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Relationship between Renewable Energy Consumption and Economic Growth in Five South Asian Countries: An Empirical Analysis

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Increased amount of fossil energy consumption in developing or emerging countries has created major concerns about global warming where renewable energy could be a good option which can assist to continue stable economic growth as well as can prevent environmental degradation. To the best of our knowledge, no studies have been conducted to investigate the relationship between renewable energy consumption and economic growth in five South Asian neighboring countries and so the aim of this paper is to investigate the relationship between the two concerned variables with the help of panel data ranging from 1981-2015. Johansen-Fisher cointegration test results show that in the long run variables are cointegrated and Dumitrescu-Hurlin panel causality test results show a bidirectional causality between renewable energy consumption and economic growth in the long runsupporting feedback hypothesis. According to Vector Error Correction Model, no causality has been found in short run and long run estimation results show coefficient of renewable energy consumption is inelastic but positive. As all of the selected countries are walking on the path of development in terms of socially and economically, policies should be taken in favor of promoting renewable energy consumption as well as development of renewable energy sector.

Field of Research: Economics

1. Introduction

Energy is a vital component for achieving sustainable economic growth. Due to the higher demand, the consumption of energy is increasing both in developed and emerging countries of the world. According to BP Statistical Review of World Energy (2016), energy consumption has increased with an average growth rate of 1.90% from the last 25 years globally. Furthermore, energy plays a very significant role in socio-economic development (Amin *et al.* 2017). Increased amount of fossil energy consumption in developing or emerging countries has created major concerns about rise in global temperature and erratic nature of climate. Renewable energy is a good option which can assist to continue stable economic growth as well as can prevent environment degradation for a nation.

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A sustainable economic prosperity or growth depends upon the utilizing resources meaningfully. Beside that nature impairment and social welfare have to be considered (Moldan *et al.* 2012). Due to the decentralized nature of renewable energy, it contributes to energy resilience which reduces negative impacts due to technical failures of the national energy grid system such as electricity. Furthermore, it also mitigates the socks of oil price and lowers the environmental degradation. Not onlyhave that, development of renewable energy market can create local labor market leading to a decline in urban-rural migration (Domac *et al.* 2005). As the chosen five south Asian countries are walking toward achieving a sustainable economic growth and social development, exploring the effects of renewable energy consumption on economic growth should be analyzed thoroughly. Findings of this paper can assist policy makers to come up with a proper policy framework to gain regional prosperity.

There are four hypothesis regarding the causal relationship between energy consumption and economic growth (Amin, 2015). These are: Growth, Feedback, Neutrality and Conservation. Growth hypothesis asserts that increase in energy consumption will boost up the economic growth of an economy. It is a unidirectional causality running from energy consumption to economic growth. Feedback hypothesis argues that as energy consumption helps the economy to grow, conversely the higher growth of the economy causes the energy consumption to rise which indicates a bidirectional causality. Neutrality hypothesis highlights the fact that both energy and economic growth do not cause each other. Lastly, conservation hypothesis validates that the causality is actually running from economic growth to energy consumption. Thus, reducing energy consumption will not harm the progress of economic growth.

Many studies have been conducted to determine the relationship between renewable energy consumption and economic growth. However, the results are mixed. Apergis *et al.* (2016); Amri (2017); Omri *et al*. (2015); Armeanu *et al*. (2017) have found unidirectional causality is running from renewable energy consumption to economic growth. Sebri and Ben-Salha (2014) have found that in short run there is a bidirectional causality between renewable energy consumption and economic growth. However, in the long run, unidirectional causality has been found among the variables. Apergis and Payne (2010) have found that there is a bidirectional causality between renewable energy consumption and economic growth both in short run and in long run. Lise and Van-Montfort (2007) have found the existence of a unidirectional causality running from economic growth to renewable energy consumption.

However, to the best of our knowledge, no studies have been done focusing on the empirical relationship between renewable energy consumption and economic growth in five selected South Asian countries (Bangladesh, India, Pakistan, Sri Lanka and Nepal). In doing so, our research questions are as follows: What are the long run and short run causalities between renewable energy consumption and economic growth? What are the estimated coefficient values of the variables?

The rest of the paper is arranged as follows: section 2 provides a review of the literature with section 3 describing the econometric methodology and data set used in the paper, followed by results and discussions in section 4, and conclusion in section 5.

