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Energy Consumption-Youth Unemployment Nexus in Europe: Evidence from Panel Cointegration and Panel Causality Analyses

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ABSTRACT

This paper employs a panel data set of 20 European countries and examines the impacts of energy consumption on youth unemployment over the period 1990-2011. We follow panel fully modified ordinary least squares (FMOLS) and panel dynamic ordinary least squares (DOLS) estimations, panel Granger causality tests based on vector error correction model and panel causality tests of Emirmahmutoglu and Kose (2011) and Dumitrescu and Hurlin (2012). According to the panel FMOLS and DOLS estimators results, there is negative impact of energy consumption on youth unemployment rates. In addition, the causality tests yield unidirectional causality from energy consumption to youth unemployment rates. The outcome of this paper explores the importance of energy policies to decrease youth unemployment rates and, hence, it may suggests policymakers follow relevant policies encouraging energy consumption and new potential energy investments to diminish youth unemployment rates.

Keywords: Energy Consumption, Youth Unemployment, Panel Analysis, European Union JEL Classifications: C33, E24, Q43

1. INTRODUCTION

World Bank and International Labor Organization (ILO) define youth unemployment as the proportion of the labor force ages 15-24 without work but available for and seeking employment. Youth unemployment is an important socio-economic problem both for developed and developing countries. It is a chronic problem in many countries and very few countries have succeeded in fighting youth unemployment (Jensen et al., 2003). Since employment of young people can have positive impact on youth self-confidence and self-esteem, creating job opportunities for young people not only contributes to economic growth but also leads to social solidarity and social peace. Therefore, the employment of young people is very important for social balances (Calderon, 2004). The youth unemployment rates are 27.6%, 25.09%, 21.3% and 16.7% in Middle East and North Africa, European Union (EU), Europe-Central Asia and North America, respectively (World Bank, 2014). These are the regions with the highest youth unemployment rates in the world. The youth unemployment

rate is 13.5% on a global level. Hence, youth unemployment is a worrisome problem on both regional and global levels.

When one considers the literature of youth unemployment, he/she observes that most of the studies mainly focus on the reasons of youth unemployment. While Korenman and Neumark (1997) and Iannelli and Smyth (2008) consider youth unemployment associated with demographic factors, such as the magnitude of the population, Neumark and Wascher (1999), O'Higgins (2001), Breen (2005), Lam et al. (2008) and Gorry (2013) remark that youth unemployment stems from the structure of labor markets, institutions, wages and educational policies. In general, the related literature yields that the major and prevailing reasons of the youth unemployment are aggregate demand shortage, economic stagnations and crises, respectively (O'Higgins, 2001; O'Higgins, 1997; Mitani, 1999; Jimeno and Palenzuela, 2002; Mlatsheni and Rospabe, 2002; Sileika et al., 2004; Verick, 2009; Bruno et al., 2013). During stagnation and crisis periods, the number of unemployed young people rises quickly as aggregate expenditures

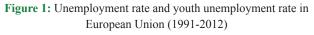
decline; expectations of business world worsen and demand for labor decreases.

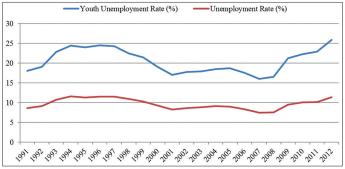
The youth unemployment problem is not new. This problem especially emerged in stagnation periods in 1970s and 1980s, and, hence, the economic policies and studies on labor markets have been focusing on this problem and its solution for four decades (Artner, 2013). The global financial crisis of 2008 affects economic performances, labor productivity and employment negatively in all countries in the world and youth unemployment rates increases on a global level (ILO, 2010; O'Higgins, 2012). Youth unemployment rates are relatively higher than unemployment rates in the world historically and the difference between them becomes more prominent during crisis. Additionally, many empirical studies show that youth unemployment rates become much worse than the adult unemployment rates during global financial crisis (Gorry, 2013; Bruno et al., 2013; O'Higgins, 2012; Duryae, 2012; Borges-Mendez et al., 2013). When one analyses unemployment rates in Europe, he/she finds out that the youth unemployment rate in EU increases very fast especially after 2008. In EU, the youth unemployment rate is almost 2 times higher than the unemployment rate in 1990s, 2000s and 2010s. Therefore, youth unemployment is considered a crucial problem in Europe especially since 2008. Figure 1 shows the development of unemployment rates in EU between 1991 and 2012.

Table 1 shows youth unemployment rates in some European countries in 2012. Accordingly, the youth unemployment rates are higher than 25% in 8 out of 12 European countries given in the table. The youth unemployment rates are higher than 50% in Greece and Spain experiencing a debt crisis since 2009. Table 1 hence, yields the urgency of youth unemployment issue in Europe and, for this reason, the main goals of employment policies are the integration of young people in labor markets and creating employment for young people in Europe, respectively (Choudhry et al., 2012). EU countries in Table 1 are chosen among others since they have relatively higher young unemployment rates in EU region.

When one follows the literature of youth unemployment, he/she may state that economies need to exhibit dynamic and stable economic growth processes to solve this issue in the long term. One may observe, throughout economic growth literature, that there are both endogenous and exogenous factors determining growth. The productivities of capital and labor, the market size and foreign trade might be considered as the basic determinants of economic growth. Beyond these basic determinants, the recent studies focus on especially the effects of energy consumption on economic growth.

