij}\, \Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + e_{it} \tag{3}$$

Equation (3) shows the regression of the pth order individual error term with both cross-sectional and serial correlation.

Im and Schmidt (2008) considered the following two-moment conditions in the RALS procedure:

$$E[e_t \otimes x_t] = 0 \tag{4}$$

$$E[(h(e_t) - K) \otimes x_t] = 0 \tag{5}$$

The first of these conditions specifies the standard moment condition of the OLS method. The second condition contains an additional $(\mathrm{J}-1) \times (\mathrm{p}+2)$ moment condition and refers to the additional moment condition based on the nonlinear functions of e_t. The following notation is used:

$$C = \begin{bmatrix} \sigma_e^2 & C'_{21} \\ C_{21} & C_{22} \end{bmatrix} \text{ and } \mathrm{D} = \begin{bmatrix} 1 \\ D_2 \end{bmatrix} \tag{6}$$

where $C_{21} = E[e_t h(e_t)]$, $C_{22} = E[h(e_t)h(e_t)']$ and $D_2 = E[h(e_t)']$. These two conditions can be shown as follows:

$$\widehat{w}_t = h(\hat{e}_t) - \bar{K} - \hat{e}_t \widehat{D}_2, \; t = 1,2,\ldots,T \tag{7}$$

where $\hat{e}_t$, denotes residuals obtained from the main regression and calculated as follows. $\bar{K} = \frac{1}{T}\sum_{t=1}^{T} h(\hat{e}_t)$, $\widehat{D}_2 = \frac{1}{T}\sum_{t=1}^{T} h'(\hat{e}_t)$ and $h(\hat{e}_t) = [\hat{e}_t^2, \hat{e}_t^3]'$ $m_j = T^{-1}\sum_{t=1}^{T} \hat{e}_t^{\,j}$, $\; for\, j =$ 2,3:

$$\begin{aligned}
\widehat{w}_t &= [\hat{e}_t^2, \hat{e}_t^3]' - \tfrac{1}{T}\textstyle\sum_{t=1}^{T}[\hat{e}_t^2, \hat{e}_t^3]' - \hat{e}_t - \tfrac{1}{T}\sum_{t=1}^{T}[2\hat{e}_t^2, 3\hat{e}_t^3]' \\
&= \begin{bmatrix} \hat{e}_t^2 - \frac{1}{T}\sum_{t=1}^{T}\hat{e}_t^2 - 2\frac{1}{T}\sum_{t=1}^{T}\hat{e}_t \\ \hat{e}_t^3 - \frac{1}{T}\sum_{t=1}^{T}\hat{e}_t^3 - 3\frac{1}{T}\sum_{t=1}^{T}\hat{e}_t^2\hat{e}_t \end{bmatrix} \\
&= \begin{bmatrix} \hat{e}_t^2 - T^{-1}\sum_{t=1}^{T}\hat{e}_t^2 \\ \hat{e}_t^3 - T^{-1}\sum_{t=1}^{T}\hat{e}_t^3 - 3T^{-1}\sum_{t=1}^{T}\hat{e}_t^2\hat{e}_t \end{bmatrix} \\
&= \begin{bmatrix} \hat{e}_t^2 - m_2 \\ \hat{e}_t^3 - m_3 - 3m_{2t}\hat{e}_t \end{bmatrix}
\end{aligned}$$

Then $\widehat{w}_t = [\hat{e}_t^2 - m_2, \hat{e}_t^3 - m_3 - 3m_{2t}\hat{e}_t]'$ is obtained (Çoban, 2018), where $m_2 = \hat{\sigma}^2_{\hat{\varepsilon}_{kt}}$ and it is the second moment or it simply represents the variance. The third moment is represented by m_3. The $\widehat{w}_t$ series obtained through residuals is included in the CADF equation, where the aim is to use the non-normal distribution information in the model structure to obtain stronger results than those obtained from other estimation methods in errors that do not show normal distribution.

