**Economics Bulletin** 

# Volume 37, Issue 3

# Electricity consumption and NSDP nexus in Indian states: a panel analysis with structural breaks

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# Abstract

This paper seeks to examine the energy-growth nexus for major Indian states for the period 1980-2012. The study uses the electricity consumption as proxy for energy consumption and economic growth is represented by net state domestic product. The study applies panel endogenous structural break models that captures cross sectional dependence as well heterogeneity across sample units. The results indicate a long-run equilibrium relationship between energy consumption and economic growth of sample states. The results of causality suggest that there is bi-directional causal relationship between energy consumption and economic growth with heterogeneity across sample states, causality running from economic growth to energy consumption is more often than otherwise. Based on these results, we infer that electricity conservation policies may be fruitful without much impact on the growth process of these states. Nevertheless, we suggest that instead of integrated policy approach for all Indian states, state specific policy would be more effective.

The authors would like to thank Dr. Wasim Ahmad, Taufeeq Ajaz, Sajjad Ahmad and Anjuman Shaheen for their help. Any omission and errors are the sole responsibility are of authors.

Citation: Md zulquar Nain and Sai sailaja Bharatam and Bandi Kamaiah, (2017) "Electricity consumption and NSDP nexus in Indian states: a panel analysis with structural breaks", *Economics Bulletin*, Volume 37, Issue 3, pages 1581-1601

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## **1** Introduction

The causal relationship between energy consumption and economic growth has been widely discussed in last three decades. The literature on this particular research avenue started with the seminal work by Kraft and Kraft(1978), for developed countries and developing countries within the framework of bivariate as well as multivariate. So far studies have covered single as well multi-country scenarios across developed and developing countries. However, the outcomes of these studies have been mixed especially in the context of drawing the causal inference between energy consumption and economic growth (income). In the wake of rising risk of global warming and unprecedented increase in energy demand observed in most of the emerging economies, the issue of energy-growth nexus has rekindled the interest of researchers and policy makers. The topic has also sought the attention because the growth trajectory of any modern economy relies on the availability and consumption of energy and India and China are no exceptions. Owing to their large economic set-up, these economies often face difficulty in implementing efficient and cost-effective energy policy. This has created a lack of consensus among the different stakeholders of the global economy to adopt an enforceable agreement to reduce greenhouse gas emissions. In summary, the examination of the causal direction from or to energy consumption is pertinent for evolving the energy policies to control increasing global warming, to achieve energy conservation goals without much impact on the business cycles of the economy. Additionally, the examination of causality direction further sharpens our understanding whether a production model that is energy consumption works as an input in growth process or a demand model that is energy consumption is considered a good, supported by the data. The former model is supported, if energy consumption is causing the economic growth, on the contrary of it, if economic growth causes energy consumption the later model is valid in the economy.

In the context of developing countries, the relationship between electricity consumption and economic growth is rather strong (see Payne, 2010a; Ozturk and Acaravci, 2011), which makes it imperative to look into the relationship between these two. All the more particularly, as pointed out by Ahmad et al. (2014), India is intensely subject to various uses of electricity, plays a critical part in driving the economy. There have been many examples of the immense demand and supply mismatch, which adversely affected the economy by bringing about overwhelming loss of income and employment (Economic Survey, 2010–11). Moreover, combined share of China and India in the total global demand for energy would be more than 50% and expected to augment by more than one-third during 2010 to 2035 (IEA 2012). Further, India, expected to be the main source of the growth for the energy demand in the 2020s in Asia overtaking China (IEA, 2013, Nain et al., 2015).

In case of Indian democratic federal structure<sup>1</sup> where states' interests are safeguarded by the constitution of the Indian Union. States have been empowered to seek and implement various policies at different levels of their economic set-up. It will be interesting to check whether energy-growth nexus examined so far for the whole economy holds the same or there is a clear case of heterogeneity. Since independence, there have been unbalanced growth across the states, as Bhattacharya and Sakthivel (2004) pointed out, though average growth rate of gross domestic product increased in the 1990s, as compared to 1980s, the regional disparity has widened, and regional inequity has risen. According to the latest available statistics, states like Goa, Delhi, Sikkim having per capita income more than double of the national average, on the contrary, states like Bihar, Uttar Pradesh, Madhya Pradesh having about half of national average<sup>2</sup>. The differential growth performance of states is often be attributed to state-specific factors or endowments (see Besley and Burgess, 2004; Kochhar, et al., 2006; Kumar, 2010; Aiyar and Mody 2011; among others). Moreover, a wide variation in the productivity level

among the states (see Kumar and Managi, 2012) also contributes a differential growth performance among the states.