There are a great number of empirical studies claiming that energy consumption affects economic growth in the long term (e.g., Stern, 1993; Cheng, 1995; Lee, 2005; Yoo and Kim, 2006; Lee and Chang, 2007; Abosedra et al., 2009; Ozturk, 2010; Apergis and Payne, 2011; Shahbaz et al., Wandji, 2013; Behmiri and Manso, 2014). Besides, some other studies investigate the effects of energy consumption on employment





Source: World Bank Database

Table 1: Youth unemployment rates in some European countries (2012)

Country	Youth unemployment rate (%)
Belgium	19.7
Bulgaria	28.2
Croatia	44.2
France	23.7
Greece	54.7
Ireland	30.2
Italy	35.2
Poland	26.3
Portugal	37.7
Spain	54.2
Sweden	24.1
UK	21.2

World Bank Database (2014)

and unemployment. Chang et al. (2001) examine the causal relationships among energy consumption, employment and GDP in Taiwan for the period 1982-1997 by conducting Johansen cointegration test and Granger causality test based on vector error correction model (VECM). According to the findings of their study, there exists bidirectional causality between energy consumption and employment and a unidirectional causality from energy consumption to GDP. Sari and Soytas (2004) analyzed the relationships among energy consumption, employment and GDP in Turkey for the period of 1969-1999 by employing generalized forecast error variance decompositions. Their study yields the conclusion that energy consumption affects GDP almost as much as employment does. Narayan and Smyth (2005) consider the causal relationships among electricity consumption, employment and GDP in Australia for the period 1966-1999 by utilizing autoregressive distributed-lag bounds test and Granger causality test with VECM. According to their findings, employment and GDP Granger cause electricity consumption in the long-term while there are no causal relationships among the variables in the short term. In other words, the past values of employment and GDP contain some specific information that can help forecast the future values of energy consumption in the long run. Tiwari (2010) investigates the causal relationships between energy consumption and employment in India for the period 1971-2006 by running Granger causality test and finds that there is bidirectional causality between the related variables. George and Oseni (2012), estimating the relationship between electricity consumption and unemployment through ordinary least squares (OLSs)' estimations in Nigeria for the period 1970-2005, yields that electricity consumption reduces unemployment.

There are two important reasons motivating us to produce this paper. First, to the best of our knowledge, there is no study that investigates the relationships between youth unemployment and energy consumption in the literature of energy and/or economics. Secondly, a conference titled "Solutions4Work: Partnerships for Jobs and Youth Employment"1 was held in Istanbul, Turkey on May 7-8, 2014. Academicians, business leaders and government ministers met to discuss solutions for youth employment and they suggested administrative people constitute additional public-private partnerships that can broaden markets and increase job growth. In this conference, however, it was not discussed whether or not the more energy consumption could lead to more job opportunities for young people and thus it was not analyzed if energy consumption could lead to lower youth unemployment rates. Both reasons stimulate us to analyze the youth unemployment-energy consumption nexus.

The rest of the paper is organized as follows: Section 2 presents data, methodology, and estimation results. Section 3 yields the conclusion with a summary of the main findings and policy implications.

2. DATA, METHODOLOGY AND ESTIMATION RESULTS

2.1. Data

The data set includes youth unemployment rates $(\ln YUR)$ and energy consumption $(\ln EC)$ in kg of oil equivalent per capita for the period 1990-2011 and covers 20 European countries. These countries are Bulgaria, Croatia, Cyprus, Estonia, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Poland, Portugal, Romania, Serbia, Slovakia, Spain, Sweden, and the UK, respectively. The data are annual and are obtained from World Bank Database. Both variables are used in logarithmic forms.

Descriptive statistics and correlation matrix are presented in Table 2. One notes that the all descriptive statistics of $\ln YUR$, except standard deviation, are lower than those of $\ln EC$. One may notice, as well, that $\ln YUR$ is negatively correlated with $\ln EC$.

Descriptive statistics of course are to provide one with some initial and/or preliminary inspection. One needs to employ, beyond table observations, more reliable statistical methodologies to obtain unbiased and efficient output through unit root, cointegration and causality estimations.

2.2. Panel Unit Root Tests

Specifying the order of integration of variables is the first step in panel data analysis since one may experience spurious regression

problem if he/she employs conventional OLS estimator. In this respect, this study employs panel unit root tests developed by Levin et al. (2002, hereafter LLC) and Im et al. (2003, hereafter IPS).

The LLC panel unit root test is run by following the panel model given in Equation (1)

$$\Delta y_{it} = \delta y_{it-1} + \sum_{L=1}^{pi} \theta_{iL} \Delta y_{it-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} m = 1, 2, 3$$
(1)

Where, Δ is the first difference operator, d_{mt} is the vector of deterministic variables and a_m is the corresponding vector of coefficients for model m = 1, 2, 3. Therefore, $d_{1t} = \emptyset$ (the empty set), $d_{2t} = \{1\}$, and $d_{3t} = \{1,t\}$. The null hypothesis of $\delta = 0$ for all *i* is tested against the alternative hypothesis of $\delta < 0$ for all *i*. The rejection of the null hypothesis indicates a panel stationary process. The parameter δ is homogenous across *i* for LLC test whereas Im et al. (2003) suggest a panel unit root test allowing δ to vary across all *i*. Hence, the Equation (1) is re-written as follows:

$$\Delta y_{it} = \delta_i y_{it-1} + \sum_{L=1}^{pi} \theta_{iL} \Delta y_{it-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} m = 1, 2, 3$$
(2)

As the null hypothesis is $\delta = 0$ for all *i*, the alternative hypothesis is $\delta < 0$ for at least one *i*. The rejection of the null hypothesis states stationary process of panel.