Using the RALS method, one can extend the RALS-CADF test equation as follows:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \gamma'_2 \widehat{w}_{it} + e_{it} \tag{8}$$

This equation uses the OLS t statistic of the b_i parameter to test the null hypothesis. It is estimated for each unit separately in order to create test statistics for the panel as a whole. The CIPS statistic based on a cross-sectional enhanced version of the Im et al. (2003, IPS), test using the RALS-CADF t statistic is as follows:

$$RALS - CIPS\,(N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T) \tag{9}$$

Equation (9) is called a RALS-CIPS statistic. Similarly, equation (3) can be extended as follows:

$$\Delta y_{it} = a_i + b_i + c_i \bar{y}_{t-1} + \sum_{j=0}^{p} d_{ij}\, \Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + \gamma'_2 \widehat{w}_{it} + e_{it} \tag{10}$$

A separate RALS-CADF regression is calculated for each unit, and the OLS t statistic of the b_i parameter is used to test the null hypothesis.

3. Monte Carlo Simulation Results for RALS-CIPS Test

In this section, the empirical size and power properties of critical values for the proposed RALS-CIPS test were examined.

3.1. Critical Values

Critical value of RALS-CADF and RALS-CIPS tests under the assumption of non-normal residuals were regressed on Δy_{1t}, $y_{1,t-1}$, $\bar{y}_{t-1}$, $\Delta\bar{y}_t$ and were obtained by simulating 10.000 Monte Carlo, for $t = 1,2,\dots,T$.

For $i = 1,2,\dots,N$ the individual series is generated $y_{it} = y_{i,t-1} + f_t + \varepsilon_{it}$. Here, f_t~iid$N(0,1)$, with $t = -50,-49,\dots,1,2,\dots,T$ for $y_{i,-50} = 0$. Finite sample critical values for 1%, 5%, and 10% in the RALS-CADF and RALS-CIPS equations created by Monte Carlo simulation are presented in Tables 1 and 2.

Table I. Critical Value Table of RALS-CADF Test

	1%	**5%**	**10%**
N = 10 and T = 50	-4.446	-3.411	-2.923
N = 10 and T = 100	-3.881	-3.112	-2.751
N = 20 and T = 50	-4.462	-3.372	-2.915
N = 20 and T = 100	-3.799	-3.080	-2.711
N = 50 and T = 50	-4.274	-3.328	-2.919
N = 50 and T = 100	-3.828	-3.064	-2.712
N = 80 and T = 50	-4.330	-3.306	-2.850
N = 80 and T = 100	-4.330	-3.306	-2.850

Table II. Critical Value Table of RALS-CIPS Test

	1%	**5%**	**10%**
N = 10 and T = 50	-2.550	-2.262	-2.126
N = 10 and T = 100	-2.357	-2.124	-1.989
N = 20 and T = 50	-2.265	-2.054	-1.951
N = 20 and T = 100	-2.105	-1.927	-1.837
N = 50 and T = 50	-2.021	-1.885	-1.809
N = 50 and T = 100	-1.896	-1.782	-1.720
N = 80 and T = 50	-1.953	-1.841	-1.769
N = 80 and T = 100	-1.851	-1.751	-1.693

3.2. Size and Power

The data generation process, which is created by considering with intercept dynamic panel model, in which the cross-sectional dependence and the serial correlation of residuals are taken into account, is as follows:

$$y_{it} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + u_{it}, \qquad i = 1,\dots,N; t = -51,-50,\dots,1,2,\dots,T$$

$$u_{it} = \gamma_i f_t + \varepsilon_{it},\ f_t \sim iid\ N(0,1)$$

where ε_{it} is as follows to show errors:

$$\varepsilon_{it} = \rho_i \varepsilon_{i,t-1} + e_{it}$$

It is possible to investigate the behavior of the developed RALS-CIPS test for various situations. In this study, three data generation processes (DGP) are discussed. Each process produces data for a different situation. These DGPs are defined as follows (Ceresa, 2008; Pesaran, 2007):

1. $\rho_i = 0$ that is, there is no serial correlation and high cross-section dependence with $\gamma_{ij} \sim Uni[-1,3]$. This situation is defined as DGP1.
2. Positive serial correlation with $\rho_i \sim Uni[0.2,0.4]$ and high cross-section dependence with $\gamma_{ij} \sim Uni[-1,3]$ and defined as DGP2.
3. Negative serial correlation with $\rho_i \sim Uni[-0.4,-0.2]$ and high cross-section dependence with $\gamma_{ij} \sim Uni[-1,3]$ and defined as DGP3.

