Does urbanization cause increasing energy demand in Pakistan? Empirical evidence from STIRPAT model

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Abstract: This paper reinvestigates the relationship between urbanization and energy consumption in case of Pakistan for the period of 1972Q1-2011Q4 by employing the STIRPAT (Stochastic Impact by Regression on Population, Affluence and Technology) model. We have employed the ARDL bounds testing approach to cointegration in the presence of structural breaks stemming in the series to count for these missing elements in other studies. Finally, the VECM Granger causality approach has been applied to examine the causal relationship between the variables. Our results show that urbanization adds in energy consumption. Affluence (economic growth) increases energy demand. Technology has positive impact on energy consumption. An increase in transportation is positively linked with energy consumption. The causality analysis indicates the unidirectional causality running from urbanization to energy consumption.

Keywords: Urbanization, Energy Demand, STIRPAT, Pakistan

1. Introduction

Economic theory postulates that urbanization is caused by economic growth and social modernization [1, 2]. Poumanyvong and Kaneko [2] argued that urbanization means a shift of the rural labor force from agricultural sector to industrial sector which is mostly situated in urban areas. This structural transformation of rural areas into urban hubs affects energy consumption significantly through various channels. For example, urbanization increases energy consumption by raising the demand for housing, food, public utilities, land use, transportation in urban areas, use of more electric appliances, the rise in demand of road use, globalization,… etc. In recent decades, urbanization has been growing rapidly. The world urban population was 1.52 billion in 1974-75 which steadily increased to 3.29 billion in 2006-07 ([3]) that is projected to double in 2050. This rapid increase in urbanization will generate more pressure on existing urban infrastructure e.g. housing, health, education, power, transportation, and other public utilities. Urban dwellers consume higher quantities of resources and add pressure to the flimsy ecosystem. International Energy Agency [4] reports that big city dwellers accounted for 67.77 per cent of world energy use. This implies that the continuous increase in urbanization will have significant impact on energy consumption.

The estimated population of Pakistan was about 62 million in 1971 with a density of 81/km and the urban population was 25.1%. Between 1971 and 2004, population increased to 148 million, which raised urban population to 34.6% while population density was of 187/km. Pakistan was listed among the most urbanized nations in the South Asia [5]. The urban population rose to 36.38% [6]. In Pakistan, urban population has increased from 25.3185 per cent as a share of total population in 1971-72 to 37.2354 per cent as a share of total population in 2010-11, which is almost a 47 per cent rise in urban population growth [6]. This increase in urbanization affected the contribution of modern sector, i.e. interaction between industrial and services sectors. The share of modern sector had increased from PRS 13.75 million in 1971-72 to PRS 148.42 million in 2010-11 which is almost 979 per cent growth in modern sector of Pakistan [6]. The urbanization also raises the demand for personnel as well as public transportation. The use of transport was 2.97 per kilometer of road in 1971-72, which has increased to 11.89 per kilometer of road in 2010-11, which is 300 per cent increase in transportation use in Pakistan [6].

We find that rapid urbanization, modern sector growth and rapid transportation growth affect energy demand in Pakistan. This motivates the researchers to conduct this piece of research for providing guidelines to help policy making authorities in designing appropriate policy for using urbanization as economic tool for efficient use of energy to maintain sustainable economic development. Therefore, this paper contributes to the existing literature in four ways: (i) Pakistan is an emerging economy and transportation sector consumes major chunk of energy such s oil consumption. So, we employ augmented STIRPAT model to investigate the relationship between urbanization and energy consumption by incorporating affluence, technology and transportation as potential determinants of urbanization and energy demand. (ii) Over the sample period of time, structural breaks occurred in urbanization, energy, industrialization, economic growth etc. due to implementation of economic, urban and energy policies by the government. These structural breaks may change the unit root behavior, impact (effect) of the variables and even change the causal relationship between the variables. In doing so, the structural break unit tests are employed to test the stationarity properties of the variables. (iii) The cointegration relationship between the variables is examined by applying the ARDL bounds testing accommodating structural breaks in the series. (iv) The VECM causality approach is used to check causal relationship between urbanization and energy demand by accommodating structural breaks occurring in the series. We find that presence of structural breaks in the series could not affect cointegration relationship between the variables i.e. cointegration exists. Additionally, urbanization is positively linked with energy consumption. Affluence and technological development positively affect energy consumption. Transportation has positive effect on energy consumption. The causality analysis reveals that energy consumption is cause of urbanization. The feedback effect is noted between technological development (transportation) and energy consumption. Affluence causes energy consumption and energy consumption causes affluence.

2. Literature Review

The relationship between urbanization and energy consumption has been widely and empirically investigated by various researchers in the existing literature. For example, Jones [7] noted that urbanization raises energy demand because urban people are more connected to electrical appliances as compared to rural individuals. In urban areas, there is an increase in private transportation with an increase in income per capita which also contributes to energy demand. Energy demand is also cause of urban density. Dhal and Erdogan [8] examined the relationship between urban population and oil consumption. They reported that an increase in urbanization is positively linked to industrialization, which increases oil consumption. Burney [9] reported that socioeconomic determinants also affect energy consumption. He found that urbanization raises energy demand, but varies across countries by keeping income per capita and industrialization constant. Imai [10] found that population and urbanization has positive impact on energy consumption but causality results exposed that urbanization is cause of population and energy consumption.

Later on, Cole and Nuemayer [11] reported that urbanization is directly linked with energy demand due to rise in demand for housing, transportation provides by government and other public utilities, urban density and stimulation of economic activity in industrial and services sectors. They found U-shaped relationship between urbanization and energy consumption and small size households adds more in energy demand. Kalnay and Cal [12] pointed out that urbanization raises pressure on agriculture sector to produce more food. This raises the use of land as well as energy demand in agriculture sector. Bryant [13] opined that urbanization is linked to industrialization, technological advancement, globalization and migration. All these factors add in energy demand. Likewise, Shen et al. [14] unveiled that supply of resources i.e. Cement, steel, aluminum and coal and the demand of timber, cement and steel, lead the process of urbanization which increases industrialization and modernization and, in resulting energy demand is increased.

Wang et al. [15] examined the impact factors of population, economic level, technology level, urbanization level, industrialization level, service level, energy consumption structure and foreign trade degree on the energy-related CO_2 emissions in Guangdong Province, China from 1980 to 2010 using an extended STIRPAT model. Empirical results indicate that factors such as population, urbanization level, GDP per capita, industrialization level and service level, can cause an increase in CO_2 emissions. However, technology level, energy consumption structure and foreign trade degree can lead to a decrease in CO_2 emissions. Mishra et al. [16] investigated the affiliation between urbanization and energy consumption by incorporating economic growth in the energy demand function in Pacific Island nations. They noted that urbanization involves structural changes throughout the economy and has important implications for energy consumption. Urbanization leads to substantial concentration of population in generating economic activities; and thus increases demand for energy. Lui [17] assessed the relationship between population growth, urbanization and energy consumption by applying the ARDL bounds testing approach and factor decomposition model in case of Chinese economy. He found that the cointegration for the long run rapport is present among the variables. The causality analysis revealed that population and economic growth have neutral impact on energy consumption, but total energy consumption is cause of urbanization. Zhao-hui [18] reinvestigated the relationship between different stages of urbanization (tortuous development, early stage and mid-stage) and energy consumption. The results showed cointegration between the variables and energy demand Granger causes both industrial development and urbanization.

