

## INTERNET USAGE, ECONOMIC GROWTH AND ELECTRICITY CONSUMPTION: THE CASE OF EU-15\*

### İnternet Kullanımı, Ekonomik Büyüme ve Elektrik Tüketimi: EU-15 Örneđi

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#### Abstract

The purpose of this study is to examine the impacts of internet usage and economic growth on electricity consumption in EU-15 countries. In this study using panel cointegration test developed by Westerlund and Edgerton (2007), the existence of a cointegration relationship in both the constant model and the constant and trend model is proved. The findings obtained by using the panel cointegration method indicate that internet usage and economic growth have a significant impact on electricity consumption in the long run. After identifying the existence of a panel cointegration relationship in EU-15 countries, the long-run cointegration coefficients were obtained with the Augmented Mean Group estimators developed by Eberhard and Bond (2009), Eberhardt and Teal (2010). The long-run coefficient results demonstrate that a change in internet usage for all EU-15 countries can reduce electricity consumption at a very low rate, but a change in economic growth increases electricity consumption. The country-based empirical findings suggest that the impact of internet usage and economic growth on electricity consumption varies in different countries.

#### Keywords:

Electricity Consumption, Internet Usage, Economic Growth, EU-15 Countries, Panel Data Analysis

#### JEL Codes:

O11, O13, Q43

#### Özet

Bu çalışmanın amacı EU-15 ülkelerinde internet kullanımı ve ekonomik büyümenin elektrik tüketimi üzerindeki etkilerini arařtırmaktır. Westerlund ve Edgerton (2007) tarafından geliştirilen panel eşbütünleşme testinin kullanıldığı bu çalışmada hem sabitli model hem de sabitli ve trendli modelde bir eşbütünleşme ilişkisinin varlığı kanıtlanmaktadır. Panel eşbütünleşme analiz yönteminden yararlanılarak elde edilen bulgular uzun dönemde internet kullanımı ve ekonomik büyümenin elektrik tüketimi üzerinde anlamlı bir etkisinin olduğunu göstermektedir. EU-15 ülkelerinde panel eşbütünleşme ilişkisinin varlığı belirlendikten sonra uzun dönem eşbütünleşme katsayıları Eberhard ve Bond (2009), Eberhardt ve Teal (2010) tarafından geliştirilen Genelleştirilmiş Ortalama Grup tahmincileri ile elde edilmiştir. Uzun dönem katsayı sonuçları EU-15 ülkelerinin tamamı için internet kullanımında meydana gelen bir değişimin elektrik tüketimini çok küçük bir oranda da olsa azaltabileceđi ancak ekonomik büyümede meydana gelen bir değişimin ise elektrik tüketimini arttırdığını göstermektedir. Elde edilen ülke bazlı ampirik bulgular internet kullanımı ve ekonomik büyümenin elektrik tüketimi üzerindeki etkisinin ülkeden ülkeye farklılıklar içerdiğini göstermektedir.

#### Anahtar Kelimeler:

Elektrik Tüketimi, İnternet Kullanımı, Ekonomik Büyüme, AB-15 Ülkeleri, Panel Veri Analizi

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## 1. Introduction

The world witnesses that the use of information and communication technologies (ICTs) has become increasingly indispensable since the 1990s. It is argued that information and communication technology is a new force that shapes the future of the world by disposing of geological limits and bringing societies and social orders closer together (Nasir and Kalirajan, 2016; Salahuddin, Alam and Ozturk, 2016). With the ICTs connecting people and communities by creating opportunities and improving living standards for people around the world by facilitating the modernization and increasing efficiency, it is expressed that there has been a dramatic transformation in the world (Mago and Mago, 2015). Investments in ICTs are regarded as the main driving force of productivity growth. Productivity growth is thought to be one of the key factors underlying improvements in the standard of living (Niebel, 2018). Based on this relationship determined in the majority of studies, including the ones conducted by Jorgenson and Stiroh (1995), Haacker and Morsink (2002), Dewan and Kraemer (1998), it is emphasized that ICTs have positive effects on productivity.

In theory, most researchers contend that ICTs are a critical stimulant of economic growth, although it is stressed that no exact answer is given in neoclassical growth theory about how technological changes occur. According to the neoclassical growth theory, growth is affected by external technological change. It is noted that theoretical approaches attempted to break away from the Neoclassical Orthodox approach to explain the origin of technological changes that originated in the 1980s (Greenhalgh and Rogers, 2010; Stanley, Doucouliagos and Steel, 2018). In the last period of the twentieth century, there is consensus on the fact that the explanations of endogenous and theoretical development of the economic growth phenomenon are generally accepted. The prevailing argument is that knowledge leading to technological change (innovation) was the main driving force for countries' economic progress. Endogenous growth theories appear to have developed approaches where the main growth factors are technological expansion, research and development activities, and international technology transfer. (Sredojević, Cvetanović and Bošković, 2016).

Some studies in the empirical literature reveal that ICTs have an expected negative effect on economic development. The majority of studies investigating the negative effects of information and communication technology deal with the argument that technical change is generally creative destruction. In the context of these discussions, it is emphasized that information and communication technology has a negative impact on the labor and employment market (Aghion and Howitt, 1998; Freeman and Soete, 1997).

Because of the decrease or disposal of some untalented positions, unskilled labor loses their jobs, thus saving labor. The disappearance of unskilled jobs reveals that a technical change must take place. The realization of technical change allows the use of ICTs to become widespread and bears similarities with various types of technical change (Satti and Nour, 2002).