In addition to the above, energy resources are also unevenly distributed across states. Coal, the major source of energy in India is predominantly distributed in eastern and south-central parts of the country. About 99 percent coal reserves are in the states of Jharkhand, Odisha, Chhattisgarh, West Bengal, Andhra Pradesh, Maharashtra and Madhya Pradesh. Interestingly, these are the states except Maharashtra and Andhra Pradesh, which lack in development that may be attributed to the lack of skilled human resources and policies in these states. Geographical distribution of crude oil follows a similar pattern. The Western Offshore (44.46 percent) holds maximum reserves followed by Assam (22.71 percent), whereas the maximum reserves of Natural gas are in the Eastern offshore (34.73percent) followed by Western offshore (31.62percent). In case of other resources also the situation is same. Installed capacity of power stations across the states depicted in figure 1, shows a wide variation across the states. Thus, the uneven distribution of energy resources among states have paved the way for a marked heterogeneity in resource availability. Thus, the unbalanced and unequal growth patterns across the states and uneven distribution of resources, creating obvious heterogeneity among the states, legitimize the need to examine the causal relationship between energy consumption and output (income) at the state level.



Figure 1: Indian States and the installed capacity of power generation as on May 2016; Source: Power Ministry, Govt. of India

With the exceptions of the studies by Mukherjee (2008) and Sen and Jamasb (2012) which are in different perspective<sup>3</sup>, the studies in India have examined the energy-output (income) relationship at the national level resulting in aggregation bias and hence getting contradictory findings (Karanfil, 2009; Ozturk, 2010). The present study fills the void in the literature of energy and economic growth relationship being the first study examining the relationship at the state level. Moreover, this paper also differs significantly from the past studies in many ways. First, panel cointegration techniques are employed, which is more appropriate. As Campbell and Perron (1991) found that small time series data reduce the power of unit root, cointegration, and causality tests, therefore giving rise to distorted and mixed results. Al-Iriani (2006) opined that use panel techniques may overcome these problems due to use panel data with the higher number of observation. Further, following Carrion-i-Silvestre et al. (2005) and Weturlund (2006), we have relaxed a restrictive assumption of cross-sectional independence of states and allowed cross-sectional dependence across the states. Moreover, the above methods also take account the issue pointed out by Perron (1989) and Bai and Carrion-i-Silvistre (2009) and Basher and Westurlund (2009) of ignoring or erroneous omission of structural breaks, which may lead to deceptive inference about the order of integration of the variables. Hence, use of such techniques provide more robust inference about the relationship between electricity consumption and economic growth. Finally, we have used panel causality test allowing the heterogeneity both in causal relationship and data generating process due to Dumitrescu and Hurlin (2012).

Our results reveal that there is a long run relationship between electricity consumption and economic growth among the states. In addition, the results reveal that there is causality running from economic growth to electricity consumption in the states, though there is other way causality also exist, but it is very weak and are in few states.

The remaining part of the paper is presented as follows. A brief review of the literature is presented in section 2. In section 3, data used for the analysis and sets out the method of analysis and the testing procedure. The results are presented in Section 4. Finally, the Section 5 presents the conclusions drawn from the present study.

# 2 A brief Literature Survey

In the existing literature<sup>4</sup> which investigates the relationship between energy consumption and economic growth can be broadly categorized as "growth hypothesis"; "conservation hypothesis" "feedback hypothesis"; and "neutrality hypothesis."

The proponents of growth hypothesis accentuate that energy is a key factor in promoting economic growth and changes in energy supply impacts economic growth. In such case causality runs from energy consumption to economic growth and energy conservation policies may be detrimental to economic growth. Moreover, it also indicates that economy is energy dependent. Within time series framework, studies like Masih and Masih (1998), Akinlo (2009), Alam et al. (2011) among others, while in panel framework studies such as Apergis and Payne (2009b, 2010a, 2010c), Narayan and Smyth (2008) support this hypothesis. In the Indian context, Paul and Bhattacharya (2004), Tiwari (2001b), Nain et al. (2012), Yang and Zhao (2014) and Nain et al. (2015) found evidence in favour of growth hypothesis.