Similarly, Poumanyvong and Kaneko [2] looked into the relationship between urbanization and energy consumption by incorporating other potential variables such as economic growth, industrial development and population growth in the energy demand function. Their empirical evidence found that urbanization, economic growth, population and industrialization add in energy demand but technical efficiency lowers it. Furthermore, they reported that in developing economies, urbanization reduces energy demand due to switch off from traditional and inefficient energy fuels to modern and efficient energy fuels. The positive effect of urbanization on energy consumption is greater in high income countries compared to middle income economies. Madlener and Sunk [19] examined the impact of urbanization and urban structure on energy consumption using data of 100 developed and developing economies. They found that urbanization affects energy demand via changes in urban structure. Their results confirmed that urbanization is cause of economic development and increase in income levels changes the consumer necessities which in turn affect energy consumption. Shahbaz and Lean [20] analyzed the relationship between urbanization and energy consumption by incorporating financial development and industrialization in energy demand function. Their empirical evidence showed that financial development, industrialization and urbanization have positive impact on energy consumption in Tunisia. Likewise, urbanization and financial development lead industrialization, which Granger causes energy demand. Similarly, Islam et al. [21] also found that population is positively linked with energy demand, but the bidirectional causal relationship is found between population and energy consumption in case of Malaysia.

Ma and Du [22] reinvestigated the relationship between urbanization, industrialization, energy prices and energy consumption using data of Chinese economy. They found that industrialization leads urbanization and urbanization has positive impact on energy demand due to an increase in urban density. Additionally, impact of tertiary industrial value added is negative on energy use due to use of advance technology and Chinese energy policy as well as environmental regulations. Apart from that, Mickieka and Fletcher [23] tested the impact of urbanization on coal consumption using the vector autoregressive framework and Toda and Yamamoto [24] Granger causality approach over the period of 1971-2009. They incorporated real GDP and electricity production as potential determinants in coal demand function. Their empirical evidence exposed that coal consumption is cause of economic growth and the unidirectional causality is found running from urbanization to electricity consumption as well as coal consumption. Coal consumption does not seem to affect real GDP. Zhang and Lin [25] analyzed the impact of urbanization on energy consumption using national, provincial and regional data by applying the STIRPAT model. Their empirical evidence opined that urbanization has positive impact on energy consumption but varies across regions. Urbanization also lowers energy demand in West, Central and Eastern regions of China due to use of energy efficient technology.

Poumanyvong et al. [26] reinvestigated the impact of urbanization on national transport and road energy use using the data of developing, middle and high income countries. Their results showed that urbanization raises more demand for transportation and hence energy in high income countries comparatively in low income countries. Surprisingly, the impact of urbanization on national transport and hence on energy consumption is positive but less in middle income countries as compared to low income countries. Sadorsky [27] collected the data of 75 developing countries, including Pakistan to examine the impact of urbanization and industrialization on energy intensity by applying the mean group estimator (MGE). He found that income effect has negative impact on energy intensity i.e. -0.45%-0.35%. This suggests that rise in income leads to employ advance and energy efficient technology for enhancing domestic production which reduces energy consumption. Furthermore, industrialization increases, i.e. 0.07%-0.12% energy intensity and impact of urbanization on energy intensity varies in various regions. Solarin and Shahbaz [28] applied the trivariate model to assess the causality between energy consumption (electricity consumption) using annual frequency data for Angola economy. They investigated the long run relationship by applying the ARDL bounds testing and the VECM Granger causality is applied for causality between the variables. Their empirical exercise exposed that electricity consumption and urbanization promote economic growth. The causality results revealed that the relationship between electricity consumption and urbanization is bidirectional.

In a comparative study, Pachauri and Jiang [29] noted that rural individuals consume more energy due to the heavy dependence on inefficient energy fuels and these energy fuels meet 85% of rural energy demand in China and India. In particular, O'Neill et al. [30] applied iPETS (integrated-Population-Economy-Technology-Science) model to reassess the impact of urbanization on energy use in India and China. Their study noted that urbanization has impact on energy use but less than proportional in both countries due to the fast rate of urbanization which provides labor supply to enhance domestic production. Moreover, rural-urban disparity between China and India also affects the household energy consumption. The non-linear relationship between urbanization and energy consumption (energy demand) is also investigated. For example, Duan et al. [31] used the data of 45 countries to assess the impact of urbanization on energy consumption by applying the ECUGA (Energy Consumption Unit Geometric Average) method. They found inverted U-shaped relationship between urbanization and energy consumption. Likewise, they noted that energy intensity increases if urbanization reaches to 40% to 50% and it starts to decline by 50% to 80% urbanization. Jiang and Lin [32] asserted that China is shifting from low-income group to middle income-group with faster economic growth which is supported by rapid industrialization and urbanization. They documented that the relationship between urbanization and energy intensity is inverted-U shaped. The theory of inverted U-shaped relationship reveals that during the process of development, industrialization follows urbanization, energy demand is inflexible and grows quickly due to rapid industrialization. This implies that energy consumption (intensity) reaches to its peak during the stage of development and starts to decline, once urbanization and industrialization are completed. Zhang and Qin (2013) criticized the findings reported by Jiang and Lin [32] and noted that the empirical model used by Zhang and Qin [33] has variable specification problems. Xia and Hu [34] exposed that urbanization tends to increase the migration of labor from rural areas to urban sector due to industrialization in China. This transformation of population has significant impact on energy consumption. Apergis and Tang [35] used the multivariate model to test the causal relationship between energy consumption and urbanization by including income and labor force in the energy demand function. They applied the Toda-Yamamoto-Dolado-Luutkepohl (TYDL) causality approach developed by Toda and Yamamoto [24] and, Dolado and Luutkepohl [36] using the data of 85 high, middle and low income countries. Overall, their empirical evidence revealed that energy consumption and urbanization are independent i.e. neutral effect while energy consumption Granger causes economic growth. Brant [13] probed the nexus between energy consumption, economic growth and urbanization using heterogeneous panel data of high, middle and low income countries. The results of Pedroni [37] reported the existence of cointegration between the variables. Urbanization leads energy demand. The link between urbanization and energy consumption shows the phenomenon of *ladder effect*. Liu and Xie [38] applied the threshold vector error correction model (TVECM) to examine the relationship between urbanization and energy intensity in the case of China. They noted that urbanization leads energy consumption quickly before the threshold point, i.e. inverted U-shaped relationship between urbanization and energy consumption. The causality analysis exposed that urbanization causes energy consumption.

Recently, Wang [39] examined the impact urbanization on residential energy consumption and energy production in case of China. The results indicated that urbanization leads residential energy demand. Urbanization stimulates industrialization, which enhances economic growth and resulting energy demand is increased. Liddle and Lung [40] used data of 105 countries to examine the direction of causality between urbanization and electricity consumption by applying the panel Granger causality test. They found that unidirectional causality is found running electricity consumption to urbanization. Shahbaz et al. [41] found that Malaysian energy consumption is positively affected by Malaysian urbanization.