ICTs have important effects on the global system. The rapid development and use of these technologies have proven to contribute to increasing efficiency and reducing energy density. Therefore, studies on the environmental impact of ICTs have attracted extraordinary attention since the 1990s. From that point forward, studies researching the effects of ICTs on energy have been explored in-depth in a macro framework (Moyer and Hughes, 2012). Internet-connected digital technologies are expected to play an important role in the transition to a more feasible and energy-efficient future. However, the expansion in the quantity of gadgets

associated with the internet, the number and sort of services, and the degrees of data flow, processing, and capacity means that the energy used to get to the web has increased significantly. The services offered by the internet are increasingly included in daily lifestyles. The proportion of Internet users has steadily increased in economically developed countries and has risen to over 90%. As digital foundations, the services, and items they uphold are continually growing, even in nations where web access is widespread, the effects of continued digitalization on energy are complex and not very apparent (Morley, Widdicks and Hazas, 2018; Salahuddin and Alam, 2016). Research on this subject argues that increasing internet connectivity in everyday life either balances energy savings or promotes more forms of energy-intensive demand. Similarly, this infers that smart home innovations could likewise be identified with increments in energy utilization both legitimately and in other utilization regions like lighting or heating (Hargreaves, Wilson and Hauxwell-Baldwin, 2018; Røpke, 2012).

In this context, this study try to figure out the effect of internet usage and economic growth on electricity consumption in the so-called EU-15 countries including Austria, Belgium, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Sweden in the period 1992-2014. For this purpose, the main hypothesis of this study is the existence of a significance relationship between internet usage and economic growth in EU-15 countries in the long run. The long run cointegration coefficients of internet usage and economic growth variables are the same for all EU-15 countries.

The study differs from many studies in the literature, especially in terms of the method, sampling, and the period investigated. In this study, as showing the effect of internet usage and economic growth on electricity consumption in developed countries such as the EU-15 can be an example for many other developing countries, this study increases its significance even more.

In the following chapters of the study, a literature review on the subject is given. After the literature review, information on the data used in the analysis is presented. The following stages include methods and findings, respectively. Finally, the results were discussed, and the study was concluded.

## **2. Literature Review**

In this part of the study, the literature is examined under two headings. Firstly, studies examining the relationships between ICTs and electricity consumption are discussed. Secondly, studies that examine the relationships between growth and electricity consumption are discussed. The last part of the literature especially reveals why this study differs from previous studies.

### **2.1. Information and Communication Technologies and Electricity Consumption**

The interrelation between ICTs and electricity consumption is a vital and current issue that's still being researched. The majority of studies figuring out the effect of ICT on electricity consumption have been carried out at the country or industry level. Different methods of analysis are used in this regard, and different results are accessed.

Laitner (2002) argues that the need for energy in the use of ICTs is often overstated. According to this perspective, it is emphasized that approximately 3% of total U.S. energy consumption is necessitated to meet current information technology requirements. Laitner (2002) emphasizes that it is less clear how ICTs will affect energy consumption, especially in the case of the development and mass adoption of a range of new information and communication technology products.

Collard, Feve and Portier (2005) apply a demand model to investigate the link between energy and ICTs within the French tertiary sector. They underline that the electrical measure of creation decreased with the extension of specialized gadgets and heightened with PCs and programming in the period 1986-1998.

Røpke, Christensen and Jensen (2010) aim to investigate the associated transformations in everyday life in Denmark related to ICTs, and in particular, to reveal their impact on residential electricity consumption. When household electricity consumption components were examined in Denmark in 1950, it was seen that 3% of household electricity consumption was used for heating and power 97% for lighting. In 1990, 18% of household electricity consumption was used for lighting, 68% for heating, and 14% for other means such as TVs, stereos, and computers. In 2006, it was concluded that household electricity consumption used for lighting was 11% and 59% for heating, and an increasing proportion for other instruments such as TVs, stereos and computers. It is therefore concluded that the integration of ICTs into everyday applications increases electricity consumption.

Sadorsky (2012) researches the effect of information and communication technology on electricity consumption in developing countries. Findings from models indicate a statistically significant and positive correlation between electricity consumption and information and communication technology once measured by means of the number of internet connections, PCs, or mobile phones. Long-term information and communication technology elasticities are smaller than income elasticities because income growth rates are much lower than information and communication technology growth rates. The findings from the study show that the effect of information and communication technology on electricity demand outweighs the impact of income on electricity demand.

Heddeghem et al. (2014) analyze how ICTs have changed from 2007 to 2012 taking account of three main categories of electricity consumption, data centers, personal computers and communication networks. They describe in detail how electricity consumption and change are calculated in these three categories. The results of the study display that the annual growth of all three categories (4%, 5% and 10%), respectively, is greater than the increase in world electricity consumption (3%) over the same period. It is observed that the relative share of this ICTs subgroup in total electricity consumption enlarged from about 3.9% in 2007 to 4.6% in 2012. The study also concludes that the certain electricity consumption of each of the three categories is approximately identical.

Salahuddin and Alam (2015) predict the long run and also short run impacts of economic growth and internet usage on electricity consumption in Australia for the period of 1985-2012. The findings from the ARDL estimations suggest that economic growth and internet usage have raised electricity consumption in Australia, but no significant relationship was found between economic growth, internet usage and electricity consumption in the short run.

Pothitou, Hanna and Chalvatzis (2017) focus on TV, computer, and electronic tools, including their equipment especially used by households. When waste energy is included in the EU-27, where 6% of residential energy demand originates from on-hold devices, it is concluded that ICTs account for about 15% of household electricity consumption. It is stated that in Europe, the household electricity consumption of small electronic devices, including ICTs, increased 2.5 times in 2011 compared to 1990.