On the contrary in "conservation hypothesis," causality runs from economic growth to energy consumption. It implies that energy saving policies that is reducing energy consumption will have little or no impact on the economic growth. Studies, Yoo (2006), Zhang and Cheng (2009), Shahbaz and Feridum (2012) among others have shown evidence supporting this hypothesis in time series framework, while studies Al-Iriani (2006), Huang et al. (2008), Herrerias et al. (2013), Liddle and Lung (2015) comes under this category in panel framework. In the case of India, Cheng (1999), Ghosh (2002, 2009), Tang et al. (2016), Kumari and Sharma (2016) showed evidence for the presence of conservation hypothesis.

The "feedback hypothesis" strand of literature points towards bi-directional causality between energy consumption and economic growth. This type of literature highlights the interdependence between energy consumption and growth-change in energy supply changes growth and changes in growth leads to changes in energy demand. Using time series analysis, studies by Stern (2000), Jumbe (2004), Lee (2006), Solarin and Shahbaz, (2013), Shahbaz et al. (2015) among others and in panel framework, studies Apergis and Payne (2009a, 2010b), Mishra et al. (2009), Dogan et al. (2016) among others have shown existence of feedback hypothesis. In Indian case studies, Ahmad et al. (2014) and Ahmad et al. (2016) have found evidence in support of the feedback hypothesis.

Lastly, the neutrality hypothesis nullifies any causal relationship between energy consumption and economic growth. Generally, the studies supporting this hypothesis used time series analysis are Altinay and Karagol (2004), Asafu (2000), Marques et al., (2014) among others. In panel framework, a study by Acaravci and Ozturk (2010) has shown the existence of neutral hypothesis. While in Indian context study by Tiwari (2011a) affirmed the neutrality hypothesis.

The conflicting results on the causal relationship between energy consumption and economic growth in the literature may be attributed to the different statistical tools applied; variables included, sample period and sample of countries/regions considered in the studies. Thus, the present study, to the best of our knowledge first of its kind attempt to provide evidence on this relationship, using recent panel econometric methods allowing cross-sectional dependence and heterogeneity across the states.

# **3** Data and Econometric Methodology

# 3.1 Data

We used electricity consumption and Net state Domestic Product (NSDP) as the proxy respectively for the energy consumption and economic growth to examine the relationship at the state level. Electricity consumption is used as the proxy for the energy consumption as it is the most direct usable form of energy and has largest share<sup>5</sup> in the total energy consumption in India. Data<sup>6</sup> of electricity consumption and Net State Domestic Product (NSDP) is collected from CMIE and Reserve Bank of India respectively for the period 1980-2012. NSDP is brought to 2004-05 constant prices base through multipoint splicing. All variables are converted to logarithm before being used in the analysis. The descriptive statistics of the variables are reported in Table1.

# 3.2 Methodology

We perform unit root tests, before the causality and cointegration tests between the variables. The panel techniques for unit root, cointegration and causality tests are employed taking account of cross-sectional dependence among the states and heterogeneity across the states. The panel techniques used additionally take account of a structural break if present. The use of panel techniques would improve the power of the tests as number of observations will be more.

# 3.2.1 Panel Unit Root Tests

Recently researchers have been utilizing panel data techniques as it overcome the problems of the size and low power of time series techniques and so is the case, to test the integration properties of the variables. Levin et al. (2002), Im et al. (2003), Breitung (2001), Maddala and Wu (1999), and Hadri (2000) are commonly used tests for panel data in the literature. The panel version of the KPSS (Kwiatkowski et al., 1992) test, the Hadri test takes stationarity as the null, whereas other tests take non-stationarity as the null.