In case of Pakistan, Alam et al. [42] examined the impact of population growth and urbanization on energy consumption and economic growth by applying simultaneous equation method. They reported that long run relationship between economic growth, population growth, urbanization and energy consumption exists. Moreover, population growth and urbanization has positive impact on energy consumption. Zaman et al. [43] investigated energy (measuring by electricity) demand function over the period of 1975-2010. Their results indicated that population leads urbanization that is positively linked with energy demand. The causality analysis showed that urbanization Granger causes energy consumption. Ali and Nitivattananon [44] explored the interrelationship between land use and energy consumption in case of Lahore applying an integrated and multi-disciplinary approach. They unveiled that industrial and residential sectors are major drivers to raise energy demand in Lahore city.

3. Theoretical Background and Model Construction

Economic growth leads to urbanization and social modernization is a well established fact [1, 2]. Urbanization is also called the renovation of rural population into urban population i.e.

conversion of rural areas into urban areas [2]. Urbanization leads to industrialization, which affects energy consumption [6, 7]. Urbanization affects energy demand by raising demand for housing, transportation and other public utilities supply by government, urban density [11]. Urbanization increases the road use due to industrial activities [45], pressurizes agriculture sector to produce more food both for rural as well as urban population [12], increases commercialization [46], changes urban structure [19], stimulates financial development which leads to promotion of investment activities and industrialization [20], raises the demand for production material [47], increases migration of labor from rural areas to the urban sector [34] and boosts economic activity [27]. These factors are also cause of urbanization and affect energy demand. But, transportation variable has been discussed theoretically in existing literature but never empirically included in IPAT (Integrated Population, Affluence and Technology) model. We have included transportation variable to capture the impact of transportation on energy demand in Pakistan as we know that transportation sector is a significant contributor to energy demand.

The above presentation leads us to apply IPAT (Integrated Population, Affluence and Technology) model which is considered very useful framework to investigate the impact of urbanization on energy consumption but it has some limitations. After making modifications in IPAT model, this model is termed as STIRPAT (Stochastic Impact by Regression on Population, Affluence and Technology). We have extended the STIRPAT model by incorporating some other potential determinant of urbanization and energy consumption such as transportation. The general form of STIRPAT model is given as follows:

$$I_t = aP_t^b A_t^c T_t^d \varepsilon_t \tag{1}$$

where, I_t is energy intensity, P_t is population, A_t is affluence, T_t is technology and ε_t is error term. We have transformed all the series into logarithmic form. The estimable version of STIRPAT model is modeled as following:

$$\ln EC_t = \varphi_0 + \underbrace{\varphi_1 \ln U_t + \varphi_2 \ln U_t^2}_{Urbanisation\ Effect} + \underbrace{\varphi_3 \ln A_t}_{Affluence\ Effect} + \underbrace{\varphi_4 \ln TEC_t}_{Technology\ Effect} + \underbrace{\varphi_5 \ln TP_t}_{Transportation\ Effect} + \varepsilon_t \tag{2}$$

Where $\ln EC_t$ is natural log of energy consumption per capita (kg of oil equivalent), $\ln U_t$ is natural log of urban population per capita, $\ln A$ is natural log of affluence (wealth or prosperity) proxies by real GDP per capita, $\ln TEC_t$ is natural log of technology (proxies by interaction term of industry and services sectors value-added) per capita, $\ln TP_t$ is natural log of use of transportation (proxies by number of cars and buses) per capita per km of road and ε_t is error term.

The data on urbanization, real income, industrial value added and services value added has been obtained from world development indicators [48]. Furthermore, world development indicators [48] is combed to collect the data on number of cars and buses) per km of road. The variable of population is used to convert all the series into per capita. We have used quadratic match-sum method to convert series from annual into quarter frequency. It has been confirmed that the results of the Denton method are indifferent from those of the quadratic match-sum method [49, 50].

4. Methods

4.1 Unit Root Test

This inefficiency of LM test is removed by Narayan and Popp [51] by introducing a new structural break unit root test. The Narayan and Popp (NP afterwards)[51] unit root test is superior to other unit root tests such as: (i) there is no need to have information about the possible timing of structural break stemming in the series because NP test determines the break dates endogenously within model. (ii) The NP test performs well if break dates are known or unknown. The reason is that critical values of unknown break points seem to converge with increasing sample size to critical values of known break points. This implies that the NP test is applicable if beak points are known or unknown. (iii) The NP test has the high explanatory power to detect break point in small sample data and it does not change the break magnitude. The NP test employs two models to test the unit root properties of the variables. The model M1 contains structural break in intercept but model M2 allows structural break in intercept as well as in the trend of the series. The functional form of both equations is modeled as following:

The model M1:

$$\Delta y_t = \beta_1 + \beta_2 t + \beta_3 y_{t-1} + \phi_1 D(TB)_{1,t} + \phi_2 D(TB)_{2,t} + \gamma_1 DU_{2,t-1} + \gamma_2 DU_{2,t-1} + \sum_{j=1}^{k} b_j \Delta y_{t-j} + \mu_{1t} \qquad (3)$$

The model M2:

$$\begin{aligned}\Delta y_t = {} & \beta_1 + \beta_2 t + \beta_3 y_{t-1} + \phi_1 D(TB)_{1,t} + \phi_2 D(TB)_{2,t} + \gamma_1 DU_{2,t-1} + \gamma_2 DU_{2,t-1} + \varphi_1 DT_{1,t-1} \\ & + \varphi_2 DT_{2,t-1} + \sum_{j=1}^{k} b_j \Delta y_{t-j} + \mu_{2t}\end{aligned} \qquad (4)$$

where $DU_{i,t} = 1(t > TB_i)$ and $DU_{i,t} = 1(t > TB_i)(t - TB_i)$, $i = 1,2,......$ show dummy variables capturing structural break points in intercept and slope stemming at time TB_1 and TB_2 respectively in the series. The process of potential structural break points in the series is explained in NP [51]. Anyway, to examine the null hypothesis of unit root problem against the alternate hypothesis of stationary, we use *t-statistic* of y_{t-1}.

4.2 The ARDL Bounds Testing Approach

Once, we have unique order of integration of the variables then we can apply Johansen and Juselius [52] maximum likelihood cointegration approach to examine cointegration between the variables. This is single-equation based cointegration technique which provides long run relationship between the variables by showing the number of cointegrating vectors in the model. The empirical exercise to investigate cointegration between the variables via Johansen and Juselius [52] becomes invalid if any variable is integrated at I(0) in the VAR system or mixed order of integration of the variables. To overcome these issues, Pesaran et al. [53] developed the ARDL bounds testing approach to cointegration which is also known as autoregressive distributed lag model (ARDL). The ARDL bounds testing approach is pertinent once we have variables stationary at I(0) or I(1) or I(0)/I(1). This shows that if none of the variables is stationary beyond these bounds i.e. I (2) then F-test computation becomes worthless. The ARDL bounds testing approach to cointegration performs better than all conventional cointegration approaches for small sample data while investigating the cointegration between the variables. The critical values are easily available for small data to compare with our calculated F-statistics. The ARDL bounds testing approach provides long run as well as short run separately. Furthermore, the general to specific modeling framework is used to generate suitable lag order for the data generating process by the ARDL bounds testing approach to cointegration [54].