2. Literature Review

Vidyarthi (2015) examined the relationship between the relationship between energy consumption and economic growth for a panel of five South Asian economies, namely Bangladesh, Pakistan, Sri Lanka Nepal, and India for the years between 1971 to 2010 within a multivariate framework. The study utilized Pedroni cointegration and Granger causality test based on panel vector error correction model for long run equilibrium relationship and direction of causation for both short and long run. Long run relationship between economic growth per capita, energy consumption per capita and real gross fixed capital formation per capita was observed. It was seen that one percent increase in energy consumption per capita increased GDP per capita by 0.84 percent for the panel. Unidirectional causality ran from energy consumption per capita and gross fixed capital formation per capita to GDP per capita in the short run. It was recommended that these South Asian countries to implement expansionary energy policies by energy efficiency measures.

Zeshan*et al.* (2012) examined the relationship between both renewable and nonrenewable energy consumption and economic growth by employing Cobb-Douglas production function, Auto Regressive Distributed Lag bound testing approach, Gregory and Hansen structural break as well Clemente-Montanes-Reyes structural break unit root test for Pakistan over the period of 1972-2011. The results confirmed cointegration between renewable energy consumption, non-renewable energy consumption, economic growth, capital and labor in the case of Pakistan. The findings further showed renewable energy consumption add in economic growth, where capital and labor are important determinants of economic growth. Hence, the economy should focus on renewable energy to spur growth and development.

Amri (2017) used ARDL model to investigate the causal relationship between economic growth and energy consumption. Total energy consumption was divided into 2 sections: non-renewable and renewable energy consumption. Author found that in the long run there is a unidirectional causality running from renewable energy consumption to economic growth. However, in the short run, no causalities were found. Hence it was recommended that long term policies should be taken to develop the renewable energy sector in both developed and developing countries.

Omri*et al*. (2015) examined the causal relationship between economic growth and energy consumption. The total energy consumption variable was composed of renewable and nuclear energy consumption of 17 developed and developing countries. Data period span was from 1991 to 2011. The results for renewable energy and economic growth suggested a unidirectional causality running from renewable energy consumption to economic growth in following countries: Hungary, India, Japan, Netherlands, and Sweden. Conversely, a unidirectional causality running from economic growth to renewable energy consumption in following countries: Argentina, Spain and Switzerland. A bidirectional causality was found in Belgium, Bulgaria, Canada, France, Pakistan and the USA.

Sebriand Ben-Salha (2014) investigated the impact of renewable energy consumption on economic growth for Brics countries with the help of panel data ranging from 1970 to 2010. The ARDL bounds testing approach and the Vector Error Correction model (VECM) technique have been employed. The results indicated that in the short run, there is a bidirectional causality running between renewable energy consumption and economic growth. In the long run, unidirectional causality was found among the variables.

Bhattacharya *et al*. (2016) by using panel data set (1991-2012) found that there is a unidirectional causality running from renewable energy consumption and economic growth in 34 OECD countries. Lise and Van Montfort (2007) asserted that there is a unidirectional causality between economic growth to renewable energy in Turkey over the period of 1990 to 2010.

Apergis *et al.* (2016) shaded light on the relationship between economic growth and renewable energy consumption for ten largest hydroelectricity consumers (Brazil, Canada, China, France, India, Japan, Norway, Sweden, Turkey and the USA). The paper used panel data ranging from 1965 to 2012. The structural break technique was applied on the results of vector error correction model. A unidirectional causality was found running from economic growth to hydroelectricity both in short run and long run before 1988. And after 1988, a feedback hypothesis was observed, which means a bidirectional causality exists between hydroelectricity and economic growth.

After the wide discussion of different literatures, we can set our hypothesis relevant to our research question. The considered set of null hypothesis as follows, H_1: renewable energy consumption does not cause GDP and H_2: GDP does not cause renewable energy consumption. Additionally, we will also estimate the coefficients of the variables. In this case, we do not need any hypothesis testing.

3. Methodology and Data Set

Economic growth model is defined by the function given below,

$$GDP = f(K, L, RC, FFC) \quad (1)$$

In equation 1, GDP= Gross Domestic Product, K= gross capital formation, L= total labor force, RC= renewable energy consumption and FFC= fossil fuel consumption. The functional form can be written in a log linear equation for a given time period t.

$$LNGDP_t = LNK_t + LNL_t + LNRC_t + LNFFC_t + e_t \quad (2)$$

For this log linear equation, we assume that there is a long run equilibrium which ensures optimal GDP. One of the main advantages of using log linear equation is that we can easily calculate elasticity of the independent variables.

For panel data analysis, Augmented Dickey Fuller or Dickey-Fuller tests are extended to check the stationarity of the variables. Extension is done because most of the tests

include it as a regression component. Five unit root tests are applied in this paper. First two tests are Levin, Lin and chu (2002) and Breitung (1999) tests respectively. These tests are common unit root tests for across cross sections. Null hypothesis for these two tests is that data are non-stationary or have unit root and alternative hypothesis is that data are stationary or do not have unit root. Other three tests are Im, Pesaran and Shin (2003), Augmented D ickey Fuller (ADF) and Phillips Perron Tests (Maddala & Wu 1999). These three tests assume individual unit root process across the cross sections.