A common drawback of these tests is the assumption of cross-sectional independence of units. In the present study this problem would be more prominent as cross-section units are part of a federal system and have different economic and geographical characteristics. Further, these tests do not take account of structural breaks. A structural break may correspond to the parameter shifts due to the policy regimes (such as in our case new economic policy adopted in 1990s and electricity reform policies) shifts or significant events (such as economic and financial crises). Ignoring or erroneous omission of structural breaks may lead to deceptive inference about the order of the integration of the variables [Perron,1989; Bai and Carrion-I-Silvestre, 2009, Basher and Westerlund 2009]. We have used, Carrion-i-Silvestre et al. (2005) panel stationarity test, which takes care of the problems mentioned above of structural breaks and cross-sectional dependence. Carrion-i-Silvestre et al. (2005) generalized the Hadri (2000) test to accommodate multiple structural breaks. The following regression model is defined, to test the null hypothesis of stationarity with multiple structural breaks;

$$y_{it} = \alpha_i + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \beta_i t + \sum_{k=1}^{m_i} \gamma_{i,k} DT_{i,k,t} + \varepsilon_{i,t}$$
(1)

Where,  $\alpha_i$  and  $\beta_i$  is constant and coefficient of trend respectively with i = 1, ..., N units and t = 1, ..., T time periods. The dummy variables  $DU_{i,k,t}$  and  $DT_{i,k,t}$  are defined as,  $DU_{i,k,t} = 1$  for  $t > T_{b,k}^i$  and 0 otherwise and  $DT_{i,k,t} = t - T_{b,k}^i$  for  $t > T_{b,k}^i$  and 0 otherwise, where  $T_{b,k}^i$  denotes the  $k^{th}$  date of break for the  $i^{th}$  individual,  $k = 1, ..., m_i, m_i \ge 1$ .

The above specification allows that structural breaks may have different effects on each time series and may be located at different date. The number of structural breaks may also vary individual to individuals.

The LM test statistics for the estimated OLS residuals  $\hat{\mathcal{E}}_{i,t}$  of equation(1), is given as,

$$LM(\lambda) = N^{-1} \sum_{i=1}^{N} (\hat{\omega}_{i}^{-2} T^{-2} \sum_{t=1}^{T} \hat{S}_{i,t}^{2})$$
(2)

Where,  $\hat{S}_{i,t} = \sum_{j=1}^{t} \hat{\varepsilon}_{i,j}$  denotes partial sum process and  $\hat{\omega}_i^2$  is consistent estimate of the long-run variance of  $\varepsilon_{i,t}$ ,  $\omega_i^2 = \lim_{T \to \infty} T^{-1} E(S_{i,T}^2)$ , i = 1, ..., N.

#### **3.2.2** Cointegration tests

In case of integrated variables, the long-run equilibrium relationship between them could be examined by tests of cointegration. In this study, we have considered panel cointegration tests with and without structural breaks. As conventional tests for cointegration in the presence of structural break are not able to differentiate between absence of cointegration and cointegration with structural change (Basher and Westerlund, 2009).

#### 3.2.2.1 Panel cointegration test without structural breaks

We used Pedroni's  $(1999)^7$  tests for panel cointegration for a case where there are no structural breaks. Pedroni (1999) suggests seven test statistics that can be used to test for cointegration in a panel framework. These are panel V-statistics, panel rho-statistics, panel PP-statistics (non-parametric), panel ADF-statistics (parametric), group rho-statistics, group PP-statistics (nonparametric) and group ADF-statistics (parametric). The common time effects were removed by demeaning the data before performing the cointegration tests as suggested by Pedroni (1999).

#### **3.2.2.2** Panel cointegration test with structural breaks

In the present study to examine the cointegration in a panel framework, we used test due to Westerlund (2006). The test allows to accommodate an unknown number of breaks, at different dates for different units Li et al. (2012). To perform the tests, we adopted the following specifications.

$$\ln g dp_{it} = d_{it'} \alpha_{i,i} + \beta_i \ln e c_{i,t} + \varepsilon_{it}$$
(3)

Where,  $gdp_{it}$  and  $ec_{it}$  represents net state domestic product and electricity consumption for *ith* state in *tth* time period. Index  $j = 1, ..., m_i + 1$  denotes structural breaks,  $d_{it}$  is vector of deterministic component s and  $\alpha_{ij}$  is the corresponding vector of parameters, indicating  $m_i$  structural breaks in both level and trend. There may lie at most  $m_i$  such breaks or  $m_i + 1$  regimes, at the dates  $T_{i1}, ..., T_{im}$ , with  $T_{i1} = 0$  and  $T_{i,m+1} = T$ . Here,  $\varepsilon_{it}$  assumed to be stationary. Further, with the cointegration vector permitted to differ across regimes and individuals, the long-run variance of  $\varepsilon_{it}$  is also permitted to vary across individuals. The null hypothesis and alternative hypothesis for all individuals in panel are;