We follow the regression based on the generalized Dickey-Fuller test to compute F-statistics. Following the ARDL bounds testing approach, unrestricted error correction model (UECM) is used to investigate the cointegration relationship between the variables. The functional form of unrestricted error correction model ($p, q_1, q_2, ...q_k$) is modeled as following:

$$\alpha(L, p)Y_t = \alpha_\circ + \sum_{i=1}^{k} \beta_i(L, q_i)X_{it} + \lambda' W_t + \varepsilon_t,\ t = 1, ..., n \tag{5}$$

where

$$\begin{aligned} \alpha(L, p) &= 1 - \alpha_{i1}L - \alpha_{i2}L^2 - .... - \alpha_{pi}L^{pi}, \\ \beta_i(L, q_i) &= \beta_{i\circ} + \beta_{i1}L + \beta_{i2}L^2 + ... + \beta_{iq_1}L^{q_1} \end{aligned}, \qquad i = 1, 2..., k.$$

where, X_t indicate the independent variables to be used in the model and α is constant term. L is lag operator i.e. $X_t = X_t - 1$. W_t is $s \times 1$ which is vector of vector of deterministic variables. These variables are constant term, time trend or independent variables having fixed lags. This shows that we can estimate the long run relationship using the following equation:

$$\varphi_i = \frac{\hat{\beta}_i(1, \hat{q}_i)}{\alpha(1, \hat{p})} = \frac{\hat{\beta}_{i0} + \hat{\beta}_{i1} + ... + \hat{\beta}_{i\hat{q}}}{1 - \hat{\alpha}_1 - \hat{\alpha}_2 - ..... - \hat{\alpha}_{\hat{p}}}, \tag{6}$$

$$i = 1, 2, ..., k.$$

where, $\hat{p}_i$ and $\hat{q}_i$, i = 1, 2… k shows the coefficient of estimates (see equation-5). The equation-3.3.2.2 is used to estimate the coefficients of long run relationship as formula is given as follows:

$$\pi = \frac{\hat{\lambda}(\hat{p}, \hat{q}_1, \hat{q}_2, ..., \hat{q}_k)}{1 - \hat{\alpha}_1 - \hat{\alpha}_2 - ... - \hat{\alpha}_{\hat{p}}}. \tag{7}$$

The ordinary least squares (OLS) estimates are reported by $\hat{\lambda}(\hat{p}, \hat{q}_1, \hat{q}_2, ...\hat{q}_k)$ which are the coefficients of λ of an unrestricted error correction model of the ARDL version (see equation-6). The F-statistics can be calculated in three steps using the ARDL approach to cointegration developed by Pesaran et al. [53]. The appropriate lag order selection is a necessary condition to calculate the F-statistics. The F-statistic varies with different lag orders. We follow AIC (Akaike Information Criteria) which performs better in small sample data as compared to SBC (Schwartz Bayesian Criteria). The performance of SBC is sensitive with sample size. Secondly, F-statistic is calculated by using the unrestricted error correction model (UECM) for cointegration between the series. The formulation of the autoregressive distributive lag model is based on $(p+1)^k$. We see that number of variables to be used in the model is shown by k and p reports the appropriate lag order of the variables. Lastly, we calculate F-statistic to examine whether cointegration exists or not between the variables [55]. We apply the unrestricted equilibrium error correction model (UECM) version of the ARDL bounds testing approach to cointegration. The UECM contains unrestricted intercept and unrestricted time trend to F-statistic for cointegration. The equation of UECM is given as follows:

$$\Delta Y_t = c_1 + c_T T + \pi_{YY} Y_{t-1} + \pi_{YX.X} X_{t-1} + \sum_{i=1}^{p-1} \beta \psi_i \Delta Z_{t-1} + \sum_{i=0}^{q-1} w \Delta X_{t-i} + c_D D + \mu_i \qquad (8)$$

The intercept term and time trend are represented by c_1 and c_T. The c_D is coefficient of dummy variable which is based on Clemente et al. [56] single unknown structural break unit root test. We use F-test or Wald test to compute F-statistic in taking decision whether cointegration exists or not between the variables. We follow null hypothesis as $H_\circ : \pi_{YY} = 0$, $H_\circ : \pi_{YX.X} = 0$ while alternate hypothesis is $H_a : \pi_{YY} \neq 0, H_a : \pi_{YX.X} \neq 0$. The calculated F-value is compared with critical bounds generated by Pesaran et al. [53] to make decision about the cointegration between the variables. We use lower critical bounds (LCB) once all the variables are integrated and if all series are integrated at I(1) then upper critical bounds (UCB) should be used. There is no cointegration between the variables if lower critical bound (LCB) exceeds our calculated F-statistic. We conclude about the cointegration if calculated F-statistic is more than upper critical bound (UCB). We cannot take decision about the cointegration between the variables once calculated F-statistic falls between lower and upper critical bounds. Then we rely on the estimate of the lagged error correction term to examine cointegration between the variables.

Once, we find the long run relationship between the variables then we apply error correction method (ECM) to examine the short run impacts of independent variables on the dependent variable. The functional form of the short run model is given as follows:

$$\Delta Y_t = \Delta \alpha_\circ - \alpha(1, \hat{p}) ECM_{t-1} + \sum_{i=1}^{k} \beta_{i\circ} \Delta X_t + \lambda' \Delta w_t - \sum_{j=1}^{\hat{p}-1} \alpha^{\bullet} j \Delta Y_{t-1}$$

$$-\sum_{i=1}^{k}\sum_{j=1}^{\hat{q}_{t-1}}\beta_{ij}\Delta X_{i,t-j}+\varepsilon_t \qquad (9)$$

The matrix of independent variables is x_t and no multi-colinearity exists between the variables. The ε_t is error term which is supposed to be normally distributed i.e. mean of the variance is zero while variance is constant. The significance of the estimate of the lagged error term corroborates our established cointegration between the variables. The short run convergence rate towards the equilibrium long run path is also indicated by the estimate of the lagged error correction term [57]. Furthermore, we apply diagnostic tests such as normality of the error term, serial correlation, ARCH test, White heteroskedasticity and functional form of the short run model. We use CUSUM and CUSUMsq tests to observe the goodness of fit of the ARDL model.

4.3 The VECM Granger Causality Approach

The next step is to determine the direction of causal relationship after the validation of cointegration between the variables. It is exposed by Granger [58] that there must be causality (in Granger sense) relation at least running from one side if variables are cointegrated and order of integration of the variables is I(1). Granger [58] argued that the presence of cointegration between the series leads us to determine the short run as well as the long run causal relationship. The concept of Granger causality reveals that Granger causality from X to Y if and only, the changes in Y are predicted by the past values of X and similarly, Y Granger causes X if and only, the past of values of Y predict the deviation in X. Granger [58] suggested to apply the Vector Error Correction Model (VECM) if the variables are integrated at I(1). The empirical equation of the VECM Granger causality is modeled as following:

$$(1-L)\begin{bmatrix}\ln X_t\\ \ln Y_t\end{bmatrix}=\begin{bmatrix}\phi_1\\ \phi_2\end{bmatrix}+\sum_{i=1}^{p}(1-L)\begin{bmatrix}\alpha_{11i} & \alpha_{12i}\\ \beta_{21i} & \beta_{22i}\end{bmatrix}+\begin{bmatrix}\theta\\ \chi\end{bmatrix}ECM_{t-1}+\begin{bmatrix}\eta_{1t}\\ \eta_{2t}\end{bmatrix} \qquad (10)$$

The difference operator is shown by $1-L$. The lagged error term i.e. ECM_{t-1} is generated using the long run OLS regression. The η_{1t} and η_{2t} are error terms which are assumed to have normal distributions with zero mean and constant variance. The presence of long run causality is validated by the statistically significance of *t*-statistic of lagged error term i.e.