Johansen (1988) first proposed two different approaches for checking the cointegration among the variables. The first one is the likelihood ratio trace statistics and other one is the maximum eigenvalue statistics.

$$\lambda_{Trace} = -T \sum_{i-r+1}^{n} \ln(1-\lambda_i) \qquad (3)$$

$$\lambda_{max}(r, r+1) = -Tln(1-\lambda_{r+1}) \quad (4)$$

Maddala & Wu (1999) used Johasen's (1998) test for cointegration considering the suggestion of Fisher (1932) to combine individual tests. Maddalaand Wu (1999) proposed an alternative of the two previous tests for testing cointegrating relationship in panel data scenario through individual cross tests for cointegration. If π_i is the p value of the cross section cointegration of *i*, then for whole cross section null hypothesis will be,

$$-2 \sum_{i=1}^{N} log_e \pi_i \quad (5)$$

Which is distributed as χ^2_{2N} in the sample

Hurlinand Dumtrescu (2012) proposed a simple Granger (1969) non causality heterogeneous panel data model opposed to time varying (fixed) coefficients. In the linear autoregressive data generating framework, the extension of the panel standard causality means investigating cross sectional linear restrictions of the coefficients of the variable in the model. In general, the information of one cross section can extend to other cross sections. Many economic matters which have causal relations in one country can also be observed in other neighboring countries. In this case, the causality can be more efficiently tested in a panel context with *NT* observations. On the other hand, working with cross sectional data involves accepting heterogeneity across the causality and this simple version of granger test allows to test causality with any heterogeneity problem.

Let us suppose that *x* and *y* are two stationary variables. These two variables are observed for *N* individuals over the time period of *T*. Here i= 1, … , N and t= 1… T.

$$Y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{\,k} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{\,k} x_{i.t-k} + \varepsilon_{it} (6)$$

Here, K belong to N and$\beta_i = (\beta_i^{\,1}, \dots, \beta_i^{\,K})'$. In this case, let us assume that α_i is fixed in the time dimension and lag order K is identical to all cross sectional units of the panel where the panel is fully balanced. Furthermore, $\gamma_i^{\,k}$ (autoregressive parameter) and $\beta_i^{\,k}$

(slope of the coefficient) are allowed to differ across the cross section units but both are constant over the time. Thus, it creates a fixed environment rather than allowing random effects to change the values of the coefficients.

Heterogeneity problem in panel data may appear from the presence of individual effect. It is known as standard source of heterogeneity. On the other hand, heterogeneity problem may appear through from the parameters. Later one directly effects the pattern of the respective agent and therefore causing problem in causality relationships. On the other hand, homogenous specification of the variables does not allow any causality relations if at least one different economic behavior of individuals is different from other individual. Thus, incorporating Homogenous Non Causality (HNC) hypothesis allows both the heterogeneity and causal relation among the parameters. The null hypothesis is defined as,

$$H_o: \beta_i = 0 \quad \forall_i = 1, \dots, N$$

For the alternative hypothesis, it is assumed that there are N_1<N individual process where no causality between x and y.

$$H_1: \beta_i = 0 \quad \forall_i = 1, \dots, N$$

$$\beta_i \neq 0 \;\; \forall_i = \; N_1 + 1, N_1 + 2, \dots, N$$

Where N_1 is unknown but satisfies the condition of $0<N_1/N<1$. When $N_1 = 0$, there is causality for all the individuals in the sample. There will be no causality when $N_1 = N$, that is the null hypothesis. The structure is very similar to Im, Pesaran and Shin (2003).

Engle and Granger (1987) asserted that if two series are cointegrated, they can be expressed with error correction mechanism. Panel vector error correction can explain both short run and long run causality among the variables of interest. Causality inferences in the multi-variate framework are made by estimating the parameters of the following VECM equations.

$$\Delta Y = \alpha + \sum_{i=1}^{m} \beta i \Delta Y_{t-i} + \sum_{j=1}^{n} \gamma_j \Delta X_{t-j} + \sum_{k=1}^{0} \delta \Delta M^{s} + \sum_{l=1}^{p} \zeta \Delta N + \theta Z_{t-1} + \varepsilon_t \qquad (7)$$

$$\Delta X = a + \sum_{i=1}^{m} b_i \Delta Y + \sum_{j=1}^{n} c_j \Delta X_{t-j} + \sum_{k=1}^{0} d \Delta M^{s} + \sum_{l=1}^{p} e \Delta N + f Z_{t-1} + \xi_t \qquad (8)$$