Table 3 depicts panel unit root test results. Accordingly, the test statistics for the first differences reject the null hypotheses and indicate that series are stationary in the first-difference form. Hence one can state that the series are integrated of order one [I(1)].

Table 2: Descriptive statistics and correlation matrix for In YUR and InEC

Statistics	ln YUR	ln <i>EC</i>
Descriptive statistics		
Mean	3.0509	7.9515
Median	3.1135	7.8764
Maximum	3.8732	8.8678
Minimum	0.9932	7.2965
SD	0.4389	0.3489
Observations	420	420
Correlation matrix		
ln <i>YUR</i>		-0.1905
lnEC	-0.1905	

lnYUR is the youth unemployment rates, and lnEC is the energy consumption. SD: Standard deviation

Table 3: Panel unit root tests

Variable	LLC ^a		IPS	
	Intercept	Intercept	Intercept	Intercept
		and trend		and trend
lnYUR	-1.259	0.243	-3.204 ^b	-1.828°
ln <i>EC</i>	-4.655 ^b	1.201	-4.425 ^b	0.831
$\Delta \ln YUR$	-10.873 ^b	-10.282 ^b	-9.876 ^b	-8.727 ^b
$\Delta \ln EC$	-11.975 ^b	-11.490 ^b	-11.944 ^b	-11.808^{b}

"Newey-West bandwidth selection with Bartlett kernel is used for LLC test. bIllustrates 1% statistical significance. CIllustrates 5% statistical significance

¹ For the details of conference: http://www.worldbank.org/en/events/ 2014/05/07/solutions4work-partnerships-for-jobs-and-youth-employment.

2.3. Panel Cointegration Tests

Pedroni (1999; 2004) suggests seven test statistics employing the null hypothesis of no cointegration in order for researcher to observe if there exists a cointegration relationship among variables in a panel data model. While large positive values imply the rejection of the null hypothesis for the panel variance statistic, large negative values result in the rejection the null of no cointegration for other six statistics (from panel rho to group augmented Dickey–Fuller) (Pedroni, 1999).

The results for the panel cointegration tests are reported in Table 4. It can be claimed that there is a cointegration relationship between $\ln YUR$ and $\ln EC$ and that the $\ln YUR$ converges to its long-run equilibrium by correcting any possible deviations from the short run from its long run equilibrium.

After determining the cointegration relationship, the next step is to estimate the cointegration (long-run) coefficients of independent variables by employing panel fully modified OLS (FMOLS) and panel dynamic OLS (DOLS) methods developed by Pedroni (2000; 2001). The FMOLS estimator generates consistent estimations of the parameters in small samples and controls for the possible endogeneity of the regressors and serial correlation (Kiran et al., 2009). The panel FMOLS estimator can be constructed as below (Pedroni, 2001).

$$\hat{\beta}^{*}_{GFM} = N^{-1} \sum_{i=1}^{N} \hat{\beta}^{*}_{FM,i}$$
(3)

Where, $\hat{\beta}^{*}_{FM,i}$ is the conventional FMOLS estimator applied to i^{th} member of the panel. The associated t-statistic can be constructed as in (4).

$$t_{\hat{\beta}_{GFM}^{*}} = N^{-1/2} \sum_{i=1}^{N} t_{\hat{\beta}_{FM,i}^{*}}$$
(4)

To obtain the panel DOLS estimator, the following model is estimated.

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{k=-K_i}^{K_i} \gamma_{ik} \Delta x_{it-k} + \varepsilon_{it}$$
(5)

Where, $-K_i$ and K_i are leads and lags. The panel DOLS estimator can be built up as is in (6).

$$\hat{\beta}_{GD}^{*} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_{D,i}^{*}$$
(6)

Where, $\vec{\beta}_{D,i}^*$ is the conventional DOLS estimator, applied to the i^{th} member of the panel. The associated t-ratio can be established as given in equation (7).

$$t_{\hat{\beta}_{GD}^*} = N^{-1/2} \sum_{i=1}^{N} t_{\hat{\beta}_{D,i}^*}$$
(7)

Table 5 denotes the output of panel FMOLS and panel DOLS estimations. The coefficient of energy consumption is negative. In other words, energy consumption affects youth unemployment rates negatively. In addition to panel FMOLS and panel DOLS estimations, we reported Individual FMOLS and DOLS estimations in Appendix Table A.

2.4. Panel Causality Tests

As the cointegration analysis is not able to present the direction of causality, the causality analyses are commonly used to investigate causal relationships between variables. Many studies rely on the panel Granger causality test based on a VECM. Emirmahmutoglu and Kose (2011) and Dumitrescu and Hurlin (2012) tests have become prominent throughout panel causality tests recently. This paper, to the best of our knowledge, is the first paper focusing on the relationship between youth unemployment rates and energy consumption by employing these causality tests to obtain more reliable results.