ECM_{t-1}. The statistical significance of the first differences of the series confirms the nature of the short run causal relationship. Y Granger causes X if $\alpha_{12i} \neq 0 \forall_i$ and Y is Granger cause of X if $\alpha_{11i} \neq 0 \forall_i$.

5. Results and Discussion

Table 1 deals with the explanation of descriptive statistics and pair-wise correlation. The Jarque-Bera test shows that all the series such as energy consumption, urbanization, affluence (economic growth), technology and transportation are normally distributed. Our results indicate that all the variables have a normal distribution. This supports us for further analysis to investigate the relation between urbanization and energy consumption. The pair-wise correlation analysis shows that urbanization is positively correlated with energy consumption. Affluence (economic growth) and energy consumption are positively interrelated. Technology and energy consumption are positively correlated. A positive correlation exists between transportation and energy consumption. The correlation between affluence (economic growth) and urbanization is positive. Technology and urbanization are positively correlated. Transportation and urbanization are associated positively. The correlation of technology (transportation) with affluence is positive. Technology and transportation are positively correlated.

[Insert Table 1 here]

The next step is to examine whether variables are I(0) or I(1) or I(0) / I(1). It is necessary to test the unit root properties of all the series to apply any standard technique of cointegration. We utilize the ARDL bounds testing to examine cointegration between the variables. This test of cointegration also requires that the integrating order of the variables should be less 2^{nd} difference. The ARDL bounds testing becomes invalid if any variable is integrated at I(2). It is necessary to ensure that all the series are I(0) or I(1) or I(0) / I(1). We apply ADF and PP unit root tests and their results are reported in Table 2. We find that energy consumption, urbanization, affluence (economic growth), technology and transportation have unit root problem at level with intercept and trend. The variables are integrated at I(1) confirmed by ADF and PP unit root tests.

[Insert Table 2 here]

The disadvantage of ADF and PP of unit root tests is that such tests are inefficient when we have small size data [59, 60]. The ADF and PP unit root tests reject the null hypothesis when it is false and vice versa due to their low power and mislead the unit root results. Additionally, the ADF and PP tests avoid the information of structural break stemming in the variable which may also be cause of unit root problem in the variables. We have applied Clemente-Montanes-Reyes [56] detrended unit root test with single and two unknown structural breaks arising in the variables. The results reported in Table 3 reveal that all the variables show unit root problem in the presence of structural breaks. The 1984Q1, 2000Q2, 2003Q2 and 1976Q1 are structural breaks found in the series of energy consumption, urbanization, affluence (economic growth), technology and transportation. The structural break in energy series is linked with the significant shift of economy towards private sector in 6^{th} five year plan i.e.1983-1988 which affected domestic production and target economic growth rate was 6.5% in Pakistan over the period of 1983-84. Furthermore, the government could not meet the electrification target of 48,974 census villages during 6th five year plan. This had affected energy demand in 1984Q1 and onwards. The structural break date in series of urbanization is linked with the implementation of government policy in 1999 to improve the urban infrastructure for achieving sustainable economic development which also affected urbanization in 2000Q2. The change in occupational structure and education opportunities as well as industrial policy in 2002 not only affected economic growth but also technological development in 2003Q2. The structural break date in transportation series is linked with conversion of nature vehicles from petroleum to compressed gas consumption due to rise in petroleum prices. The variables are integrated at I(1) and same findings are reported by Clemente-Montanes-Reyes [56] de-trended unit root test with two unknown structural breaks. This implies that our variables of interest are I(1). The findings reported by NP [51] unit root test also reveal that all the variables are non-stationary at level with intercept and trend. This concludes that the series are integrated at I(1) (see lower segment of Table-3). After knowing that all the variables have unique order of integration, the next step is to investigate the existence of cointegration by applying the ARDL bounds testing approach. The ARDL bounds testing approach is a two step procedure. Firstly, we choose a suitable lag length of the variables using unrestricted VAR. The F-statistic varies with various levels of lag length. We follow Akiake Information Criteria (AIC) to select an appropriate lag span due its high explanatory power.

[Insert Table 3 here]

[Insert Table-4 here]

Our results are reported in Table 4 and we found that lag length 6 is appropriate following AIC. The next step is to apply the ARDL bounds testing to compute F-statistic to decide whether long run relationship subsists. We find from the results reported in Table-5 that our computed F-statistics exceed upper critical bounds at 1% and 5% levels, respectively once we used energy consumption, economic growth, technology and transportation as dependent variables. Our empirical evidence shows four cointegrating vectors which confirm the presence of long run relationship among energy consumption, urbanization, economic growth, technology and transportation in Pakistan.

[Insert Table 5 here]

The long run impact of urbanization, affluence, technology and transportation on energy consumption are presented in Table 6. We find that linear and non-linear terms of urbanization impact energy consumption positively and significantly at 1 per cent level. This shows that a 1 per cent increase in linear and non-linear terms of urbanization will increase energy demand by 4.9388 per cent and 0.9833 per cent respectively by keeping other things constant. Our findings are contradictory with Alam et al. [42], who noted that urbanization is positively linked to energy consumption via economic growth. Zaman et al. [43] also reported that urbanization increases electricity consumption in Pakistan, but Jiang and Lin [32] found inverted U-shaped relationship between urbanization and energy consumption using Chinese data. The studies conducted by Poumanyvong and Heneko [2], Hossain [61]) and Poumanyvong et al. [26] supported our findings using the data of cross-country, newly-industrialized countries and, low, middle and high income countries respectively.

[Insert Table 6 here]

The effect of affluence on energy consumption is positive and significant at 5 per cent. If all other things remain constant then a 1 per cent add in wealth is associated with 0.3414 per cent increase in energy demand. This empirical evidence is supported by Alam and Butt [62] who measured affluence by real GNP per capita and found that affluence leads energy consumption. The relationship between technology (interaction between industry and services sectors) and energy demand is positive and significant at 5 per cent level. A 1 per cent increase in technology adoption to increase domestic output is related to energy demand by 0.0633 per cent, all else is same. This exposes that *Rebound Effect* does not work in case of Pakistan. The Rebound effect discloses that “technological improvement will increase energy efficiency and lower demand of energy resources” [63]. This indicates that Pakistan is using energy intensive technology, which highlights the importance of enhancing research and development expenditures to introduce energy efficient technology. These results are contradictory with Linn [64], he found that adoption of advanced technology saves energy via lowering energy intensity and the same is noted by Popp [65] in the case of the USA.

The short run findings are shown in Table 7. The linear and non-linear terms of urbanization impact energy demand positively and significantly at 1 per cent level. The relationship between affluence (economic growth) and energy consumption is positive and significant at 10 per cent significance level. The impact of technology adoption is positive but statistically insignificant. Transportation and energy consumption are positively linked at 1 per cent level of significance. The negative sign with statistically significance of lagged error term i.e. ECM_{t-1} confirms our determined long run relation between the variables.