 $H_0: \phi_i = 0$  for all i = 1, ..., N against the alternative hypothesis  $H_A: \phi_i \neq 0$  for  $i = 1, ..., N_1$  and  $\phi_i = 0$  for  $i = N_1 + 1, ..., N$ 

The null hypothesis assumes that all individuals in the panel are cointegrated and alternative hypothesis allows  $\phi_i$  to differ across the individuals. It means alternative hypothesis indicate that there is cointegration for a fraction of the panel such that  $N_1 / N \rightarrow z$  as  $N \rightarrow \infty$ , Where  $z \in (0,1)$ . Thus from the rejection of null hypothesis, we may infer the presence of cointegration for some individual units in the panel.

The panel LM test statistics is defined as;

$$Z(m) = \sum_{i=1}^{N} \sum_{j=1}^{m_i+1} \sum_{t=T_{ij-1}+1}^{T_{ij}} (T_{ij} - T_{i,j-1})^{-2} \hat{\omega}_{i1,2}^{-2} S_{it}^2$$
(4)

Where,  $\hat{\omega}_{i1,2}^{-2} = \hat{\omega}_{i1,1}' - \hat{\omega}_{i21}' \hat{\Omega}_{i22}^{-1} \hat{\omega}_{i21}$  and  $S_{it} = \sum_{k=T_{it}+1}^{t} \hat{\varepsilon}_{it}^{*}$  where,  $\hat{\varepsilon}_{it}^{*}$  is any estimate of  $\varepsilon_{it}$ . The test statistic is written as a function of breaks i.e.  $m(m_i, ..., m_N)'$ . The asymptotic distribution of the statistics depends on the number of the breaks and constituted for a certain number of breaks.

The tests of Carrion-i-Silvestre et al. (2005) and Westerlund (2006) which tests for panel stationarity and panel cointegration respectively, suggest the use of Bootstrap methods in the presence of cross-section dependence for robust inference, which is very likely to be present in this particular problem. The bootstrap method adopted in the present study is due to Westerlund and Edgerton  $(2007)^8$ .

#### 3.2.3 Panel causality test

Next, we examine the causal relationship among the variables. In a panel context, as pointed out by Venet and Hurlin (2001), it is possible to use both cross-sectional and time series information to test the causality relationship between variables. A larger number of observations in this framework are available, that increase degrees of freedom and reduces collinearity among the explanatory variables in turn, the efficiency of Granger causality tests improve notably. However, in a panel data framework, the issue of potential heterogeneity of the states (units) must be addressed. Mainly there are two possible types of heterogeneity that exist, one is due to distinct intercepts; this type of variation is addressed with a fixed effects (FE) approach another is causal variation across units, which needs more complex analytical response.

Holtz-Eakin et al. (1988) proposed the following model for the panel Granger test, which takes care of first kind of heterogeneity. Formally,

$$y_{i,t} = \sum_{k=1}^{p} \gamma^{(k)} y_{i,t-k} + \sum_{k=1}^{p} \beta_i^{(k)} x_{i,t-k} + V_{i,t}$$
(5)

With  $v_{i,t} = \alpha_i + \varepsilon_{i,t}$ , where  $\varepsilon_{i,t}$  are i.i.d.  $(0, \sigma_{\varepsilon}^2)$ . i = 1, ..., N, t = 1, ..., T  $y_{i,t}$  and  $x_{i,t}$  are covariance stationary.  $\alpha_i$  are the fixed individual effect. While for all cross-section units, coefficients  $\gamma^{(k)}$  and  $\beta^{(k)}$  are implicitly assumed to be identical. The null for the proposed Granger tests is given as,

 $H_0: \beta^{(1)} = \beta^{(2)} = \dots = \beta^{(k)} = 0$ 

This model ignores the heterogeneity of second kind which is more crucial in case of causality test that is heterogeneity related to the parameter  $\beta^{(k)}$ . As Pesaran and Smith (1995) point out, estimates under the wrong assumption  $\beta_i = \beta_j \forall (i, j)$  are biased. Further as pointed out by Hurlin (2004), this approach may have shortcomings. First, as Nickell (1981) pointed this test involves estimators for  $\gamma^{(k)}$  and  $\beta^{(k)}$ , but in dynamic models, the fixed-effect estimators tend to be biased and inconsistent if N is large and T is relatively small (Nickell,1981). Second, the Wald-type statistic may not have a standard distribution associated with null hypothesis when T is short (Venet and Hurlin, 2001). Last, the alternative hypothesis against the null hypothesis of above is that  $\beta^{(k)} \neq 0$ , for some  $k \in (1,...,K)$ , . That is causality from x to y for all cross-sectional units, which is quite a strong assumption (Granger, 2003).