z t-1 is the error-correction term which is the lagged residual series of the cointegrating vector. Deviations of the series from the long run equilibrium relation is measured by the error-correction term. For instance, from equation (7), the null hypothesis that X does not Granger cause Y is rejected if the set of estimated coefficients on the lagged values of X is jointly significant. Furthermore, in those instances where X appears in the cointegrating relationship, the hypothesis is also supported if the coefficient of the lagged error-correction term is significant. Changes in an independent variable may be interpreted as representing the short run causal impact while the error-correction term

provides the adjustment of Y and X toward their respective long run equilibrium. Thus, the VECM representation allows us to differentiate between the short- and long-run dynamic relationships. The Chi-Square test statistic is used to determine the short run causalities between pairs of variables in the model.

In fixed effect models, parameters are known to be fixed or non-random quantities. The model refers to a regression model where group means are kept fixed (non-random) from a population (Ramsey & Schafer 2002). Usually, sample data set can be grouped according to the several observed factors where the mean is group specific-fixed quantity. In contrast to a fixed effect model, random effect model or mix effect model refer to a model in which perimeters are considered to be as random variables and group mean is not fixed (Diggle *et al*. 2002).

These models are used for controlling the unobserved heterogeneity. Especially when heterogeneity is constant over the time period. There are two assumptions: random effect assumption and fixed effect assumption. The random effect assumption asserts that the individual–specific effects are uncorrelated with the independent variables. On the other hand, fixed effect assumption says that the individual–specific effects are correlated with the independent variables. The Durbin–Wu–Hausman test is often used to find out which of the models is efficient for a particular situation (Nerlove 2005)

Let us consider the following linear unobserved effects model for *N* observations and *T* time periods:

$$Y_{it} = X_{it}\beta + \alpha_i + u_{it} \quad (9)$$

Where, t= 1, 2, 3…, T and i= 1, 2, 3…, N

Here Y_{it} is the dependent variable for individual entity i at time t. X_{it} is the time variant (*1x k* Matrix), α_i is the unobserved parameter and u_{it} is the error term. In the random effect model α_i is independent of X_{it} for time t. However, fixed effect model allows α_i to be correlated with regressor matrix. In fixed effect model, we can eliminate the α_i through within transformation.

$$Y_{it} - \bar{Y}_i = (X_{it} - \bar{X}_\iota)\beta + (\alpha_{it} - \bar{\alpha}_\iota) + (u_{it} - \bar{u}_\iota) \quad (10)$$

$$\ddot{Y}_{\iota t} = \ddot{X}_{\iota t}\beta + \ddot{u}_{\iota t} \quad (11)$$

Where, $\bar{X}_\iota = \frac{1}{T}\sum_{t=1}^{T} X_{it}$ and $\bar{u}_\iota = \frac{1}{T}\sum_{t=1}^{T} u_{it}$

As α_{it} is constant, $\alpha_{it} = \bar{\alpha}_\iota$. Thus, the effect is eliminated. Beside this, transformation can also be done by incorporating dummy variables in the model or by using consecutive reiterations approach to local and global estimations (David *et al*. 1986).

Generalized Method of Moments (GMM) estimation approach was developed by Lars Peter Hansen in 1982. Since then it has become one of the most widely used methods of estimation for models in economics and finance. In contrast to the likelihood

estimation (MLE), GMM does not require complete knowledge of the distribution of the data. It only needs specified moments derived from the concerned model. GMM model is far more effective in the log- normal stochastic volatility models.

$$Y_t = z_t\delta + \varepsilon_t \text{ Where, } t = 1, 2, 3, \ldots, n \quad (12)$$

In equation (12), z_t indicates explanatory variables which can be expressed by L × 1 vector. δ is a vector of unknown coefficient and $\varepsilon_t$is the error term. Equation (12) allows the possibility that some or all elements of explanatory variables are related with the error term. Then endogenity problem will arise. It is well known that if z_t contains endogenous variables then the least squares estimator of δ in (12) is biased and inconsistent.

Let us assume that we have K × 1 vector of instrumental variables $x_t$that may contain some or all the elements ofz_t. The instrumental variables x_t satisfy the set of K orthogonality conditions.

$$E[g_t(w_t, \delta)] = E[x_t\varepsilon_t] = E[x_t(Y_t - z_t\delta] = 0 \quad (13)$$

Rewriting equation (13) gives,

$$\sum xy = \sum xz\,\delta$$

Where $\sum xy = E[x_tY_t]$ and $\sum xz = E[x_tz_t]$.

For identification of δ, it is required that the K × L matrix $E[x_tz_t] = \sum xz$ has to be full rank L. The solution of δ is ensured by the rank condition. If K=L then, $\delta = \sum xz^{-1} \sum xy$. It is worth mentioning that the number of instrumental variables must be greater or equal to the explanatory variables. If not, then the model will fail to estimate the coefficient values.