The size and power properties of the tests were investigated with 10,000 Monte Carlo simulations. The null hypothesis for all i is $\phi_i = 1$, and the heterogeneous alternative hypothesis is taken as $\phi_i \sim iid\ Uni[0.85,0.95]$. Tests were performed according to 5% nominal size and for all combinations of $N = 10, 20, 50, 80$ and $T = 50, 100$. Under the alternative hypothesis, $\mu_i \sim iid\ Uni[0,0.02]$, and all parameters, μ_i, ϕ_i, ρ_i, and γ_i are defined under the assumption that they are independent of the errors. Under the unit root null hypothesis, the aim is to examine the size and power properties of the RALS-CIPS test using the knowledge of non-normal distribution of residuals with Monte Carlo simulation experiments. In these experiments, the error terms are not normally distributed.

Table III. Size and Power Properties of CIPS and RALS-CIPS Tests Under No Serial Correlation and High Cross-Section Dependence Assumptions

	CIPS		**RALS-CIPS**	
N/T	50 Size-Power	100 Size-Power	50 Size-Power	100 Size-Power
10	0.0847-0.464	0.1889-0.9942	0.0469-0.5563	0.0488-0.9981
20	0.1828-0.8376	0.3833-1.000	0.0512-0.8948	0.0507-1.000
50	0.4024-0.9978	0.7306-1.000	0.0538-0.999	0.0557-1.000
80	0.5119-1.000	0.8504-1.000	0.0541-1.000	0.0499-1.000

According to these results, one can see that the size properties of the CIPS test are far from the nominal level. Unlike the CIPS test, the size properties of the RALS-CIPS test remain at the nominal level.

The simulation results of the CIPS and RALS-CIPS tests under the assumptions of positive serial correlation and high cross-section dependence are presented in Tables 4–5. These results are similar to the findings of Pesaran (2007). In addition, as suggested by Pesaran, results are also reported for cases involving high-degree lagged values of the dependent variable.[3] It was taken into account as $\sum_{j=1}^{p} \Delta y_{it-j}$ $(p = 1,2,3)$.

Table IV. Size and Power Properties of CIPS and RALS-CIPS Tests Under Positive Serial Correlation and High Cross-Section Dependence Assumptions

$\boldsymbol{for\ p = 1}$

[3] Pesaran (2007) examined cases where only 0 and 1 lagged, respectively CADF (0) and CADF (1). CADF (0): $\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_{i0} \Delta \bar{y}_t + u_{it}$ and CADF (1): $\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_{i0} \Delta \bar{y}_t + d_{i1} \Delta \bar{y}_t + \delta_{i1} \Delta y_{i,t-1} + u_{it}$. In this study, RALS-CADF (0): $\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_{i0} \Delta \bar{y}_t + \gamma_2' \widehat{w}_{it} + u_{it}$ and RALS-CADF (1): $\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_{i0} \Delta \bar{y}_t + d_{i1} \Delta \bar{y}_t + \delta_{i1} \Delta y_{i,t-1} + \gamma_2' \widehat{w}_{it} + u_{it}$ is happening. In this study, besides 1 lag, 2 and 3 lag cases were also examined. In other words, RALS-CADF (2) and RALS-CADF (3) cases have also been tested.

	CIPS		RALS-CIPS	
N/T	50 Size-Power	100 Size-Power	50 Size-Power	100 Size-Power
10	0.0839-0.3415	0.1787-0.9747	0.051-0.4157	0.0463-0.9918
20	0.1705-0.6553	0.3674-0.9999	0.0535-0.7304	0.0554-1.000
50	0.354-0.9554	0.6789-1.000	0.0576-0.9805	0.0537-1.000
80	0.4528-0.9917	0.8093-1.000	0.0589-0.998	0.0467-1.000

$$\boldsymbol{for\ p = 2}$$

	CIPS		RALS-CIPS	
N/T	50 Size-Power	100 Size-Power	50 Size-Power	100 Size-Power
10	0.0632-0.2525	0.1608-0.947	0.0483-0.3155	0.0427-0.9782
20	0.1259-0.4823	0.3304-0.9997	0.0454-0.5679	0.0494-1.000
50	0.2727-0.8315	0.6302-1.000	0.0449-0.9036	0.0424-1.000
80	0.3577-0.9298	0.7594-1.000	0.0414-0.9764	0.0386-1.000