Because of the above shortcomings we conduct Granger causality tests by following Dumitrescu and Hurlin (2012) approach, which adopts the specification of equation(5), but more general than Holtz-Eakin et al. (1988). In this approach, the coefficients  $\gamma^{(k)}$  and  $\beta^{(k)}$  incorporate heterogeneity among the cross-sectional units. The null hypothesis, called "homogeneous non-causality" (HNC) hypothesis to be tested is

 $H_0: \beta_i^{(1)} = \beta_i^{(2)} = \dots = \beta_i^{(k)} = 0$ , for all  $i = 1, \dots, N$ .

The alternative hypothesis of this allows for the causality from x to y for some but not all crosssectional units, which makes it different from the above. This may be conducted in following steps. First, the Wald statistic under the null that  $\beta_i^{(1)} = ... = \beta_i^{(k)} = 0$  for each cross-section unit *i*, is computed, denoted by  $W_{i,T}$ . In the next step, the average of the Wald statistics is to be calculated from the earlier step as follow

$$W_{N,T}^{HNC} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T}.$$
(6)

Following Dumitrescu and Hurlin (2012) has shown that, the average Wald statistics  $W_{N,T}^{HNC}$  converges in standard normal distribution if T is sufficiently large that is

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}} (W_{N,T}^{HNC} - K) \xrightarrow{d} N(0,1).$$
(7)

where  $T, N \to \infty$  denotes the fact that  $T \to \infty$  first and then  $N \to \infty$ .

If T is small, the last result does not hold<sup>9</sup>. But, Dumitrescu and Hurlin (2012) shown that if T > 5 + 2K, we can still have the standardized average statistic  $\hat{L}$  converging in distribution as;

$$\widetilde{\mathcal{L}} \qquad \sqrt{\frac{N}{2 \times K} \times \frac{(T - 2K - 5)}{(T - K - 3)}} \times \left[\frac{(T - 2K - 3)}{(T - 2k - 1)} W_{N,T}^{Hnc} - K\right] \xrightarrow{d} (N(0, 1)$$
(8)  
with  $W_{N,T}^{Hnc} = (\mathcal{V}_N) \sum_{i=1}^{N} W_{i,T}$ .

In the presence of cross-sectional dependence, critical values of panel Granger causality is corrected by a block bootstrap procedure (Dumitrescu and Hurlin (2012)<sup>10</sup>).

### 4 Empirical results

The descriptive statistics reported in Table 1 support the point of an unbalanced and unequal growth across the states. There is wide variance in the average income over the year across the states. Similarly, there is wide variance in electricity consumption pattern across the states.

# 4.1 Panel unit root tests

As a first step in the empirical analysis we have to determine the order of integration of the two variables. If they are I(1), then we can proceed to examine the long run relationship. To confirm this, panel unit root test without structural breaks and panel stationary tests of Carrion-i-Silvestre et al. (2005) which incorporates structural breaks is employed. Panel unit root tests of Levin et al. (LLC, 2002) and Im et al. (IPS, 2003) with common null of non-stationary have been employed. The results reported in Table 2 show that the variables follow I(1) process i.e. are integrated of order one with the exception of LLC tests for the NSDP, when trend in included in the equation. Overall, it may be infer that variables are integrated of order one.

We employed stationary tests of Carrion-i-Silvestre et al. (2005) to overcome the limitation of cross-sectional independence and omission of structural breaks to confirm the order of integration. To conduct the stationary tests of Carrion-i-Silvestre et al. (2005), two maximum breaks have been allowed as our sample size is small, and this may lead to imprecise break estimates. The Bootstrap critical values are calculated, using replications and a sieve order of  $4(T/100)^{2/9}$  to address the issue of cross-sectional dependence.

Table 1: Descriptive Statistics

NAME/ veriables	LNSDP				LEC		
	Mean	Max	Min.	Mean	Max	Min.	