The Dynamic OLS (DOLS) approach was proposed by Stock & Watson (1993). DOLS is an improvement version of OLS approach where we can deal with small sample size and dynamic sources of bias. It is a robust single equation approach corrects the regressor endogeneity by incorporating lags and leads. DOLS can estimate long run equilibrium where variables are integrated in same or different order. This is one of the major advantage of this approach. Moreover, it has the same kind of optimality like Johansen distribution. Since our sample size is small, we applied DOLS approach for avoiding false estimation. If Y_t is the dependent variable with regressors $X_{i,t}$=1,2,3…,n then,

$$Y_t = \beta_1X_{1,t} + \beta_2X + \cdots + \beta_kX_{k,t} + \sum \alpha_{i\Delta}X_{1,t-1} + \sum y_{i\Delta}X_{2,t-1} + \cdots + \sum \delta_{i\Delta}X_{k.t-1} + \varepsilon_t \quad (14)$$

The paper is based on annual data covering the period of 1981-2015. Data on total labor force, gross capital formation ($US), gross domestic product ($US) are taken from World Development Indicator (WDI) Renewable energy consumption data is taken from OECD data bank. Fossil fuel data is obtained by subtracting the renewable energy

consumption from the total energy consumption.

4. Results and Discussions

Unit root tests are conducted to determine the order of integration of the data series. Optimal lag is chosen by Schwartz Information Criterion (SIC). Table 1 shows the ADF statistics and corresponding critical values of all the variables in their level and first differenced forms.

Unit root tests have non-standard and non-normal asymptotic distribution. These distributions are extremely affected by the inclusion of deterministic terms such as constant, time trend etc. (Amin, 2011). An extraneous regressor whose enclosure reduces the power of the test is called time trend. Yet if the true data generating process were trend stationery, failing to include a time trend also results in a decline in power of the test. Additionally, this loss of power from without a time trend when it should be present is more severe than the reduction in power associated with including a time trend when it is extraneous. One of the main issues in unit root testing is lag length selection. Including a moderately long lag length and select the model by the usual t-test is one of the approach. When the t-statistics on lag p is insignificant at some stated critical value, the regression should be frequently assessed using a lag length (p-1) until the lag is significantly different from zero. From the table it is clear that the variables would yield spurious results unless the variables are cointegrated. The results, however, allow to proceed to the next stage of testing for cointegration. The Johansen Fisher cointegration test results indicate that our variables have four cointegrating relationships. Maximum Eigen value test and the trace test (Table 2) both point out 4 cointegrating relationships at 95%. After the Cointegration test, we performed panel causality test.

Table 1: Unit Root Test Results

Variable	Lavin, Lin & Chu (Prob)	Breitung (Prob)	Im, Pesaran& Shin (prob)	ADF-Fisher Chi-Square	PP-Fisher Chi-Square	Decision on Stationarity
Levels						
LNGDP	0.65438 (0.7436)	0.99861 (0.8410)	1.84952 (0.9678)	2.42608 (0.9919)	2.60646 (0.9892)	Non Stationary
LNK	0.33766 (0.6322)	-0.86985 (0.1922)	0.33861 (0.6319)	7.32107 (0.6948)	8.60701 (0.5698)	Non Stationary
LNL	0.74739 (0.9937)	-0.56910 (0.3045)	0.19042 (0.8374)	8.28301 (0.9632)	8.99324 (0.4489)	Non Stationary
LNRC	1.30585 (0.9042)	1.95282 (0.9636)	1.10981 (0.9746)	8.42342 (0.5876)	19.4190 (0.3450)	Non Stationary
LNFFC	0.97461 (0.8951)	1.61642 (0.9570)	0.8174 (0.7924)	7.94104 (0.6347)	7.07311 (0.7185)	Non Stationary
First Difference						
LNGDP	-2.9914 (0.0107)	-3.77304 (0.0001)	-4.34660 (0.0000)	37.3917 (0.0000)	74.9953 (0.0000)	Stationary
LNK	-4.60327 (0.0000)	-2.95307 (0.0016)	-4.43053 (0.0000)	38.4340 (0.0000)	74.2045 (0.0000)	Stationary
LNL	-5.73944 (0.0001)	-2.33016 (0.0016)	-7.03488 (0.0345)	43.3452 (0.0000)	79.8934 (0.0000)	Stationary
LNRC	-6.01103 (0.0000)	-4.28607 (0.0000)	-6.1775 (0.0000)	54.9987 (0.0000)	400.167 (0.0000)	Stationary
LNFFC	-5.83459 (0.0000)	-2.90675 (0.0018)	-4.91690 (0.0000)	41.5899 (0.000)	97.9430 (0.0000)	Stationary