[Insert Table 7 here]

We find the estimate of ECM_{t-1} i.e. -0.1078 with negative sign which is statistically significant at 1 per cent significance level. Our empirical results indicate that the short run deviations stem in energy demand function is corrected by 10.78 per cent in each quarter and will take 2 years and 5 months to achieve stable long run equilibrium path. The short run model seems to fulfill all assumptions of the classical linear regression model (CLRM). Our empirical results reported in Table 7. The normal distribution of error term is confirmed by Jarque-Bera normality test. There is no presence of serial correlation as well as autoregressive conditional heteroskedisticity in the short run model. The short run model confirms the existence of homoskedisticity rather than white heteroskedistiity. The Ramsey reset test provides the evidence of well formulation of the short run model.

We have applied stability tests such as CUSUM and CUSUMsq to examine the reliability of long and short run estimates. Pesaran and Shin [66] also suggested to apply CUSUM and CUSUMsq. We may reject the null hypothesis of CUSUM and CUSUMsq if the plots of both tests exceed the critical bounds. We may accept null hypothesis which reveal that the model is well specified if critical bounds remain between critical bounds.

[Insert Figure 1 and 2 here]

Both graphs of CUSUM and CUSUMsq are lying between upper and lower limits (see Figure 1 and 2). This leads us to conclude that long and short run estimates are consistent and reliable. Furthermore, estimates of the ARDL bounds testing are also efficient.

We applied the VECM Granger causality test to detect the causal relationship between urbanization, affluence, technology, transportation and energy consumption. Our results reported in Table-8 show that energy consumption is Granger cause of urbanization in the long run. The feedback effect exists between affluence and energy consumption. It implies that affluence and energy consumption are complementary and the findings are consistent with Alam and Butt [62] in the case of Pakistan. It may suggest for the exploration of new sources of energy supply to sustain long run economic growth.

[Insert Table 8 here]

The causality affiliation between technology and energy demand is bidirectional. This implies that research and development expenditures must be increased for innovating energy efficient technologies which in resulting, not only lowers energy intensity but also enhances domestic production. This empirical evidence is consistent with Tang and Tan [67] who reported the feedback relationship between technological innovations and energy (electricity) demand in the case of Malaysia. Transportation Granger causes energy consumption and in resulting, energy consumption Granger causes transportation. This shows that transportation and energy consumption are complementary and we can use energy consumption as a tool in forecasting transportation in Pakistan.

Additionally, urbanization Granger causes affluence (economic growth), technology and transportation. The feedback hypothesis exists between economic growth and technology. Economic growth Granger causes transportation and in the resulting, transportation Granger causes economic growth. The causality relationship between technology and transportation is also bidirectional. In the short run causality analysis, we find the feedback effect between urbanization and technology. The feedback hypothesis is validated between affluence and technology. The unidirectional causality is found running from urbanization to transportation i.e. urbanization leads transportation.

6. Conclusion and Policy Recommendations

This study deals with impact of urbanization on energy consumption, by incorporating economic growth, technology and transportation in energy demand function, in Pakistan.

Traditional unit root tests such as ADF and PP as well as unit root tests accommodating structural break stemming in the variables such as Clemente-Montanes-Reyes [56] detrended unit root test along with NP [51] structural break unit root test were applied in the case of Pakistan for the period of 1972Q1-2011QQ4. Furthermore, The ARDL bounds testing approach to cointegration in the presence of structural breaks has been applied to examine cointegration. The direction of causal relationship between the variables has been investigated by applying the VECM Granger causality approach.

The empirical results show the presence of cointegration between the variables. Further, urbanization leads energy consumption (confirmed by both linear and non-linear terms of urbanization). Affluence (economic growth) raises energy demand. The relationship between technology and energy consumption is positive. An increase in transportation enhances energy consumption. The causality analysis shows that energy consumption is Granger cause of urbanization. Urbanization Granger causes affluence (economic growth), technology and transportation. The feedback effect exists between energy consumption and affluence. Technology and transportation are bidirectional Granger caused. The relationship between technology and affluence is bidirectional and same is true for affluence and transportation. The bidirectional causality is also found between technology and energy consumption and same inference is drawn for transportation and energy consumption.

The positive impact of urbanization on energy consumption calls for an important need for attention of policy makers to meet the challenge of rising energy demand due to rise in urban population. In such situation, the question is how Pakistan can achieve sustained economic growth by cutting down energy demand given the bidirectional causality that exists between economic growth and energy consumption. So, energy demand increases day-by-day due to increase in per capita income as well as urbanization. Reducing urbanization seems to be a possible way to control energy demand. However, reduction in urbanization and energy consumption has detrimental impact on economic growth as urbanization Granger causes economic growth and feedback effect exists between economic growth and energy consumption. To support urbanization and hence economic growth as well as industrialization, there is a need of urban policies to improve urban infrastructure and to bring into use additional economically feasible sources of energy. In this regard, the investment opportunities in renewable energy sources should be explored and policies be developed to encourage such opportunities. The government should build energy efficient urban infrastructure and implement energy saving-projects to decline energy intensity not only at urban level particularly but also at national level generally. Additionally, energy efficient policy must be implemented in urban areas to accelerate the switch from high energy intensive household durables to low energy intensive items.

We find that affluence (economic growth) and technology are positively linked with energy demand. The government must invest in existing power stations as well as build new power stations to meet energy demand-supply gap and to dig-out load-shedding. We find that Pakistan's industrial and services sector use technology which is energy intensive as technology is positively related with energy consumption. This implies that government should pay more attention to allocate more funds for research and development activities to invent energy efficient technology for industrial and services sectors. This will not only save energy but also enhance domestic output and hence economic development.

Finally, the relationship between transportation and energy consumption was found positive as expected. In Pakistan, vehicles (per kilometer of road) were 7 in 2007 but increased to 9 in 2011. The growth of motor vehicles on road is 28.57%. The major share of overall vehicles in the form of cars and minibus is owned by private sector. The government should implement rapid bus transit system in all urban areas of the country and banning the use of CNG for car is not a proper and permanent solution. In this regard, rapid bus transit system should be implemented in urban areas to meet the rising demand for transportation due to rapid increase in urban population. The Metrobus system in Lahore is a good example of public transport facility. Additionally, rapid train transit system should be implemented within cities but also to connect urban areas of the country following United Kingdom and other European countries. The trolleybus electric rapid bus system should also be encouraged in urban areas to reduce fuel consumption and hydropower sources of energy can be used for it. The hydropower electricity generation is useful for two reasons: (i) hydropower electricity can be produced at cheaper rate by reducing tariff rates and, (ii), hydropower plants produce clean energy. The trolleybus electric rapid bus system is cheaper than motorbuses. The non-motorized modes of transportation such as rapid train transit system and trolleybus electric rapid bus system are less energy intensive while same is true for Metrobus transit system. The quality of services must be maintained to attract the people for public transport facility otherwise allocation of public funds without knowing the source of problem is not good strategy. So, this would be a possible way to save energy and we can utilize saved energy to meet the rising demand of agriculture, industry and services sectors for sustainable economic development and better living standard.