Saidi, Toumi and Zaidi (2017) explore the effect of economic growth and information communication technology on electricity consumption for 67 countries through the dynamic panel data model. The findings demonstrate that ICTs have a meaningful and positive effect on electricity consumption once quantified using mobile phones and internet connections.

Yan, Shi and Yang (2018) study the interaction between ICTs and energy consumption in terms of energy efficiency with a data set of 50 countries in the period of 1995-2013. The findings conclude that the development of ICTs is significantly associated with improving energy efficiency.

## **2.2. Growth and Electricity Consumption**

The empirical literature offers different results regarding growth and energy consumption. These differences arise from the use of country-specific heterogeneity, economic development, and energy consumption models.

Kraft and Kraft (1978) research the causality relation between growth and energy consumption in the United States. Empirical results indicate the existence of a strong statistical interaction between growth and energy consumption. The test results also show unidirectional causality from growth to energy consumption, while there is no a causality from energy consumption to growth. Therefore, while the level of economic activity may affect energy consumption, it is expressed that the degree of energy consumption has no underlying effect on economic activity.

Yang (2000) investigates the causality interaction between growth and energy consumption using the data of Taiwan for 1954-1997. The causality link between growth and the total energy consumption is investigated, in addition to the causality link between disaggregated energy consumption categories, including oil, natural gas, coal, and electricity. The results obtained through the granger causality method reveal that there is bidirectional causality between total energy consumption and growth. Moreover, it is determined that there are different causality aspects between growth and other categories of energy consumption types.

Ghosh (2002) examines the linkage between per capita gross domestic product and per capita electricity consumption for India. The study results confirm that there is no long-run equilibrium point between variables, however there is unidirectional causality from economic growth to electricity consumption.

Shiu and Lam (2004) investigate the causality interaction between electricity consumption and growth for China. Estimation findings show that there is a cointegration between these two variables for China, as well as one-way causality from electricity consumption to growth, however there is no causality vice versa.

Yoo (2005) studies the causality connection between economic growth and electricity consumption in Korea through the cointegration models. The results indicate two-way causality between variables. These results mean that the escalation in electricity consumption exactly affects economic growth and that economic growth correspondingly prompts larger electricity consumption.

Ciarreta and Zarraga (2010) analyzes causality interaction between electricity consumption and economic growth in Spain for the period 1971-2005 through the linear and nonlinear form. While one-way directional linear causality relationship from real gross domestic product to electricity consumption was determined, no signal of nonlinear Granger causality was found between the series in either direction.

Narayan, Narayan and Popp (2010) examine Granger causality between electricity consumption and real gross domestic product for seven panels of 93 countries. In the long run, a causality from real gross domestic product to electricity consumption was in the Middle East countries, whereas it was determined that there is bidirectional Granger causality relationship between electricity consumption and real gross domestic product in other panel countries. Finally, the estimations for the G6 panel have a negative sign, meaning that electricity consumption in the G6 reduces gross domestic product.

Wolde-Rufael (2014) examines the Granger causality interaction between electricity consumption and economic growth for 15 transition economies using the bootstrap panel causality approach. The empirical results indicate that there is unidirectional causality from economic growth to electricity consumption in the Russian Federation, Latvia, Czech Republic and Lithuania and from electricity consumption to economic growth in Bulgaria and Belarus. There is no causality in Slovenia, Serbia, Macedonia, Moldova, Romania, Poland, Slovak Republic and Albania, whereas there is two-way causality only in Ukraine.

Liu et al. (2018) explores the connection between economic growth and electricity consumption in Beijing with Granger causality using sectoral data. The study results show unidirectional causality from economic growth to electricity consumption at the collective level. At the sectoral level, electricity consumption for the primary sector affects its value added by a delay of two quarters, and there is one-way causality from economic growth towards electricity consumption for the secondary sector and tertiary sector.

Aydin (2019) investigates the interaction between non-renewable and renewable electricity consumption and economic growth for 26 OECD countries. The results of the Dumitrescu-Hurlin test results show the presence of bidirectional causality between non-renewable electricity consumption and economic growth. In contrast, empirical results from Croux and Reusens demonstrate that there is bidirectional transitory and lasting causality relationship between these variables.

Balcilar, Bekun and Uzuner (2019) study the relations between carbon dioxide emissions, real gross domestic product, and electricity consumption in Pakistan. The Maki cointegration test shows that there is a cointegration relationship between these variables. Empirical causality results from the Toda-Yamamoto test show that there is one-way causality from economic growth towards electricity consumption.

Lin and Wang (2019) seek to explain the inconsistency between electricity consumption and economic growth, based on China's panel data. Although the growth rate in China was

close to 6.9% in 2015, there was only a 2.9% increase in electricity consumption. However, a 6.6% growth in the gross domestic product in 2018 would require an 8.5% increase in electricity. The results show that as the economy grows faster than electricity consumption, the increase in stock, fixed capital, and industrial electricity consumption can narrow or widen the difference.

As the literature is examined in general, there are few studies investigating the effects of both internet usage and economic growth on electricity consumption. This study differs from many studies above in terms of examining the effect of these two variables on the electricity consumption of EU-15 countries.

### 3. Research Data

In this study, the data of “Individuals Using the Internet (% of the population)” for the variable internet usage (NET), “Electricity Consumption (kWh per capita)” for the variable electricity consumption (LEC) and “GDP and PPP per capita (constant 2011 international \$)” for the variable economic growth (LGDPPC) belonging to Austria, Belgium, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Sweden, which were named as EU-15 countries, for the period 1992-2014 are used. The data are obtained from the World Bank database. In the study, LEC and LGDPPC variables were used in their logarithmic form. The reason this study covers 1992-2014 for EU-15 is that the data of the electricity consumption variable before 1992 and after 2014 are not available. The fourth enlargement of the European Union took place in 1995. The EU-15 countries participating in this enlargement have taken on the role of leading countries in the development of all Europe. At the same time, the countries involved in this enlargement have facilitated the implementation of economically compatible policies with the European Union. Therefore, EU-15 countries, which are the pioneers of the European Union, are selected in the study.