Table 2: Johansen-Fisher Cointegration Test Results

Hypothesized No. of CE(s)	Fisher Statistic (Trace Test)	Probability	Fisher Statistic (Max-Eigen Test)	Probability
None	178.0	0.0000	110.9	0.0000
At most 1	84.62	0.0000	48.14	0.0000
At most 2	44.79	0.0000	37.78	0.0004
At most 3	21.87	0.0185	17.58	0.0625
At most 4	12.44	0.2566	12.44	0.2566

Table 3: Dumitrescu-Hurlin Panel Causality Test Results

Variable	Null Hypothesis	W-Statistic	P-Value	Conclusion
Causality Test Statistics between LNGDP and LNK				
LNGDP	LNK does not homogenously cause LNGDP	1.15097	0.3351	LNGDP Causes LNK
LNK	LNGDP does not homogenously cause LNK	4.18816	0.0505	
Causality Test Statistics between LNGDP and LNL				
LNGDP	LNL does not homogenously cause LNGDP	6.72134	0.00005	LNL Causes LNGDP
LNL	LNGDP does not homogenously cause LNL	2.3359	0.8628	
Causality Test Statistics between LNGDP and LNRC				
LNGDP	LNRC does not homogenously cause LNGDP	476555	0.0121	Bidirectional Causality
LNRC	LNGDP does not homogenously causes LNRC	4.45489	0.0270	
Causality Test Statistics between LNGDP and LNFFC				
LNGDP	LNFFC does not homogenously cause LNGDP	1.55639	0.5658	LNGDP Causes LNFFC
LNFFC	LNGDP does not homogenously causes LNFFC	4.39728	0.0311	

Table 3 above shows 4 sets of null hypothesis. Third set of null hypothesis is related with our research objective. From the third set, we can reject both of the null hypothesis. It means that there is a bidirectional causality running between renewable energy consumption and economic growth supporting feedback hypothesis. (answering the first research question from long run pint of view). It means both variables can cause each other. If we think from renewable energy consumption side, then increase in renewable energy consumption could cause economic growth in the economy. When consumption of renewable energy would increase, the pressure from non-renewable energies would decline in certain degree. Thus, subsidies provided by government for non-renewable energy import, production or consumption might decline as well. Consequently, government can utilize the saved money to subsidize other important sectors which can positively influence economic growth such as education or health or even agriculture. This process is known as subsidy diversification. On the other hand, government can increase its expenditure too. Both subsidy diversification and increase in public expenditure could lead to higher growth. Now, if we think from the economic growth,

then increasing trend of economic growth also increases awareness about the protection of environment. Thus, government can promote to increase renewable energy consumption so that the economy can grow at a stable speed as well as environment is not being harmed.

After observing the long run causal relationship, we now move to investigate the short run causal relationship among the variables through VECM approach (with same set of hypothesis). The results from the VECM approach are given in the table 4.

Table 4: Panel VECM Test Results

Variable	Null Hypothesis	Chi Square Statistic	P-Value	Conclusion
Causality Test Statistics between LNGDP and LNK				
LNGDP	LNK does not cause LNGDP	0.012269	0.9878	No Causality
LNK	LNGDP does not cause LNK	0.024539	0.9867	
Causality Test Statistics between LNGDP and LNL				
LNGDP	LNL does not cause LNGDP	0.153463	0.8579	No Causality
LNL	LNGDP does not cause LNL	0.306925	0.8577	
Causality Test Statistics between LNGDP and LNRC				
LNGDP	LNRC does notcauseLNGDP	0.0975	0.9072	No Causality
LNRC	LNGDP does not cause LNRC	0.1949	0.9071	
Causality Test Statistics between LNGDP and LNFFC				
LNGDP	LNFFC does not cause LNGDP	1.021470	0.3625	No Causality
LNFFC	LNGDP does not cause LNFFC	2.042940	0.3601	

According to the VECM results, no causality was found between our variables of interest. One of the possible reasons for this is that the intensity effect of energy consumption is subject to time lag to be observed

Now we move to analyze the long run estimations. As stated earlier, we have used Fixed Effect, Random Effect, Panel GMM and Panel DOLS for estimation. Hausman test was conducted to determine which effect is more appropriate in this scenario. Result of Hausman test revealed that fixed effect is more appropriate. Table 5 shows the result of Hausman test result.