Panel VECM is established by augmenting a vector auto regression (VAR) model in first differences with one-lagged error correction term (ECT) in order to investigate causal interactions between variables as below in equations (8) and (9) (Apergis and Payne, 2009):

$$\Delta y_{it} = \alpha_{1i} + \sum_{k=1}^{q} \beta_{11ik} \Delta y_{it-k} + \sum_{k=1}^{q} \beta_{12ik} \Delta x_{it-k} + \lambda_{1i} \hat{\varepsilon}_{it-1} + \upsilon_{1it}$$
(8)

$$\Delta x_{it} = \alpha_{2i} + \sum_{k=1}^{q} \beta_{21ik} \Delta x_{it-k} + \sum_{k=1}^{q} \beta_{22ik} \Delta y_{it-k} + \lambda_{2i} \hat{\varepsilon}_{it-1} + \upsilon_{2it}$$
(9)

Where, Δ is the first-difference operator, *q* is the optimal lag length, $\hat{\varepsilon}_{ii}$ is the residuals obtained from the panel FMOLS estimation and v is the serially uncorrelated error term. Through (8) and (9), one may examine both short-run and long-run causal relationships. The short-run causality from energy consumption to youth unemployment rates is tested using a Wald test by executing the null hypothesis of $\beta_{12ik} = 0$. The long-run causality is examined according to statistical significance of the coefficient of the ECT

Table 4: Panel co-integration tests

Test ^a	Intercept	Intercept and trend
Panel v-statistic	3.276 ^b	0.286
Panel rho-statistic	-3.293 ^b	-1.413°
Panel PP-statistic	-3.852 ^b	-4.221 ^b
Panel ADF-statistic	-4.800^{b}	-6.533 ^b
Panel rho-statistic	-0.090	1.510
Group PP-statistic	-1.406°	-1.464°
Group ADF-statistic	-3.536 ^b	-4.996 ^b

^aNewey-West bandwidth selection with Bartlett kernel is used. ^bIllustrates 1% statistical significance. ^cIllustrates 10% statistical significance. ADF: Augmented Dickey–Fuller

Table 5: Panel co-integration coefficients (ln YUR is the dependent variable)

Variable	Panel FMOLS ^a	Panel DOLS ^a
lnEC	-1.57 ^b [-8.42]	-0.93 ^b [-6.57]

"The values in bracket are t-statistics. bIllustrates 1% statistical significance. FMOLS: Fully modified ordinary least squares, DOLS: Dynamic ordinary least squares represented by λ . The statistically significant λ_{1i} indicates that energy consumption Granger causes youth unemployment rates in the long run.

OLS estimators and Wald statistics are valid if variables in a VAR process are stationary. However, if one or more variables have a unit root, the Wald statistics based on OLS estimation of level VAR model will have non-standard asymptotic distributions (Sims et al., 1990; Xie and Chen, 2014). Toda and Yamamato (1995) produce an alternative approach to test coefficient restrictions of a level VAR model using a modified Wald test in a lag augmented VAR (LA-VAR) which has a conventional asymptotic Chi-square distribution when a VAR (q + dmax) is estimated. Here, q is the lag length and dmax is the maximum order of integration.

Emirmahmutoglu and Kose (2011) propose a panel causality approach based on meta-analysis in heterogeneous mixed panels by extending the LA-VAR approach. They use Fisher test statistics proposed by Fisher (1932) to test the Granger non-causality hypothesis in heterogeneous panels. Fisher (1932) considers combining several significant levels (P values) identical but independent tests. If the test statistics are continuous, P values P_i (i = 1, ..., N) are independent uniform (0,1) variables. In this case, the Fisher test statistic (λ) is written as follows:

$$\lambda = -2\sum_{i=1}^{N} ln(p_i), i = 1, 2, ..., N$$
(10)

Where, P_i is the P value corresponding to the Wald statistic of the i^{th} individual cross-section. This test statistic has a Chi-square distribution with 2N degrees of freedom. This test is valid only if N is fixed as $T \rightarrow \infty$. Emirmagnutoglu and Kose (2011) consider the level VAR model with $k_i + dmax_i$ in heterogeneous mixed panels:

$$x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i + dmax_i} A_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i + dmax_i} A_{12,ij} y_{i,t-j} + u_{i,t}^x$$
(11)

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i + dmax_i} A_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + dmax_i} A_{22,ij} y_{i,t-j} + u_{i,t}^y$$
(12)

Where, $dmax_i$ is the maximal order of integration suspected to occur in the system for each *i*. They focus on testing causality from *y* to *x* in equation (11) and a similar procedure is applied for causality from *x* to *y* in equation (12). For example, there is a one-way Granger causality from *y* to *x* as all $A_{21,ij}$ are zero.

Another panel causality test based on the individual Wald statistic of Granger non-causality is produced by Dumitrescu and Hurlin (2012). They launch two stationary series and follow testing procedure taking into account heterogeneity of causal relationships. Hence Dumitrescu and Hurlin (2012) consider the following linear model:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t}$$
(13)

For simplicity, the individual effects α_i and δ_i are assumed to be fixed in the time dimension. Initial conditions $(y_{i,-K^2}, \dots, y_{i,0})$ and $(x_{i,-K^2}, \dots, x_{i,0})$ of both individual processes $y_{i,i}$ and $x_{i,i}$ are given and observable. They assume that lag orders *K* are identical for all cross-section units of the panel and the panel is balanced. Additionally, they allow the autoregressive parameters $\gamma_i^{(k)}$ and $\theta_i^{(k)}$ the regression coefficients slopes $\beta_i^{(k)}$ and $\lambda_i^{(k)}$ to differ across groups. Dumitrescu and Hurlin (2012) propose to test the homogeneous non-causality (HNC) hypothesis implying that no individual causality relationship from *x* to *y* exists. Under the heterogeneous non-causality hypothesis (HENC) hypothesis, Dumitrescu and Hurlin (2012) assume that there is a causal relationship from *x* to *y* for a subgroup of individuals. The null hypothesis of HNC is defined as is in (14):

$$\mathbf{H}_{0} = \boldsymbol{\beta}_{i} = 0 \ \Lambda i = 1, \dots, N \tag{14}$$