### 4. Methodology

The impacts of internet usage and economic growth on electricity consumption in the EU-15 countries for the period 1992-2014 are examined in five stages. In the first stage, the presence of the cross-sectional dependency on variables and models is tested. The levels of stationarity of the second stage variables are determined by the unit root test developed by Smith, Leybourne, Kim and Newbold (2004). The homogeneity of the slope coefficients obtained in the model used in the third stage is demonstrated by the test developed by Pesaran and Yamagata (2008). In the fourth stage, the cointegration test developed by Westerlund and Edgerton (2007) is used to determine the existence of long-run relationships between variables. Also, the method developed by Eberhardt and Bond (2009) and Eberhardt and Teal (2010) is used for the estimation of cointegration coefficients. The following is information about these methods and their reasons for selecting them, respectively.

*Stage 1: Testing of the Cross-Sectional Dependency on Variables and Model:* The cross-sectional dependency is a phenomenon that needs to be tested in panel data econometrics. In order to determine whether a shock occurring in one of the models or variables of the countries included in the data set of the panel being examined causes a shock in other countries, the cross-

sectional dependency must be tested. Besides, there are two important econometric reasons for testing the cross-sectional dependency in variables and models. The first is the selection of the unit root test to be used in the stationarity test, and the second is the necessity of considering the cross-sectional dependency in the selection of the cointegration test in which long-run relationships are investigated. If the variables and/or models have a cross-sectional dependency, second-generation tests should be used.

For the cross-sectional dependency tests in panel data econometrics, the tests<sup>1</sup> of  $BP_{LM}$  developed by Breusch and Pagan (1980),  $CD_{LM}$  developed by Pesaran (2004),  $LM_{adj}$  developed by Pesaran, Ullah and Yamagata (2008) and finally  $LM_{BC}$  developed by Baltagi, Feng and Kao (2012) are frequently used. The most important feature that distinguishes these tests from one another is that the panel has advantages over country/unit (N) and time (t) size. The stages of how to test cross-sectional dependency with the help of the model used in the study are explained below.

In order to test the cross-sectional dependency in Model 1<sup>2</sup>, the model is first estimated by the Ordinary Least Squares (OLS) method. Subsequently, the residual term represented by  $e_{i,t}$  is derived, and the cross-sectional dependency tests are performed on this residual term. In addition, processes for each variable are conducted as similar to  $e_{i,t}$ .

$$LEC_{i,t} = \beta_0 + \beta_{1,i}NET_{i,t} + \beta_{2,i}LGDPPC_{i,t} + e_{i,t} \quad (1)$$

$\beta_0$  represents the constant coefficient of the model, while  $\beta_{1,i}$  and  $\beta_{2,i}$  represent the slope coefficients. In other words, they are the coefficients that show to what extent and in what direction the changes occurring in the relevant independent variables will affect the dependent variable  $LEC_{i,t}$ . The index i in the model indicates the country size of the model, and the index t indicates the time dimension of the model. For this study, as stated above, i= Austria, Belgium,, Sweden is a total of N=15 countries, t=1992,1993,..., 2014 being a total T=23 in a row. Using the residual term  $u_{i,t}$  obtained after deriving the model, an auxiliary regression is obtained as follows:

$$e_{i,t} = \alpha_i + \delta'_i x_{i,t} + \omega_{i,t} \quad (2)$$

In the model,  $x_{i,t}$  represents independent variables. These arguments are nothing but the lags of  $\omega_{i,t}$  and are as follows:  $x_{i,t} = (e_{i,t-1}, \dots, e_{i,t-p})$ .  $\alpha_i$  is the constant term coefficient and  $\delta'_i$  is the slope coefficient. For each country, the residual terms of Model 2 are assumed as  $(\omega_{i,t} = \omega_{1,t}, \dots, \omega_{N,t}) \omega_{i,t} \sim IID(0, \sigma_{i,\omega}^2)$ . In this model, the following hypotheses are decided by applying the tests mentioned above:

$H_0: cov(\omega_{i,t}, \omega_{j,t}) = 0$  or  $\sigma_{ij} = 0$  and  $i \neq j$ . (No cross-sectional dependency in the variable/model.)

$H_1: cov(\omega_{i,t}, \omega_{j,t}) \neq 0$  or  $\sigma_{ij} \neq 0$  (Cross-sectional dependency in the variable/model.)

$H_0$  hypothesis is rejected if the test statistics obtained are greater than their critical values or if the probability values of the test statistics are smaller than their statistical significance levels. This means that there is a cross-sectional dependency on variables/models. On the

<sup>1</sup>Since all of these tests are applied to variables and models in the study, no detailed information about the tests is given.

<sup>2</sup>Imitated from the model that Salahuddin and Alam (2015) used in their study.



contrary, the  $H_0$  hypothesis is not rejected, meaning that there is no cross-sectional dependency on variables/models.

**Stage 2: Panel Bootstrap Unit Root Test (Smith et al. (2004)):** Stationarity is an issue that should be taken into consideration especially in long t dimensions because if there is no stationarity in the variables, the problem of regression emerges, that is, the obtained estimations cannot be trusted. For this reason, the stationarity of the variables should be examined first, and then a decision should be made about the analysis to be made according to whether it is stationary or not. In the case of cross-sectional dependency on variables in panel data econometrics<sup>3</sup>, it is recommended to use second-generation panel unit root tests when examining the stationarity levels of variables. Therefore, this study uses the panel bootstrap unit root test developed by Smith et al. (2004), a second-generation panel unit root test. Also, Smith et al. (2004) emphasized that this unit root test, which they developed based on the bootstrap method, has stronger aspects than many other unit root tests.