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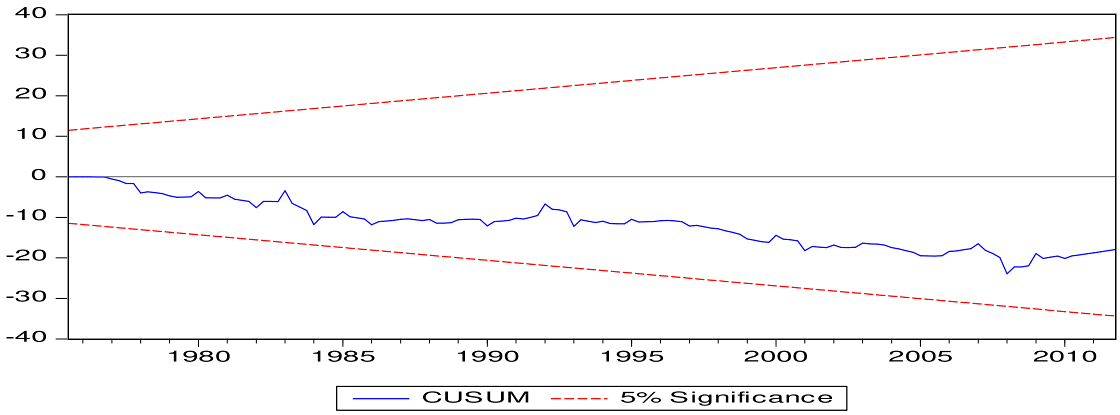
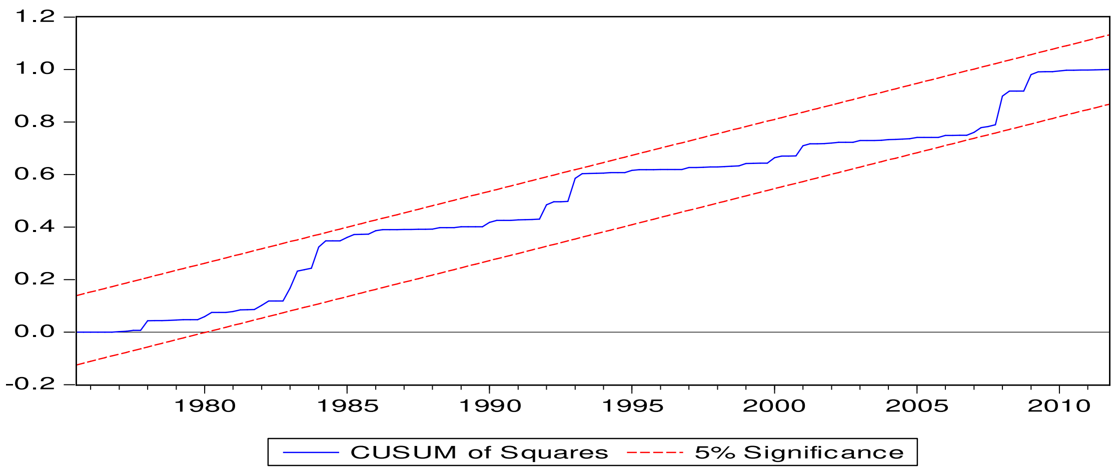
Figure 1: Plot of Cumulative Sum of Recursive Residuals



The straight lines represent critical bounds at 5% significance level

Figure 2: Plot of Cumulative Sum of Squares of Recursive Residuals



The straight lines represent critical bounds at 5% significance level

Table 1: Descriptive Statistics and Correlation Matrix

Variables	$\ln EC_t$	$\ln U_t$	$\ln Y_t$	$\ln TEC_t$	$\ln TP_t$
Mean	4.5701	-1.1740	10.0384	4.2488	1.9334
Median	4.5977	-1.1716	10.0960	4.3635	2.0047
Maximum	4.8846	-0.9879	10.4573	5.3350	2.4756
Minimum	4.2376	-1.3736	9.5749	2.9566	1.0885
Std. Dev.	0.1967	0.1091	0.2629	0.6904	0.3988
Skewness	-0.1045	-0.0494	-0.1815	-0.1555	-0.4907
Kurtosis	1.7101	2.0072	1.9808	2.0196	2.1333
Jarque-Bera	2.9236	1.6589	1.9507	1.7630	2.8572
Probability	0.2318	0.4362	0.3770	0.4141	0.2396
Observation	160	160	160	160	160
$\ln EC_t$	1.0000				
$\ln U_t$	0.1546	1.0000			
$\ln Y_t$	0.4356	0.0108	1.0000		
$\ln TEC_t$	0.4518	0.1772	0.7035	1.0000	
$\ln TP_t$	0.0164	0.3045	0.1074	0.2452	1.0000

Tsable 2: Unit Root Tests without Structural Break

Variables	Augmented Dickey-Fuller Test		Philips-Perron Test	
	T-statistics	Prob. Values	T-statistics	Prob. Values
$\ln EC_t$	-2.6542(9)	0.2573	-2.3110 [3]	0.3252
$\ln U_t$	-2.1212 (9)	0.5593	-2.7789 [3]	0.2073
$\ln Y_t$	-2.1353 (9)	0.5216	-1.7322 [6]	0.7324
$\ln TEC_t$	-2.1496 (4)	0.3134	-2.1255 [6]	0.5256
$\ln TP_t$	-3.0510 (6)	0.1221	-26.9119 [15]*	0.0000
$\Delta \ln EC_t$	-3.7551 (8)**	0.0216	-6.7525 [6]*	0.0000
$\Delta \ln U_t$	-4.8647 (7)*	0.0006	-6.7551 [6]*	0.0000
$\Delta \ln Y_t$	-3.7990 (4)**	0.0191	-6.0931 [6]*	0.0000
$\Delta \ln TEC_t$	-3.5907 (4)**	0.0339	-5.3757 [6]*	0.0001
$\Delta \ln TP_t$	-5.5168 (9) *	0.0000	-5.2394 [6]*	0.0001

Note: * and ** show significance at 1 per cent and 5 per cent respectively. () and [] indicate lag order and bandwidth based on AIC for ADF and PP unit root tests respectively.

Table 3: Unit Root Tests with Structural Break

Clemente-Montanes-Reyes Detrended Structural Break Unit Root Test						
Variable	Innovative Outliers			Additive Outlier		
	T-statistic	TB1	TB2	T-statistic	TB1	TB2
$\ln EC_t$	-2.013 (6)	1984Q1	….	-5.059 (3)*	1985Q1	….
	-3.800(6)	1985Q1	2001Q2	-5.373 (5)**	1986Q1	2001Q1
$\ln U_t$	-2.808 (3)	2000Q2	….	-4.713 (6)**	2006Q1	….
	-3.525 (6)	1996Q2	2006Q2	-5.672 (6)*	1979Q1	2006Q1
$\ln Y_t$	-1.885 (6)	2003Q2	….	-6.896 (3)*	1980Q2	….
	-4.867 (2)	1979Q1	2003Q1	-8.611 (3)*	1992Q1	2001Q1
$\ln TEC_t$	-2.285 (6)	2003Q2	….	-6.619 (3)*	2007Q1	….
	-4.468 (3)	1977Q1	2003Q1	-7.641 (3)*	2003Q1	2007Q1
$\ln TP_t$	-3.313 (4)	1999Q1	….	-7.715 (6)*	2006Q2	….
	-4.194 (5)	1976Q1	1996Q1	-7.735 (5)*	1999Q1	1999Q3
Narayan and Popp Structural Break Unit Root Test						
Variables	Model M_1			Model M_2		
$\ln EC_t$	-2.0597 (4)	1987Q1	2004Q1	-2.2927 (5)	1987Q1	2004Q1
$\ln U_t$	-1.549 (5)	1995Q4	2001Q2	-2.252 (5)	1995Q4	2001Q2
$\ln Y_t$	-2.673 (5)	1999Q1	2005Q4	-3.190 (4)	1994Q4	2004Q2
$\ln TEC_t$	-1.679 (5)	1978Q1	1987Q4	-3.341 (4)	1988Q4	2001Q3
$\ln TP_t$	-3.208 (4)	1983Q4	1990Q2	-4.319 (5)	1983Q4	1998Q3

Note: * and ** significant at 1 per cent and 5 per cent levels respectively. () indicates lag length to be used. The critical values of NP unit root test are (-5.259, -5.949) and (-4.154, -5.181) for Model M_1 and Model M_2 at 1 per cent and 5 per cent levels respectively.