Andaman & Nicobar Islands	2.456	3.612	1.619	5.217	6.326	3.744
Andhra Pradesh	6.651	7.594	5.722	5.910	7.054	4.623
Arunachal Pradesh	2.933	3.909	1.757	4.492	6.577	2.684
Assam	5.925	6.543	5.351	4.580	5.521	3.513
Bihar	6.303	7.267	5.675	4.574	4.989	3.592
Delhi	6.297	7.571	5.079	6.601	7.386	6.001
Goa	4.190	5.498	3.138	6.582	7.723	5.411
Gujarat	7.005	8.179	6.054	6.474	7.493	5.363
Haryana	6.287	7.422	5.342	6.273	7.451	5.343
Himachal Pradesh	4.866	5.888	4.045	5.714	7.230	4.196
Jammu & Kashmir	5.147	5.883	4.601	5.590	6.950	4.315
Karnataka	6.888	7.868	5.984	5.924	7.029	4.984
Kerala	6.530	7.535	5.803	5.492	6.446	4.623
Maharashtra	7.780	8.922	6.814	6.245	7.122	5.471
Manipur	3.450	4.225	2.713	4.336	5.866	2.052
Meghalaya	3.615	4.673	2.779	5.147	6.537	3.435
Madhya Pradesh	6.612	7.518	5.925	5.688	6.624	4.608
Nagaland	3.475	4.594	2.283	4.446	5.593	3.465
Odisha	6.180	6.982	5.530	5.778	7.098	4.736
Puducherry	3.480	4.730	2.590	6.781	7.898	5.379
Punjab	6.448	7.263	5.664	6.624	7.495	5.705
Rajasthan	6.623	7.670	5.659	5.652	6.889	4.599
Sikkim	2.258	3.889	0.937	5.148	6.787	3.617
Tamil Nadu	7.193	8.288	6.284	6.154	7.152	5.179
Tripura	3.824	5.078	2.858	4.278	5.691	2.679
Uttar Pradesh	7.512	8.254	6.866	5.241	6.109	4.158
West Bengal	7.097	8.040	6.259	5.348	6.387	4.762

No of Obs. for each states included in the study is 33 Units for measurement for Net State Domestic Product (NSDP) and Electricity Consumption is Rs Billion and Kilo Watt per hour (KWH) respectively

We performed the test for two models with different deterministic specification. The first model considers a constant and trend without structural breaks. Whereas the second model includes structural breaks both in constant and trend. Results are reported in Table 3. First panel of the table shows the statistics for each variable in levels and the second-panel reports at first difference.

First, second and third row respectively consist the test statistics, the asymptotic p-value, and the bootstrapped p-value for each model. From the test statistics and zero asymptotic p-values for the first model, reveal that variables at the level are non-stationary with both specifications. However, bootstrapped p-value is considered to allow cross-section dependence and results suggest that null hypothesis of stationary cannot be rejected for each variable as bootstrapped p-values is not equal to zero. Furthermore, for the variables in first difference, the results of each variable cannot reject the null hypothesis of stationary, for both models i.e. without breaks and with breaks. In summary, although there might be some deviations between the results, generally we found that the variables seem to be integrated of order one, I(1). Therefore, we can proceed to examine the long-run relationship between the variables under consideration.

LI	C(t-adjusted)	]	IPS(W-stat)		
constant	Constant + trend	Constant	Constant + trend		
6.567	-2.505	14.201	-0.396		
(1.000)	(0.006)	(1.000)	(0.346)		
0.290	0.319	5.812	-0.058		
(0.614)	(0.625)	(1.000)	(0.477)		
-27.149	-28.622	-25.964	-28.273		
(0.000)	(0.000)	(0.000)	(0.000)		
-26.101	-23.651	-24.267	-21.788		
(0.000)	(0.000)	(0.000)	(0.000)		
	LL constant 6.567 (1.000) 0.290 (0.614) -27.149 (0.000) -26.101 (0.000)	$\begin{tabular}{ c c c c } \hline LLC(t-adjusted) \\\hline \hline constant & Constant + trend \\\hline 6.567 & -2.505 \\\hline (1.000) & (0.006) \\\hline 0.290 & 0.319 \\\hline (0.614) & (0.625) \\\hline -27.149 & -28.622 \\\hline (0.000) & (0.000) \\\hline -26.101 & -23.651 \\\hline (0.000) & (0.000) \\\hline \end{tabular}$	$\begin{tabular}{ c c c c c c } \hline LLC(t-adjusted) & \hline l \\ \hline constant & Constant + trend & Constant \\ \hline 6.567 & -2.505 & 14.201 \\ \hline (1.000) & (0.006) & (1.000) \\ \hline 0.290 & 0.319 & 5.812 \\ \hline (0.614) & (0.625) & (1.000) \\ \hline -27.149 & -28.622 & -25.964 \\ \hline (0.000) & (0.000) & (0.000) \\ \hline -26.101 & -23.651 & -24.267 \\ \hline (0.000) & (0.000) & (0.000) \\ \hline \end{tabular}$		