Smith et al. (2004, p. 148, 150-151) use  $\overline{IPS}(\bar{t}_s)$ ,  $\overline{Max}_s$ ,  $\overline{Min}_s$ ,  $\overline{LM}_s$  and  $\overline{WS}_s$  statistics<sup>4</sup> to test whether the variables are stationary. Using these statistics, the following hypotheses are tested:

$H_0$ : There is unit root (not stationary).

$H_1$ : There is no unit root (stationary).

In order to decide on hypotheses, probability values of  $\overline{IPS}(\bar{t}_s)$ ,  $\overline{Max}_s$ ,  $\overline{Min}_s$ ,  $\overline{LM}_s$  and  $\overline{WS}_s$  test statistics are calculated using the critical values acquired using the bootstrap method.  $H_0$  is rejected if the probability values of the test statistics are less than the statistical significance levels. That is, it is decided that the variable is stationary. Otherwise,  $H_0$  cannot be rejected. If the variable is not stable at its level, this test process is applied to the variable again by taking the difference of the variable as in all unit root tests. For example, if the variable is stationary in the first difference, it is decided that this variable is I(1), which is stationary in the first difference.

**Stage 3: Homogeneity Test:** In case all variables are stationary at the same level<sup>5</sup>, the cointegration relationship between the variables should be sought (Engle and Granger, 1987). If it is investigated whether there is a cointegration relationship between variables belonging to a country group by using panel data, it is definitely necessary to perform a homogeneity test beforehand. The meaning of homogeneity is that  $\beta_{1,i}$  coefficients in the equation shown in Model 1 are equal to a single  $\beta_1$  coefficient and  $\beta_{2,i}$  coefficients are equal to a single  $\beta_2$  coefficient (Pesaran and Yamagata, 2008). To test this situation, Pesaran and Yamagata (2008) have developed a method base on which is originated in the ‘‘Random Coefficient Regression’’ estimator developed by Swamy (1970). In this method, Pesaran and Yamagata (2008) test whether the coefficients in the model are equal to a single coefficient using the asymptotically strong  $\tilde{\Delta}$  and  $\tilde{\Delta}_{adj}$  test statistics. If the probability values of the obtained  $\tilde{\Delta}$  and  $\tilde{\Delta}_{adj}$  test statistics are smaller than the statistical significance levels, and it means that the coefficients  $\beta_1$  and  $\beta_2$  mentioned above vary in different countries, and the model is determined

<sup>3</sup>According to the results of the cross-sectional dependency test, all variables have cross-sectional dependency. See: Table 1.

<sup>4</sup>Refer to Smith et al. (2004) for detailed information on the test statistics.

<sup>5</sup>According to the unit root test results, all the variables were found to be I(1). See: Table 2.

to be heterogeneous. Otherwise, it is decided that the model is homogeneous. In the cointegration tests and cointegration parameter estimations to be made after this stage, the selection should be made in light of this information.

**Stage 4: Westerlund and Edgerton (2007) Cointegration Test:** Analyzing long-run relationships in economic data is regarded as essential. Hence, there are many cointegration tests that have been introduced to econometrics literature to analyze long-run relationships. Westerlund and Edgerton (2007) developed a method for use in panel data models. Westerlund and Edgerton (2007, p. 185-186) stated that the basis of the cointegration test they developed based on the bootstrap method was based on the study of McCoskey and Kao (1998) and Westerlund (2005, 2006). Westerlund and Edgerton (2007, p. 186) use the Lagrange Multiplier (LM) statistic developed by McCoskey and Kao (1998) when investigating the cointegration relationship in an equation as in Model 1. The test is first estimated using Model 1's Ordinary Least Squares and/or the Yule-Walker method, and then the LM test statistic is calculated using some of the information in this model. This test statistic is compared with the critical values obtained by bootstrap to determine the test hypotheses. Because of the existence of cross-sectional dependency, bootstrap critical values should be used. The hypotheses for the test are as follows:

$H_0$ : There is a cointegration relationship in the model.

$H_1$ : There is no cointegration relationship in the model.

In order to decide on hypotheses, it is necessary to check the bootstrap probability values of asymptotic and/or bootstrap critical values of LM Test statistics. As stated above, bootstrap probability values should be checked because there is a cross-sectional dependency in the model.  $H_0$  cannot be rejected if the probability values of the LM test statistic obtained are greater than 10%. This means that there is a cointegration relationship in the model, and the meaning of this for Model 1 is that LNET and LGDPPC have a significant effect on the LEC in the long run. On the contrary, it is decided that there is no cointegration relationship in the model.

**Stage 5: Cointegration Parameter Estimation:** After determining the existence of a significant cointegration relationship, it is important to estimate in which direction and to what extent the relevant independent variables affect the dependent variables. To this end, the Augmented Mean Group method developed by Eberhardt and Bond (2009) and Eberhardt and Teal (2010) is used in the study to estimate cointegration parameters. The most important feature of this method is that it takes into account the cross-sectional dependency between countries and estimates the coefficient for each country separately. In addition, the average of the long-run coefficients obtained for each country can be estimated within the entire panel<sup>6</sup>.

## 5. Findings

In this part of the study, the analysis findings obtained using the methods described above are included. The findings begin with the examination of the results of cross-sectional dependency.

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<sup>6</sup>See Eberhardt and Bond (2009) and Eberhardt and Teal (2010) for detailed information about estimators.