Table 4: VAR Lag Order Selection Criteria

VAR Lag Order Selection Criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
1	3497.793	4074.022	1.05e-26	-45.6288	-45.0320	-45.3864
2	3677.301	333.0358	1.38e-27	-47.6618	-46.5676	-47.2173
3	3691.350	25.1387	1.59e-27	-47.5177	-45.9262	-46.8712
4	3697.798	11.1156	2.05e-27	-47.2736	-45.1848	-46.4250
5	3836.501	229.9551	4.62e-28	-48.7697	-46.1835	-47.7191
6	3984.881	236.2364*	9.22e-29*	-50.393*	-47.3096*	-49.1405*
7	3994.246	14.2930	1.15e-28	-50.1874	-46.6065	-48.7327
8	3998.132	5.67561	1.56e-28	-49.9096	-45.8313	-48.2529

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 5: The Results of Cointegration Tests

Bounds Testing to Cointegration			Diagnostic tests		
Estimated Models	F-statistics	Structural Break	$\chi^2 NORMAL$	$\chi^2 SERIAL$	$\chi^2 REMSAY$
$F_{EC}(EC/U,Y,TEC,TP)$	5.607*	1984Q1	0.1506	[1]: 0.1026	[1]: 0.0595
$F_{U}(U/EC,Y,TEC,TP)$	1.822	2000Q2	0.5958	[2]: 3.7538	[2]: 0.0014
$F_{Y}(Y/EC,U,TEC,TP)$	5.634*	2003Q2	0.3824	[2]: 0.5547	[1]: 0.2631
$F_{TEC}(TEC/EC,U,Y,TP)$	5.292*	2003Q2	0.8945	[3]: 0.4104	[1]: 0.1349
$F_{TP}(TR/EC,U,Y,TEC)$	3.992***	1998Q1	0.2419	[5]: 1.6577	[3]: 0.1842
Significant level	Critical values (T = 160)				
	Lower bounds $I(0)$	Upper bounds $I(1)$			
1 per cent level	3.60	4.90			
5 per cent level	2.87	4.00			
10 per cent level	2.53	3.59			

Note: ** and *** significant at 5 per cent and 10 per cent levels respectively. The optimal lag is determined by AIC. Upper and lower critical bounds are obtained from Pesaran et al. [53].

Table 6: Long Run Results

Dependent Variable = $\ln EC_t$				
Variable	Coefficient	Std. Error	t-Statistic	Prob. values
Constant	7.5247*	2.5672	2.9310	0.0039
$\ln U_t$	4.9388*	1.7057	2.8954	0.0043
$\ln U_t^2$	0.9833*	0.3687	2.6669	0.0085
$\ln Y_t$	0.3414**	0.1678	2.0345	0.0436
$\ln TEC_t$	0.0633**	0.0314	2.0175	0.0454
$\ln TP_t$	0.1764*	0.0673	2.6188	0.0097
DUM_t	-0.0322*	0.0058	-5.4767	0.0000
R-squared		0.8965		
Adj. R-squared		0.8766		
F-statistic		57.2055*		
Durbin-Watson Test		1.9495		

Note: * and ** shows significance at 1 per cent and 5 per cent levels of significance respectively.

Table 7: Short Run Results

Dependent Variable = $\Delta \ln EC_t$				
Variable	Coefficient	Std. Error	t-Statistic	Prob. Values
Constant	0.0084*	0.0026	3.2537	0.0014
$\Delta \ln EC_{t-1}$	0.5038*	0.0676	7.4485	0.0000
$\Delta \ln U_t$	3.2518*	0.9469	3.4341	0.0008
$\Delta \ln U_t^2$	0.0650*	0.0188	3.4451	0.0007
$\Delta \ln Y_t$	0.1328***	0.0719	1.8479	0.0666
$\Delta \ln TEC_t$	0.0293	0.0309	0.9467	0.3453
$\Delta \ln TP_t$	0.0101*	0.0032	3.1632	0.0019
DUM_t	-0.0013	0.0016	-0.8075	0.4206
ECM_{t-1}	-0.1078*	0.0270	-3.9786	0.0001
R-squared		0.4179		
Adj. R-squared		0.3907		
F-statistic		15.3858*		
Durbin-Watson Test		2.0097		
Diagnostic Tests		F-statistic	Prob. Value	
$\chi^2 NORMAL$		0.1781	0.9523	
$\chi^2 SERIAL$		0.0165	0.8979	
$\chi^2 ARCH$		0.094	0.8428	
$\chi^2 WHITE$		1.4087	0.1230	
$\chi^2 REMSAY$		0.0205	0.8801	
Note: *, ** and *** shows significance at 1, 5 and 10 per cent levels respectively. Normality of error term, serial correlation, autoregressive conditional heteroskedasticity, white heteroskedasticity and functional of short run model is indicated by $\chi^2 NORMAL$, $\chi^2 SERIA$, $\chi^2 ARCH$, $\chi^2 WHITE$ and $\chi^2 REMSAY$ respectively.				

Table 8: Long-and-Short Run Causality

Dependent Variable	Direction of Causality					
	Short Run					Long Run
	$\Delta \ln EC_{t-1}$	$\Delta \ln U_{t-1}$	$\Delta \ln Y_{t-1}$	$\Delta \ln TEC_{t-1}$	$\Delta \ln TP_{t-1}$	ECM_{t-1}
$\Delta \ln EC_t$	….	0.2287 [0.7958]	0.8273 [0.4390]	0.9201 [0.4001]	0.1091 [0.8967]	-0.1087* [-3.6675]
$\Delta \ln U_t$	0.8505 [0.4292]	….	1.4677 [0.2338]	4.0729** [0.0190]	1.6392 [0.1976]	….
$\Delta \ln Y_t$	1.3742 [0.2563]	2.2284 [0.1113]	….	3.8947** [0.0203]	0.5661 [0.5690]	-0.1217* [-4.6041]
$\Delta \ln TEC_t$	0.9676 [0.3824]	5.0789* [0.0074]	3.9097** [0.0306]	….	0.5319 [0.5886]	-0.1032* [-4.4495]
$\Delta \ln TP_t$	0.0656 [0.9365]	2.3360*** [0.1003]	0.3788 [0.6653]	0.7143 [0.4912]	….	-0.0098* [-14.1663]
Note: *, ** and *** show significance at 1 per cent, 5 per cent and 10 per cent levels respectively.						