Table 5: Hausman Test Result

Null hypothesis	Chi Square Statistic (prob)
Random Effect is appropriate	222.72 (0.000)

Table 6 shows the long run estimation results of different approaches. We can see that the coefficient of renewable energy is inelastic and positive. The values are significant as well. Therefore, increase in renewable energy consumption positively effects economic growth in 5 five concerned South Asian countries in the long run. The coefficient of renewable energy consumption value is lower than the coefficient of fossil fuel (expect fixed effect estimation). It indicates that fossil fuel still to a certain extent dominates the five economies. On the other hand, it can be seen that coefficient of labor is insignificant in all the approaches and in fixed effect approach, it is negative as well. One of the main reasons for this is that the data quality in developing countries are poor (Bhattacharyya & Timilsina, 2010). The estimation result answers the second research question.

Table 6: Panel Estimation Results

Variable	Fixed Effect	GMM	DOLS
LNK	0.68 (0.0002)	0.67 (0.002)	0.75 (0.0008)
LNL	-0.21 (0.155)	0.04 (0.247)	0.004 (0.962)
LNFFC	0.11 (0.254)	0.87 (0.000)	0.35 (0.000)
LNRC	0.92 (0.0007)	0.16 (0.006)	0.23 (0.0001)
Adjusted R^2	0.995919	0.993891	0.995112

Probabilities in Parenthesis

5. Conclusion

It is said that desired level of access to energy shapes the destiny of a nation. However, the world is facing a scarcity of the conventional energy resources which halts the access to energy. Beside that there are other problems like, oil price volatility and environmental negative impacts are hindering the sustainable economic growth of the developing nation's worldwide. Introducing renewable energy side by side with the conventional energies will ensure energy security, climate change alleviation and socio-economic development and provide sustainable energy solutions (Amin *et al.,* 2016)

In this paper, we have empirically analyzed the short run and long run causal relationship between renewable energy consumption and economic growth of five neighboring countries with the help of panel data ranging from 1981 to 2015. We have also estimated the long run coefficient of renewable energy consumption. We have found that in the short run there is no causality between renewable energy consumption and economic growth (consistent with Amri 2017). However, in the long run, we have found a bidirectional causality running between renewable energy consumption which proves the feedback hypothesis (consistent with Apergis & Payne 2010). On the other hand, from the long run estimation results, it is clear that the coefficient of renewable energy consumption is inelastic in nature and positive as well. Policy makers should create a framework which can help to develop the renewable energy sector. For instance, policies in favor of sectoral foreign direct investment can enhance the

development process of renewable energy sector in all five countries. On the other hand, beside the sectoral development, to increase the consumption, polices should be taken to promote renewable energies and create awareness of climate change.

One of the main limitation of this paper is data constraint. It is difficult to capture the intra sectoral changes, technology penetration in renewable energy sector, transitions of energy markets over the years, economic structure of the nation, governance and many more. By adding more control variables, we could have gained more knowledge on the relationship between economic growth and renewable energy consumption. This paper can be further expanded by analyzing the effect of renewable energy on each component of GDP. Furthermore, an analysis can be done to see the effects of renewable energy on economic growth at disaggregate level to observe how different renewable energy sources can impact the chosen five economies. Having such insight can make policy makers to come up with a policy framework that can help to achieve prosperity in this region.

Reference

Amin, SB, Chadni, MH, Khan, F & Rahman, S 2017, 'Generations of biofuel: Case of Bangladesh', *World Journal of Social Science*, *Vol.7, No.2, Pp. 88-98*.

Amin, SB, Islam, SL, Kamal, TZ & Mithila, NN 2017, 'Prospects and Constraints of Renewable Energy Sector in Bangladesh: An Analytical Exercise', *World Journal of Social Science*, *Vol.6, No.2, Pp. 1-12*.

Amin, SB, 2015, 'The Macroeconomics of Energy Price Shocks and Electricity Market Reforms: The Case of Bangladesh', Durham E-thesis, Durham University.

Amin, SB, 2011, 'Quantity Theory of Money and its Applicability: The Case of Bangladesh', World Review of Business Research, Vol.1, No. 4, Pp.33-43.

Amri, F 2017, 'Intercourse across economic growth, trade and renewable energy consumption in developing and developed countries', *Renewable and Sustainable Energy Reviews*, *Vol.69, Pp. 527-534*.

Apergis, N, Chang, T, Gupta, R & Ziramba, E 2016, 'Hydroelectricity consumption and economic growth nexus: Evidence from a panel of ten largest hydroelectricity consumers', *Renewable and Sustainable Energy Reviews*, *Vol.62, Pp. 318-325*.

Apergis, N. & Payne, JE 2010, 'Renewable energy consumption and economic growth: Evidence from a panel of OECD countries', *Energy Policy, Vol.38, 656-660*.

Armeanu, DS, Vintilă, G & Gherghina, SC 2017, 'Does renewable energy drive sustainable economic growth? Multivariate panel data evidence for EU-28 countries', *Energies,Vol.10. Pp. 1-21*.