With $\beta_i = (\beta_i^{(1)}, \dots, \beta_i^{(\kappa)})'$. Additionally, β_i may differ across groups under the alternative (model heterogeneity). Dumitrescu and Hurlin (2012) also allow for some, but not all, of the individual vectors β_i to be equal to 0 (non-causality assumption). Dumitrescu and Hurlin (2012) assume that there are $N_1 < N$ individual processes with no causality from *x* to *y* under H₁. Their test is a not a test of non-causality assumption against causality from *x* to *y* for all the individuals. The HENC hypothesis is defined as is in (15):

$$H_{1}: \beta_{i} = 0 \Lambda i = 1, ..., N_{1}$$
(15)

$$\beta_i \neq 0 \ \Lambda i = N_1 + 1, N_1 + 2, \dots, N$$

Where, N_1 is unknown but meets the condition $0 \le N_1/N \le 1$. The rejection of the null hypothesis with $N_1 = 0$ indicates that *x* Granger causes y for all the units of the panel while the rejection of the null hypothesis with $N_1 > 0$ indicates that the causal relationship is heterogeneous (the regression model and the causal relationships are different from one individual from the sample to another). In this context, Dumitescu and Hurlin (2012) use the average of individual Wald statistics associated with the test of the non-causality hypothesis for units i = 1, ..., N. The average statistic $W_{N,T}^{HNC}$ associated with the null HNC hypothesis is defined as is in (16).

$$W_{N,T}^{Hnc} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T}$$
(16)

Where, $W_{i,T}$ denotes the individual Wald statistics for the *i*th cross section unit. Under the null hypothesis of non-causality, each individual Wald statistic converges to a Chi-squared distribution with *K* degrees of freedom for $T \rightarrow \infty$:

$$W_{iT} \to \chi^2(K), \Lambda i = 1, \dots, N \tag{17}$$

The standardized test statistic is as follows:

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}} \left(W_{N,T}^{HNC} - K \right) \to N(0,1)$$
(18)

Table 6: Panel causality tests' results

Panel Granger causality test based on VECM ^{a,b}			
The methodology	Short-run	Long-run causality	
	ΔlnYUR	ΔlnEC	ECT
$\Delta \ln Y U R$		8.852 ^d (0.002)	-0.382^{d} [-8.769]
$\Delta \ln EC$	0.434 (0.509)		-0.002 [-0.184]
Emirmahmutoglu and Kose (2011) test ^{a,c}			
Statistic	$\ln YUR \rightarrow \ln EC$		$\ln EC \rightarrow \ln YUR$
Wald	51.626 (0.102)		53.281° (0.078)
Dumitrescu and Hurlin (2012) test ^{a,c}			
Statistic	$\ln YUR \rightarrow \ln EC$		$\ln EC \rightarrow \ln YUR$
$Z_{\scriptscriptstyle N,T}^{\scriptscriptstyle HNC}$	-0.280 (0.383)		1.680° (0.097)

"The values in parentheses are P values. ^bThe values in brackets are t-statistics. ^cln*YUR* \rightarrow ln*EC* means that the causality runs from youth unemployment rates to energy consumption, ln*EC* \rightarrow ln*YUR* means that the causality runs from energy consumption to youth unemployment rates. ^dIllustrates 1% statistical significance. ^cIllustrates 10% statistical significance. ECT: Error correction term, VECM: Vector error correction model

Where, first $T \to \infty$ and second $N \to \infty$. For large N and T samples, if the realization of the standardized statistic $Z_{N,T}^{HNC}$ is superior to the corresponding normal critical value for a given level of risk, the HNC hypothesis is rejected.

Table 6 presents panel causality tests' results. According to the results of panel VECM, energy consumption Granger causes youth unemployment rates in long and short terms. The finding concerning long-term relationship is consistent with panel FMOLS and panel DOLS results. On the other hand, youth unemployment rates Granger cause energy consumption neither in the long term nor in the short term. The results of Emirmahmutoglu and Kose (2011) test and Dumitrescu and Hurlin (2012) test support the results of panel VECM. Accordingly, both tests indicate that there is a unidirectional causal relationship from energy consumption to youth unemployment rates. When findings of causality tests are taken into account along with panel cointegration tests' results, it can be claimed that the more energy consumption may lead to lower youth unemployment rates in the selected European countries. In addition to panel causality test results, we reported Emirmahmutoglu and Kose (2011) and Dumitrescu and Hurlin (2012) test results for each country individually in Appendix Table B.

3. CONCLUSION AND POLICY IMPLICATIONS

Especially within last two decades, EU politicians consider prominently the youth unemployment issue among other related issues. In order to cope with young unemployment problem in EU, the European Commission (2013) has suggested a number of proposals (programs) that might be able to have positive impacts on youth employment level through December, 2012 and March, 2013 Youth Employment Packages with an approximate cost of six billion Euros. These proposals encouraging employment of youth have been agreed by some EU members. According to European Commission (2013), seven steps (programs) should be taken into consideration without any delay to get young people back into work. These steps cover, (i) the implementation of the Youth Guarantee Program for young people under 25 no matter whether or not they are registered with employment services, (ii) the investment program for young people through the European Social Fund, (iii) the front-loading of the Youth Employment Initiative Program, (iv) the support program for intra-EU labor mobility with European Employment Services, (v) the program to get Europe's educated young people into work by increasing the supply of high-quality apprenticeships and traineeship, (vi) the program accelerating the related labor market reforms and, (vii) a program supporting job creation and promoting the hiring of young people especially through small and medium enterprises in EU.