$$\boldsymbol{for\ p = 3}$$

	CIPS		RALS-CIPS	
N/T	50 Size-Power	100 Size-Power	50 Size-Power	100 Size-Power
10	0.0639-0.2189	0.1579-0.9151	0.0505-0.2703	0.0441-0.9625
20	0.1171-0.4014	0.316-0.9991	0.0485-0.469	0.048-0.9998
50	0.2467-0.7243	0.6114-1.000	0.0502-0.8083	0.0443-1.000
80	0.3244-0.8395	0.7337-1.000	0.0469-0.9152	0.0388-1.000

The simulation results of the CIPS and RALS-CIPS tests under the assumptions of negative serial correlation and high cross-section dependency are as following tables.

Table V. Size and Power Properties of CIPS and RALS-CIPS Tests under Negative Serial Correlation and High Cross-Section Dependence Assumptions

$$\boldsymbol{for\ p = 1}$$

	CIPS		RALS-CIPS	
N/T	50 Size-Power	100 Size-Power	50 Size-Power	100 Size-Power
10	0.0829-0.4268	0.1928-0.9895	0.0566-0.5291	0.0514-0.997
20	0.1884-0.7794	0.3791-1.000	0.055-0.8487	0.0536-1.000
50	0.4027-0.9944	0.7146-1.000	0.0617-0.9982	0.0585-1.000
80	0.4974-0.9996	0.8327-1.000	0.0626-1.000	0.0535-1.000

$$\boldsymbol{for\ p = 2}$$

	CIPS		RALS-CIPS	
N/T	50 Size-Power	100 Size-Power	50 Size-Power	100 Size-Power
10	0.0669-0.3071	0.1734-0.9749	0.0503-0.4064	0.0468-0.9912
20	0.141-0.6069	0.3415-0.9999	0.0465-0.6986	0.0484-1.000

50	0.3114-0.942	0.6631-1.000	0.0475-0.9746	0.0503-1.000
80	0.396-0.9869	0.7793-1.000	0.0445-0.9973	0.0419-1.000

$$\boldsymbol{for\ p = 3}$$

	CIPS		RALS-CIPS	
N/T	50 Size-Power	100 Size-Power	50 Size-Power	100 Size-Power
10	0.0653-0.2514	0.1687-0.9548	0.0494-0.3427	0.047-0.98
20	0.1314-0.5091	0.3275-0.9996	0.0456-0.6009	0.0482-1.000
50	0.282-0.8635	0.6388-1.000	0.0543-0.9282	0.0503-1.000
80	0.3623-0.9406	0.753-1.000	0.0454-0.9803	0.0417-1.000

According to the results that were reported up to three lags of the dependent variable, one can see that the CIPS test does not have good size properties. In contrast, the size properties of the RALS-CIPS test are at the nominal level. CIPS and RALS-CIPS tests show similar characteristics as power properties.

4. Empirical Application

The stationarity of the real gross domestic product (GDP) per capita variable in 15 European Union member states is examined for the empirical application of the proposed test. The best way to measure economic growth is to consider real GDP per capita. This variable is also used in predicting the future trend of economic growth and in analyzing the effects of economic policies.

Table 6. CADF, CIPS, and RALS-CADF and RALS-CIPS Test Results

	Individual Test Statistics		**Individual Test Statistics**
Austria	-3.166		-3.548
Belgium	-3.433		-3.377
Denmark	-1.476		-1.214
Finland	-1.952		-0.998
France	-2.390		-2.025
Germany	-2.157		-2.149
Greece	-1.664		-1.935
Ireland	-1.627		-4.046
Italy	-0.087		-0.461
Luxembourg	-2.255		-2.200
Netherlands	-2.614		-2.460
Portugal	-2.504		-2.437
Spain	-3.149		-3.010
Sweden	-1.938		-1.704
United Kingdom	-3.197		-3.082
CIPS Test Statistics	-2.240	**RALS-CIPS Test Statistics**	-2.310
	1% 5% 10% -2.465 -2.264 -2.161		**1% 5% 10%** -2.265 -2.054 -1.950

Note: The critical values for CADF and RALS-CADF tests were obtained by 10,000 Monte-Carlo simulations and are -3.884, -3.273, and -2.929 and -4,462, -3,372, and -2,915, respectively.