Breitung, J 1999, 'The local power of some unit root tests for panel data', Discussion Papers, Interdisciplinary Research Project 373: Quantification and Simulation of Economic Processes.

Bhattacharyya, SC, & Timilsina, GR 2010, *Energy Demand Models for Policy Formulation*, Development Research Group, Environment and Energy Team, Washington, World Bank.

Bhattacharya, M, Paramati, SR, Ozturk, I & Bhattacharya, S 2016, 'The effect of renewable energy consumption on economic growth: Evidence from top 38 countries', *Appl. Energy*, *Vol.162, Pp. 733-741*.

BP Statistical Review of World Energy. Technical Report. 2016, BP Global.

David, T, Cieszewski, CJ & Bella, IE 1986, 'The stand dynamics of lodge pole pine', *Can. J. For. Res*, *Vol. 18, Pp. 1255–1260*.

Diggle, PJ, Heagerty, P, Liang, KY & Zeger, SL 2002, *Analysis of longitudinal data,* 2nd edn, Oxford University Press. *Pp. 169-171*.

Dumitrescu, EI & Hurlin, C 2012, 'Testing for Granger non-causality in heterogeneous panels', *Economic Modelling*, *Vol.29, No.4, Pp. 1450-1460*.

Fisher, RA, 1932, *Statistical Methods for Research Workers*, 4th Edition. Oliver and Boyd, Edinburgh.

Garcia, O. 1983, 'A stochastic differential equation model for the height growth of forest stands', *Biometrics*, *Pp. 1059–1072*.

Granger, CWJ 1969, 'Investigating causal relations by econometric models and cross-spectral methods', *EconometricaVol.37, Pp. 424-438*.

Hansen, LP 1982, 'Large sample properties of generalized method of moments estimators', *Econometrica*, *Vol.50, No.4, Pp. 1029-1054*.

Holtz-Eakin D, Newey, W & Rosen HS 1988, 'Estimating vector auto regressions with panel data', *Econometrica,Vol.56, Pp. 1371-1396*.

Im, KS, Pesaran, M & Shin, Y 2003, 'Testing for unit roots in heterogeneous panels', *Journal of Econometrics, Vol. 115, Pp. 53 - 74*.

Johansen, S 1988, 'Statistical analysis of cointegration vectors, *Journal of Economic and Control,Vol.12, Pp. 231 - 254*.

Levin, A, Lin, F & Chu, CJ 2002, 'Unit root tests in panel data: Asymptotic and finite-sample properties', *Journal of Econometrics*, *Vol.108, Pp. 10-24*.

Lise, W.; Van Montfort, K 2007, 'Energy consumption and GDP in Turkey: Is there a co-integration relationship?', Energy Econ, *Vol.29, Pp. 1166–1178*.

Maddala, GS & Wu, S 1999, 'A comparative study of unit root tests with panel data and a new simpletest', *Oxford Bulletin of Economics and Statistics,Vol.61, Pp.631-652.*

Moldan, B, Janouskova, S &Hak, T 2012, 'How to understand and measure environmental sustainability: Indicators and targets', *Ecol. Indic.*, *Vol.17, Pp. 4-13*.

Nerlove, M 2005, *Essays in panel data econometrics*, Cambridge University Press, *Pp. 36-39.*

Omri, A, Mabrouk, NB & Sassi-Tmar, A, 2015, 'Modeling the causal linkages between nuclear energy, renewable energy and economic growth in developed and developing countries', *Renewable and Sustainable Energy Reviews*, *Vol.42, Pp.1012-1022.*

OECD data bank, 2015

Ramsey, F & Schafer, D 2002, *The statistical sleuth: A Course in methods of data analysis*, 2nd edn, Duxbury Press.

Sebri, M & Ben-Salha, O, 2014, 'On the causal dynamics between economic growth, renewable energy consumption, CO 2 emissions and trade openness: fresh evidence from BRICS countries', *Renewable and Sustainable Energy Reviews*, *Vol.39, Pp.14-23*.

Stock, JH, & Watson, MW 1993, 'A simple estimator of cointegrating vectors higher order integrated systems, *Econometrica, Vol.61, No.4, Pp. 783-820*.

Vidyarthi, H 2015, 'Energy consumption and growth in South Asia: evidence from a panel error correction model', *International Journal of Energy Sector Management*, *Vol.9, No.3, Pp. 295-310*.

World Development Indicators (WDI) 2015, World Bank Open Database, <https://data.worldbank.org/products/wdi>

Zeshan, M 2012, *Renewable energy consumption and economic growth in Pakistan*, Sustainable Development Policy Institute (SDPI), Islamabad, Pakistan.