Hence, within last two decades, the related literature discusses the possible related determinants and possible solutions of youth unemployment in EU. This paper specifically investigates the causal nexus between youth unemployment rates and energy consumption by employing annual data from 1991 to 2011 for the selected 20 European countries with relatively higher unemployment rates among other EU members. After conducting panel unit root tests, this paper follows panel FMOLS and DOLS estimations suggested by Pedroni (2000; 2001). Then, paper follows panel Granger causality test based on VECM, Emirmahmutoglu and Kose (2011) and Dumitrescu and Hurlin (2012) panel Granger causality tests. Panel FMOLS and DOLS estimations show that youth unemployment rates are negatively related to energy consumption. Panel Granger causality tests' results are consistent with panel FMOLS and panel DOLS estimations. Therefore, there is a unidirectional causality from energy consumption to youth unemployment rates.

In terms of today, the world faces a worsening youth unemployment crisis as ILO² remarks. This paper, upon its estimation results, indicates that more energy consumption can lead to lower youth unemployment rates. Policies encouraging energy consumption and new investments on energy sectors may decrease youth unemployment by leading up new businesses in many sectors. Therefore, energy policies should be considered important employment policies. This paper eventually asserts that the discussions about relative importance of energy policies to lower youth unemployment rates should be launched through international conferences or platforms where academicians, NGOs, business leaders, and government officers convene.

² See http://www.ilo.org/global/topics/youth-employment/lang--de/index.htm.

REFERENCES

- Abosedra, S., Dah, A., Ghosh, S. (2009), Electricity consumption and economic growth, the case of Lebanon. Applied Energy, 86, 429-432.
- Apergis, N., Payne, J.E. (2009), Energy consumption and economic growth: Evidence from the commonwealth of independent states. Energy Economics, 31, 641-647.
- Apergis, N., Payne, J.E. (2011), The renewable energy consumption– growth nexus in central America. Applied Energy, 88, 343-347.
- Artner, A. (2013), Is youth unemployment really the major worry? Debatte: Journal of Contemporary Central and East Europe, 21, 183-205.
- Behmiri, N.B., Manso, J.R.P. (2014), The linkage between crude oil consumption and economic growth in Latin America: The panel framework investigations for multiple regions. Energy, 72, 233-241.
- Borges-Mendez, R., Denhardt, L., Collett, M. (2013), Global and local youth unemployment: Dislocation and pathways. New England Journal of Public Policy, 25, 1-12.
- Breen, R. (2005), Explaining cross-national variation in youth unemployment market and institutional factors. European Sociological Review, 21, 125-134.
- Bruno, G.S., Choudhry, M.T., Marelli, E., Signorelli, M. (2013), The Short-and Long-Run Impacts of Financial Crises on Youth Unemployment in OECD Countries. Mimeo.
- Calderon, E.R. (2004), Getting young people into work: A challenge and an opportunity. In: Baker, J., editor. Policy Proposal for Decent Work. Geneva: ILO. p65-76.
- Chang, T., Fang, W., Wen, L.F. (2001), Energy consumption, employment, output, and temporal causality: Evidence from Taiwan based on cointegration and error-correction modelling techniques. Applied Economics, 33, 1045-1056.
- Cheng, B.S. (1995), An investigation of cointegration and causality between energy consumption and economic growth. Journal of Energy and Development, 21, 73-84.
- Choudhry, M.T., Marelli, E., Signorelli, M. (2012), Youth unemployment rate and impact of financial crises. International Journal of Manpower, 33, 76-95.
- Dumitrescu, E.I., Hurlin, C. (2012), Testing for Granger non-causality in heterogeneous panels. Economic Modelling, 29, 1450-1460.
- Duryae, S. (2012), Economic crisis and school-to-work transition. In: Lundberg, M., Wuermli, A., editors. Children and Youth Crisis: Protecting and Promoting Human Development in Times of Economic Shocks. Washington, DC: The World Bank. p195-206.
- Emirmahmutoglu, F., Kose, N. (2011), Testing for Granger causality in heterogeneous mixed panels. Economic Modelling, 28, 870-876.
- European Commission. (2013), Working Together for Europe's Young People: A Call to Action on Youth Unemployment. Available from: http://ec.europa.eu/europe2020/pdf/youth_en.pdf/. [Last accessed on 2014 Oct31].
- Fisher, R.A. (1932), Statistical Methods for Research Workers. 4th ed. Edinburgh: Oliver and Boyd.
- George, E.O., Oseni, J.E. (2012), The relationship between electricity power and unemployment rates in Nigeria. Australian Journal of Business and Managerial Research, 2, 10-19.
- Gorry, A. (2013), Minimum wages and youth unemployment. European Economic Review, 64, 57-75.
- Iannelli, C., Smyth, E. (2008), Mapping gender and social background differences in education and youth transitions across Europe. Journal of Youth Studies, 11, 213-232.
- ILO. (2010), Global Employment Trends for Youth: Special Issue on the Impact of the Global Economic Crisis on Youth. Geneva: International Labour Office.
- ILO. Available from: http://www.ilo.org/global/topics/youth-employment/

lang--de/index.htm. [Last accessed on 2014 Aug 03].