Table 1 presents the test results for variables and cross-sectional dependency for the model. As a result of the analysis, the presence of cross-sectional dependency in both variables and models was determined according to the probability values of all cross-sectional dependency test statistics. The fact that there is a cross-sectional dependency in variables and models suggests that a shock occurring in a variable of one country or the corresponding model causes a shock in other countries as well. It is expected to identify cross-sectional dependency, especially in countries with similar characteristics such as EU-15. This finding suggests that tests that consider cross-sectional dependency for both variables and models should be used in later stages in econometric terms. In this study, while the unit root test was performed for the variables, the test developed by Smith et al. (2004), one of the second generation unit root tests, was therefore selected. In addition, the cointegration test and cointegration parameter estimators take into account these findings.

**Table 1. Cross-sectional Dependency Test Results**

<b>Variables:</b>	<b>LEC</b>		<b>NET</b>		<b>LGDP</b>	
<b>Test</b>	Calculated Statistics Value	Probability Value	Calculated Statistics Value	Probability Value	Calculated Statistics Value	Probability Value
<b>BP<sub>LM</sub></b>	1379.823	0.0001*	2282.129	0.0001*	2017.965	0.0001*
<b>CD<sub>LM</sub></b>	86.93606	0.0001*	149.2011	0.0001*	134.767	0.0001*
<b>LM<sub>BC</sub></b>	86.59515	0.0001*	148.8602	0.0001*	134.426	0.0001*
<b>LM<sub>adj</sub></b>	30.1634	0.0001*	47.75733	0.0001*	45.326	0.0001*
<b>Model</b>						
	<b>Test</b>	Calculated Statistics Value	Probability Value			
	<b>BP<sub>LM</sub></b>	1506.429	0.0001*			
	<b>CD<sub>LM</sub></b>	95.67267	0.0001*			
	<b>LM<sub>BC</sub></b>	95.33176	0.0001*			
	<b>LM<sub>adj</sub></b>	8.968686	0.0001*			

\* There is a cross-sectional dependency on the variables according to all statistical significance levels.

In Table 2, Smith et al. (2004) panel unit root test results of the variables are seen. According to these results, it is observed that the three variables that are subject to analysis are stationary in the first difference, i.e., I(1) according to all test statistics. As Engle and Granger (1987) stated, if two or more variables are equally stationary, there can be long-run relationships between them. Hence, it is required to test the relationship between them. Otherwise, long-run information losses occur in regression analysis by taking the differences of the variables. For this reason, it was decided to conduct a cointegration test for the related equality in the later stages of the study.

**Table 2. Smith et al. (2004) Panel Bootstrap Unit Root Test Results**

Variable: LEC				
Test	Constant Model		Constant-Trend Model	
	Level	First Difference	Level	First Difference
$\overline{IPS}(\bar{t}_s)$ , Statistics (Probability)	-1.942 (0.135)	-3.051 (0.001)*	-0.665 (0.998)	-4.774 (0.001)*
$\overline{Max}_s$ Statistics (Probability)	-0.033 (0.969)	-3.031 (0.001)*	-0.665 (0.998)	-4.084 (0.001)*
$\overline{LM}_s$ Statistics (Probability)	4.749 (0.057)	6.870 (0.002)*	1.401 (0.997)	11.875 (0.001)*
$\overline{Min}_s$ Statistics (Probability)	1.197 (0.770)	6.816 (0.002)*	1.401 (0.997)	9.777 (0.001)*
$\overline{WS}_s$ Statistics (Probability)	-0.554 (0.901)	-3.309 (0.001)*	-1.107 (0.995)	-4.569 (0.001)*
Variable: NET				
Test	Constant Model		Constant-Trend Model	
	Level	First Difference	Level	First Difference
$\overline{IPS}(\bar{t}_s)$ , Statistics (Probability)	-0.483 (0.993)	-2.825 (0.001)*	-1.532 (0.946)	-3.038 (0.011)
$\overline{Max}_s$ Statistics (Probability)	0.246 (0.999)	-2.666 (0.001)*	-0.798 (0.994)	-2.752 (0.001)*
$\overline{LM}_s$ Statistics (Probability)	1.833 (0.935)	6.558 (0.001)*	3.324 (0.935)	7.505 (0.008)*
$\overline{Min}_s$ Statistics (Probability)	1.134 (0.874)	6.072 (0.001)*	1.525 (0.998)	6.612 (0.001)*
$\overline{WS}_s$ Statistics (Probability)	0.217 (0.999)	-2.889 (0.001)*	-1.315 (0.999)	-3.125 (0.001)*
Variable: LGDP				
Test	Constant Model		Constant-Trend Model	
	Level	First Difference	Level	First Difference
$\overline{IPS}(\bar{t}_s)$ , Statistics (Probability)	-2.138 (0.108)	-3.011 (0.011)*	-1.123 (0.951)	-3.892 (0.007)*
$\overline{Max}_s$ Statistics (Probability)	0.424 (0.989)	-2.797 (0.001)*	-1.073 (0.894)	-3.165 (0.005)*
$\overline{LM}_s$ Statistics (Probability)	4.700 (0.101)	7.034 (0.011)*	2.098 (0.947)	9.939 (0.006)*
$\overline{Min}_s$ Statistics (Probability)	1.514 (0.539)	6.407 (0.001)*	1.972 (0.870)	7.847 (0.005)*
$\overline{WS}_s$ Statistics (Probability)	0.007 (0.962)	-3.101 (0.001)*	-1.523 (0.897)	-3.504 (0.005)*

\* refers to stationarity at a 5% statistical significance level.