5. Conclusion

One of the basic assumptions in econometrics is that error terms have a normal distribution. Accepting a series that does not distribute normally as if it is normally distributed may cause biased and misleading results. For this reason, in this study, a new unit root test is proposed using RALS terms, which takes into account the non-normal distribution of residuals. This proposed test is a version of the CIPS test developed by Pesaran (2007) for non-normally distributed errors. The RALS structure uses the second and third moments of the error terms. With this information, RALS estimators are not sensitive to the assumption of normal distribution on errors. Thus, stronger and more reliable results can be obtained even if the residuals do not show normal distribution.

The size and power properties of the proposed RALS-CIPS test were investigated using Monte Carlo. For this purpose, three separate data generation processes have been established. Size and power values were calculated on the basis of critical values obtained by 10,000 Monte Carlo simulations. The size and power properties of the CIPS and RALS-CIPS tests were reported according to the assumptions of the presence and absence of autocorrelation for the residuals that non-normal distributed and has high cross section dependence. In case of autocorrelation, the lag values of the dependent variable to be added are taken exogenous in order to eliminate this problem.

Under the assumption that there is no autocorrelation of the RALS-CIPS test, it is seen that the size properties is at nominal level and power properties are good. In cases of positive and negative serial correlation, the RALS-CIPS test appears to be good in terms of size feature. In other words, when the cross-sectional dependence is high and the residuals are not normally distributed, the size properties of the RALS-CIPS test are at the 5% significance level with the autocorrelation taken into account. However, the sizes of the CIPS test are far from the nominal level. Although there are some losses in low observations in terms of power properties, there is an improvement in its performance with increasing N and T for the sample size used here.

Based on these findings, the RALS-CIPS test can be recommended as one of the tests that can be used in the presence of autocorrelation and cross-sectional dependence, where a normal distribution condition is not met for the error term. In line with the knowledge that RALS estimators give strong results when errors are not normally distributed, the expectation that the RALS-CIPS unit root test will be strong in the same situation was confirmed by simulation study.

In the study, the per capita growth series for 15 EU countries was investigated using annual data for the 1970-2018 periods. According to the results obtained, CADF and CIPS as well as RALS-CADF and RALS-CIPS tests were applied. According to these test results, Pesaran (2007) gives the result that the CIPS test is stationary only level of 10% for the all panel. According to the results of the RALS-CIPS test, which is the focal point of the study, the series indicates a stationary structure at 1% significance level for all panels. In the RALS-CIPS test, the expectation that it would give a stronger result because the assumption of normality was stretched was met at the same time with the empirical research.

The economic meaning of the stationary of a series is that it enables policy makers to obtain more effective results with less cost. As stated, the stationary of the overall GDP series means that economic shocks will not cause any permanent effects and so the series will turn its own natural path without the need for any intervention. Here it is needed to mention that temporariness and permanence of the effects of economic shocks on subcomponents of GDP series may differ however it is accepted that taking directly overall GDP series into consideration is better, especially in country / regional-scale studies. Paralleling the neo-classical macroeconomic suggestions, this shows that the trust in markets and confidence in economic functioning in the face of shocks is sufficient and no intervention is required. Thus, instead of short-term panic-based economic intervention policies, the public resources may be directed to long-term and wiser structural transformation and development investments, such as education, health, poverty alleviation, dissemination of renewable energy resources, environmentally sensitive projects, and innovative investments.

The European Union has adopted many common policies since its establishment. It is aimed to create a common market in which free movement of goods, services, capital and persons among the EU member states is ensured. In addition, cooperation has been established in which economic activities will develop in a harmonious and balanced way by establishing an economic and monetary union and the implementation of common trade and competition policies. For example, at the end of the period in which the oil crisis was experienced, European Union countries were less affected than the countries importing from OPEC countries. EU countries make their imports within themselves and mostly from countries such as America, England and Japan. For this reason, the capacity of member countries to absorb economic shocks has increased thanks to the positive exogeneities that have emerged as they take part in economic integration.

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