- Im, K.S., Pesaran, M.H., Shin, Y. (2003), Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115, 53-74.
- Jensen, P., Rosholm, M., Svarer, M. (2003), The response of youth unemployment to benefits, incentives, and sanctions. European Journal of Political Economy, 19, 301-316.
- Jimeno, J.F., Palenzuela, D.R. (2002), Youth Unemployment in the OECD: Demographic Shifts, Labour Market Institutions, and Macroeconomic Shocks. European Central Bank Working Paper. 155.
- Kiran, B., Yavus, N.C., Guris, B. (2009), Financial development and economic growth: A panel data analysis of emerging countries. International Research Journal of Finance and Economics, 30, 87-94.
- Korenman, S., Neumark, D. (1997), Cohort Crowding and Youth Labor Markets: A Cross-National Analysis. NBER Working Paper. 6031.
- Lam, D., Leibbrandt, M., Mlatsheni, C. (2008), Education and youth unemployment in South Africa. Southern Africa Labour and Development Research Unit Working Paper. 22.
- Lee, C.C. (2005), Energy consumption and GDP in developing countries: A cointegrated panel analysis. Energy Economics, 27, 415-427.
- Lee, C.C., Chang, C.P. (2007), Energy consumption and GDP revisited: A panel analysis of developed and developing countries. Energy Economics, 29, 1206-1223.
- Levin, A., Lin, C.F., Chu, C.S.J. (2002), Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108, 1-24.
- Mitani, N. (1999), The Japanese employment system and youth labour market. Preparing Youth for the 21st Century: The Transition from Education to the Labour Market. Paris: OECD. p305-328.
- Mlatsheni, C., Rospabe, S. (2002), Why is Youth Unemployment so High and Unequally Spread in South Africa? Available from: http:// www.dspace.africaportal.org/jspui/bitstream/123456789/7553/1/ Why%20is%20Youth%20Unemployment%20so%20High%20 and%20Unequally%20spread%20in%20South%20Africa.pdf?1. [Last accessed on 2014 Aug 20].
- Narayan, P.K., Smyth, R. (2005), Electricity consumption, employment and real income in Australia evidence from multivariate Granger causality tests. Energy Policy, 33, 1109-1116.
- Neumark, D., Wascher, W. (1999), A cross-national analysis of the effects of minimum wages on youth employment. NBER Working Paper. 7299.
- O'Higgins, N. (1997), The challenge of youth unemployment. International Social Security Review, 50, 63-93.
- O'Higgins, N. (2001), Youth Unemployment and Employment Policy: A Global Perspective. Available from: http://mpra.ub.unimuenchen.de/23698/1/MPRA_paper_23698.pdf. [Last accessed on 2014 Aug 20].
- O'Higgins, N. (2012), This time it's different? Youth labour markets during the great recession. Comparative Economic Studies, 54, 395-421.
- Ozturk, I. (2010), A literature survey on energy–growth nexus. Energy Policy, 38, 340-349.
- Pedroni, P. (1999), Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulleting of Economics and Statistics, 61, 653-670.
- Pedroni, P. (2000), Fully modified OLS for heterogeneous cointegrated panels. Advances in Econometrics, 15, 93-130.
- Pedroni, P. (2001), Purchasing power parity tests in cointegrated panels. Review of Economics and Statistics, 83, 727-731.
- Pedroni, P. (2004), Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econometric Theory, 20, 597-625.
- Sari, R., Soytas, U. (2004), Disaggregate energy consumption, employment and income in Turkey. Energy Economics, 26, 335-344.

- Shahbaz, M., Zeshan, M., Afza, T. (2012), Is energy consumption effective to spur economic growth in Pakistan? New evidence from bounds test to level relationships and Granger causality tests. Economic Modelling, 29, 2310-2319.
- Sileika, A., Rupsys, V., Gruzevskis, B. (2004), Youth unemployment and its reduction measures. Journal of Business Economics and Management, 5, 119-131.
- Sims, C.A., Stock, J.H., Watson, M.W. (1990), Inference in linear time series models with some unit roots. Econometrica, 58, 113-144.
- Stern, D.I. (1993), Energy and economic growth in the USA: A multivariate approach. Energy Economics, 15, 137-150.
- Tiwari, A. (2010), On the dynamics of energy consumption and employment in public and private sector. Available from: http://www. mpra.ub.uni-muenchen.de/24076/5/MPRA_paper_24076.pdf. [Last accessed on 2014 Aug 22].
- Toda, H.Y., Yamamoto, T. (1995), Statistical inference in vector autoregressions with possibly integrated processes. Journal of

Econometrics, 66, 225-250.

- Verick, S. (2009), Who is Hit Hardest During a Financial Crisis? The Vulnerability of Young Men and Women to Unemployment in an Economic Downturn. IZA Discussion Papers. 4359.
- Wandji, Y.D.F. (2013), Energy consumption and economic growth: Evidence from Cameroon. Energy Policy, 61, 1295-1304.
- World Bank. Available from: http://data.worldbank.org/indicator. [Last accessed on 2017 Jul 07].
- World Bank. Available from: http://www.worldbank.org/en/ events/2014/05/07/solutions4work-partnerships-for-jobs-and-youthemployment. [Last accessed on 2014 Aug 02].
- Xie, Z., Chen, S.W. (2014), Untangling the causal relationship between government budget and current account deficits in OECD countries: Evidence from bootstrap panel Granger causality. International Review of Economics and Finance, 31, 95-104.
- Yoo, S.H., Kim, Y. (2006), Electricity generation and economic growth in Indonesia. Energy, 31, 2890-2899.