Pesaran and Yamagata (2008) homogeneity test results conducted to determine whether slope coefficients are homogeneous in the relevant model before continuing with the cointegration test are given in Table 3. Considering the probability value of both test statistics, it was found that the null hypothesis that the slope coefficients were equal to a single slope coefficient was rejected; that is, the coefficients were heterogeneous. This means that the effects of NET and LGDPPC on LEC differ in various countries for EU-15 countries.

**Table 3. Homogeneity Test Results**

Test	Test Statistics	Prob.
$\tilde{\Delta}$	27.105	0.0001
$\tilde{\Delta}_{adj}$	29.976	0.0001

\* refers to stationarity at a 1% statistical significance level.

Due to the heterogeneous nature of the model subject to analysis, the cointegration test developed by Westerlund and Edgerton (2007) was used. Table 4 shows the results of this cointegration test. According to the results of the analysis, there is a significant cointegration relationship for Model 1, and when the probability values of the LM statistical values obtained are analyzed, it was found that the null hypothesis of the test, which is “there is a cointegration

relationship in the model” hypothesis, cannot be rejected. In addition, this relationship is valid for both the constant model and the constant and trend model.

**Table 4. Westerlund and Edgerton (2007) Panel Bootstrap Cointegration Test Results**

<b>Constant Term Model -OLS Estimator Results</b>		
<i>LM Statistics Value</i>	<i>Bootstrap Probability</i>	<i>Probability</i>
0.579	0.883*	0.281*
<b>Constant Term Model - Yule Walker Estimator Results</b>		
<i>LM Statistics Value</i>	<i>Bootstrap Probability</i>	<i>Probability</i>
0.579	0.999*	0.281*
<b>Constant and Trend Term Model -OLS Estimator Results</b>		
<i>LM Statistics Value</i>	<i>Bootstrap Probability</i>	<i>Probability</i>
1.159	0.992*	0.123*
<b>Constant and Trend Term Model - Yule Walker Estimator Results</b>		
<i>LM Statistics Value</i>	<i>Bootstrap Probability</i>	<i>Probability</i>
1.159	0.999*	0.123*

\* It represents significant cointegration relationship.

The meaning of this cointegration relationship is that the variables of NET and LGDPPC have a significant effect on LEC in the long run. After identifying the existence of a significant cointegration relationship, the results of the cointegration parameters (long run coefficients) obtained by using the “Augmented Mean Group” estimator developed by Eberhard and Bond (2009) and Eberhardt and Teal (2010) are presented in Table 5. For the EU-15 countries, the 1-unit increase in the NET variable decreased the LEC variable by 0.0009%, while the 1% increase in the LGDPPC variable increased the LEC variable by 0.3319%. Both of these coefficients are statistically significant. Also, according to Wald statistics, the model is significant as a whole.

**Table 5. Cointegration Parameter Estimates**

<b>Coefficient Estimates for the Whole Panel</b>							
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>				
NET	-0.0009*	-2.08	0.0370				
LGDPPC	0.3319*	3.53	0.0001				
constant	5.2305*	5.02	0.0010				
<b>Wald Chi2=16.76*</b>				<b>Prob&gt; chi2=0.0002</b>			
<b>Coefficient Estimates for Austria</b>				<b>Coefficient Estimates for the United Kingdom</b>			
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>	<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>
NET	0.0039*	4.73	0.0001	NET	-0.0030*	-7.06	0.0001
LGDPPC	-0.6829*	-2.99	0.0030	LGDPPC	0.3251*	2.73	0.0060
constant	15.8178*	6.64	0.0001	constant	5.2732*	4.320	0.0001
<b>Coefficient Estimates for Belgium</b>				<b>Coefficient Estimates for Greece</b>			
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>	<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>
NET	-0.0022*	-9.09	0.0001	NET	0.0025*	8.81	0.0001
LGDPPC	0.4657*	6.36	0.0001	LGDPPC	0.3760*	9.04	0.0001
constant	4.0290*	5.30	0.0001	constant	4.3280*	10.06	0.0001
<b>Coefficient Estimates for Germany</b>				<b>Coefficient Estimates for Ireland</b>			
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>	<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>
NET	-0.0012*	-2.37	0.0180	NET	-0.0012*	-7.04	0.0001
LGDPPC	0.3031	1.52	0.1280	LGDPPC	0.3561*	16.53	0.0001
constant	5.5466*	2.68	0.0070	constant	4.7455*	21.33	0.0001
<b>Coefficient Estimates for Denmark</b>				<b>Coefficient Estimates for Italy</b>			
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>	<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>
NET	-0.0021*	-6.90	0.0001	NET	-0.0005*	-7.15	0.0001
LGDPPC	-0.0247	-0.19	0.8470	LGDPPC	0.5162*	18.13	0.0001
constant	9.0011*	6.65	0.0001	constant	3.0129*	10.14	0.0001
<b>Coefficient Estimates for Spain</b>				<b>Coefficient Estimates for Luxembourg</b>			
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>	<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>
NET	-0.0001	-0.80	0.4250	NET	-0.0021*	-3.85	0.0001
LGDPPC	0.9068*	18.97	0.0001	LGDPPC	0.3172*	2.28	0.0230
constant	-0.9520**	-1.95	0.0510	constant	5.9936*	3.87	0.0001
<b>Coefficient Estimates for Finland</b>				<b>Coefficient Estimates for Netherland</b>			
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>	<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>
NET	-0.0014*	-2.82	0.0050	NET	-0.0004	-1.55	0.1220
LGDPPC	0.2974*	3.01	0.0030	LGDPPC	0.2356*	2.65	0.0080
constant	6.4500*	6.41	0.0001	constant	6.1507*	6.62	0.0001
<b>Coefficient Estimates for France</b>				<b>Coefficient Estimates for Portugal</b>			
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>	<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>
NET	-0.0001	-1.03	0.3050	NET	0.0029*	18.68	0.0001
LGDPPC	-0.2308*	-3.37	0.0010	LGDPPC	0.7563*	19.74	0.0001
constant	11.1504*	15.70	0.0001	constant	0.4128	1.07	0.2830
<b>Coefficient Estimates for Sweden</b>							
<b>Variable</b>	<b>Coefficient</b>	<b>z statistic</b>	<b>Prob.</b>				
NET	-0.0012*	-2.44	0.0150				
LGDPPC	-0.3634*	-2.89	0.0040				
constant	13.3797*	10.34	0.0010				

\*, \*\* show 5% and 10% statistical significance levels, respectively

Because of the heterogeneous nature of EU-15 countries, the coefficients of these two variables vary in different countries. Based on the size of the coefficient value, the NET variable negatively affects the LEC variable in United Kingdom (0.003%), Belgium (0.0022%), Denmark (0.0021%), Luxembourg (0.0022%), Finland (0.0014%), Germany (0.0012%), Ireland (0.0012%), In Sweden (0.0012%) and Italy (0.005%), while it positively affects Austria (0.0039%), Portugal (0.0029%) and Greece (0.0025%). In Spain, France, and the Netherlands, the NET variable has no significant effect on the LEC variable.

Based on the size of the coefficient value, the LGDPPC variable has a negative effect on the LEC variable in Austria (0.6829%), Sweden (0.3634%) and France (0.2308%), respectively, and a positive effect in Spain (0.9068%), Portugal (0.75639%), Italy (0.5162%), Belgium (0.4657%), Greece (0.3760%), Ireland (0.3561%), the United Kingdom (0.3251%), Luxembourg (0.3172%), Finland (0.2974%) and the Netherlands (0.2356%). In Germany and Denmark, the LGDPPC variable does not have a significant effect on the LEC variable.

## **6. Conclusion**

According to the cointegration test results in the study, it was found that there were significant long-run relationships between internet usage and economic growth and electricity consumption in the EU-15 countries between 1992 and 2014. According to cointegration parameter estimates, the increase in internet usage for all EU-15 countries reduced electricity consumption, while the increase in per capita income increased electricity consumption. However, the elasticity of internet usage is quite smaller than the elasticity of economic growth. Since the panel has a heterogeneous structure, the effects of internet usage and economic growth vary in different countries. In some countries, it has an increasing effect. In some, it has a reducing effect, and in others, it has no significant effect.

The countries where internet usage positively affects electricity consumption are Austria, Greece, and Portugal. These findings for these countries bear similarities with the results of Sadorsky (2012), Heddeghem et al. (2014), Salahuddin and Alam (2015), and Saidi et al. (2017) studies. When the effects of per capita income on electricity consumption are examined in these countries, it is observed that this effect is negative in Austria, and it is positive in Greece and Portugal. When these results are evaluated, it is an expected finding that internet usage increases electricity consumption because internet usage is based on the infrastructure of electricity. The negative effect of economic growth on electricity consumption for Austria shows that increases in per capita income are occurring efficiently. In addition, the positive effect of economic growth in Greece and Portugal is an expected economic finding.

The countries where internet usage negatively affects electricity consumption are the United Kingdom, Belgium, Denmark, Luxembourg, Finland, Germany, Ireland, Sweden, and Italy, respectively. The negative impact of internet usage on electricity consumption is due to the efficiency interaction between ICTs and energy consumption, as in the study of Yan et al. (2018). Yan et al. (2018) state that the development of ICTs has improved energy efficiency. From this point of view, especially in terms of ICTs, as in this study, it can be said that savings can be achieved in electricity usage by increasing internet usage as well as increasing the efficiency of electricity consumption. The effect of economic growth on electricity consumption in these countries is as follows: It has a positive effect in Spain, Italy, Belgium, Ireland, the UK,

Luxembourg, Finland, and the Netherlands. This finding is an expected finding in terms of economics. Nevertheless, an increase in economic growth in Sweden negatively affects electricity consumption.

The negative impact of internet usage on electricity consumption is the highest per capita income in the EU-15. In addition, the positive impact of per capita income on electricity consumption in most of these countries is an important finding. The fact that this finding is especially positive in countries such as Spain, Portugal, Italy, can be associated with the increase in time spent at home in these countries. The increase in per capita income contributes to the increase of time people spend in their homes. Thus, the more frequent use of computers, televisions, electrical kitchen equipment used at home increases the electricity consumption. The country that attracts the most attention here is Sweden. Sweden's elasticity of both internet usage and per capita income is negative. The consumption of electricity in Sweden has also been steadily decreasing since the mid-1990s.

Consequently, the effect of reducing electricity consumption, especially in terms of internet usage and per capita income, is evaluated in terms of energy efficiency. However, these effects can differ in various countries and regions. Especially in developed countries, the fact that the spread of internet usage has a negative effect on electricity consumption is one of the important findings of this study. Similarly, the positive effect of per capita income in these countries shows that productivity is still not fully achieved. In Sweden, it is regarded that energy saving is achieved by providing efficiency in both internet usage and per capita income electricity consumption.

Although the EU-15 countries are seen as the same group of countries within a union, the effect of internet usage and economic growth on electricity consumption in each of these countries is different. Therefore, EU-15 countries should develop country-based policies rather than developing common policies to determine the impact of internet usage and economic growth on electricity consumption. Suggesting country-based policies will make it easier to determine why the effects of internet usage and economic growth on electricity consumption differ in these countries and will contribute to the development of common policies in the long run.



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