APPENDICES

I I · · ·		
Country	Individual	Individual DOLS ^{a,b} [lnEC]
	FMOLS ^a [lnEC]	
Bulgaria	-2.83 [-1.43]	-0.34 [-0.18]
Croatia	0.36 [0.65]	1.35 [1.56]
Cyprus	0.12 [0.08]	0.19 [0.09]
Estonia	-0.95 [-0.63]	-3.21 ^d [-2.38]
Finland	-2.03° [-5.10]	-3.15° [-4.58]
France	-3.10^{d} [-2.25]	1.01 [0.72]
Greece	-0.61 [-1.50]	0.78° [2.86]
Hungary	0.59 [0.20]	3.78 [0.76]
Ireland	-5.13° [-7.67]	-5.97° [-8.89]
Italy	-1.37 [-1.48]	2.11 ^d [2.14]
Latvia	-1.26 [-1.28]	-0.89 [-1.21]
Lithuania	-2.62° [-3.27]	-4.14° [-3.14]
Poland	-4.62° [-3.47]	-3.62° [-3.79]
Portugal	-1.10 [-1.06]	-1.54° [-2.05]
Romania	0.28 [0.71]	-0.35 [-1.28]
Serbia	0.60 [1.34]	2.96° [3.19]
Slovakia	-0.83[-0.34]	-0.89 [-0.37]
Spain	$-2.87^{\circ}[-7.05]$	-2.85° [-8.10]
Sweden	-1.64 [-0.93]	-2.39° [-1.76]
UK	-2.49° [-3.15]	-1.49° [-2.97]

Appendix Table A: Individual FMOLS and DOLS results

^aThe values in brackets are t-statistics. ^bThe individual tests are done with 1 lag for each cross-section. ^cIllustrates 1% statistical significance. ^dIllustrates 5% statistical significance. ^cIllustrates 10% statistical significance. FMOLS: Fully modified ordinary least squares, DOLS: Dynamic ordinary least squares

Appendix Table B: Individual results	of Emirmahmutoglu and Kose (2011) and Dumitrescu and Hurlin (2012) tests

Countries	Emirmahmutoglu a	and Kose (2011) test	Dumitrescu and	Hurlin (2012) test
	Wald statistic ^{a,b}		Wald statistic ^{a,b}	
	ln <i>YUR</i> →ln <i>EC</i>	ln <i>EC</i> →ln <i>YUR</i>	ln <i>YUR</i> →ln <i>EC</i>	ln <i>EC</i> →ln <i>YUR</i>
Bulgaria	0.01 (0.97)	4.45° (0.04)	0.62 (0.43)	4.61° (0.03)
Croatia	0.48 (0.49)	1.01 (0.32)	0.03 (0.85)	1.41 (0.23)
Cyprus	0.12 (0.72)	0.86 (0.36)	1.01 (0.31)	1.30 (0.25)
Estonia	0.11 (0.74)	0.86 (0.36)	0.12 (0.72)	$3.92^{\circ}(0.04)$
Finland	0.01 (0.94)	$4.10^{d}(0.06)$	1.34 (0.24)	2.30 (0.12)
France	0.66 (0.42)	0.84 (0.36)	1.21 (0.27)	2.10 (0.14)
Greece	0.02 (0.87)	0.08 (0.77)	0.72 (0.39)	1.50 (0.21)
Hungary	0.36 (0.55)	0.03 (0.85)	0.07 (0.79)	0.72 (0.39)
Ireland	7.04° (0.02)	2.13 (0.16)	4.31° (0.04)	1.09 (0.29)
Italy	0.95 (0.34)	1.63 (0.215)	0.42 (0.51)	1.98 (0.15)
Latvia	0.53 (0.47)	0.27 (0.60)	1.20 (0.27)	0.14 (0.70)
Lithuania	$6.48^{\circ}(0.02)$	0.32 (0.57)	0.89 (0.34)	1.33 (0.24)
Poland	0.06 (0.81)	4.18 ^d (0.06)	0.38 (0.53)	3.36 ^d (0.07)
Portugal	4.31 ^d (0.06)	0.27 (0.60)	1.26 (0.26)	0.26 (0.60)
Romania	5.96° (0.02)	2.07 (0.16)	2.66 (0.10)	0.06 (0.80)
Serbia	0.28 (0.60)	$4.46^{\circ}(0.04)$	0.71 (0.39)	2.58 (0.10)
Slovakia	0.01 (0.93)	0.12 (0.72)	0.77 (0.37)	0.60 (0.43)
Spain	0.88 (0.35)	0.44 (0.51)	0.24 (0.61)	0.75 (0.38)
Sweden	0.06 (0.81)	0.06 (0.79)	0.12 (0.72)	0.06 (0.80)
UK	2.15 (0.15)	0.36 (0.55)	0.03 (0.77)	0.49 (0.48)

^aThe values in parentheses are P values. ^bln $YUR \rightarrow$ ln EC means that the causality runs from youth unemployment rates to energy consumption. ln $EC \rightarrow$ ln YUR means that the causality runs from energy consumption to youth unemployment rates. ^cIllustrates 5% statistical significance. ^dIllustrates 10% statistical significance