Table 2: Panel unit root test statistics without structural breaks: At level and first difference

Note: In parenthesis are probability values

Table 3: Panel unit root test statistics with structural breaks: At level and first difference

Models	Tests	NSGDP		EC	
No breaks		constant	constant and trend	constant	constant and trend
	Value	2.158	3.646	2.087	1.714
	P-value <sup>a</sup>	0.015	0.000	0.018	0.043
	P-value <sup>b</sup>	0.046	0.016	0.046	0.408
Breaks					
	Value	-0.262	3.706	0.754	2.636
	P-value <sup>a</sup>	0.603	0.000	0.225	0.004
	P-value <sup>b</sup>	0.628	0.526	0.148	0.822
			ΔNSGDP		ΔΕС
No breaks		constant	constant and trend	constant	constant and trend
	Value	-1.397	2.803	1.346	1.268
	P-value <sup>a</sup>	0.919	0.003	0.089	0.102
	P-value <sup>b</sup>	0.866	0.216	0.142	0.676
Breaks					
	Value	-1.434	4.447	0.060	1.331
	P-value <sup>a</sup>	0.924	0.000	0.476	0.092
	P-value <sup>b</sup>	0.922	0.558	0.494	0.876

Note: <sup>a</sup> The p-values based on the asymptotic normal distribution. <sup>b</sup>The p-values based on the bootstrapped distribution.  $\Delta$  represents difference at first level.

# 4.2 Panel cointegration tests

After determining that variables are integrated of order one, we examine long run relationship between the variables by employing cointegration tests. We employed cointegration tests without and with structural breaks.

# 4.2.1 Panel cointegration tests without structural breaks:

Once we established through panel unit root tests and panel stationary tests that variables are integrated of order one, we first used Pedroni's (1999) tests to find panel cointegration. Pedroni (1999) proposes seven tests of two kinds, panel and group, that can be used in the absence of

breaks in the data. The first four test statistics are based on the "within" dimension (panel statistics). If the null is rejected, then NSDP and electricity consumption are cointegrated for all states. The last three test statistics are based on the "between" dimension (group statistics). In this case, cointegration among NSDP and electricity consumption exists for at least one of the all states. Following recommendation of Pedroni (1999), we performed cointegration test after removing common time effect through demeaning the data. The results are reported in Table 4, it can be inferred that when trend is not included in the model, the results suggest that there exists cointegration between electricity consumption and economic growth for all the states. On the other hand, when trend is included, the results suggest conflicting inference. Some statistics reveal cointegration while others do not. Over all we may infer that there is cointegration between electricity consumption and economic growth, as Herrerias et al. (2013) pointed out for small time series, the group ADF test has the best power properties compared to other tests.

Test Statistics	Withou	it trend	With trend		
Test Statistics	Statistic	Prob.	Statistic	Prob.	
Panel v-statistics	4.3269	0.0000*	-0.0233	0.5093	
Panel rho-statistics	-2.8712	0.0020*	0.6220	0.7330	
Panel PP-statistics	-3.2562	0.0006*	-0.9849	0.1623	
Panel ADF-statistics	-3.0105	0.0013*	-0.5798	0.2810	
Group rho-statistics	-1.8173	0.0346**	0.5366	0.7042	
Group PP-statistics	-3.4601	0.0003*	-1.9536	0.0254**	
Group ADF-statistics	-3.3769	0.0004*	-1.8301	0.0336**	

Table 4: Panel conitegration test: without structural breaks(Pedroni(1999))

\*, and \*\* denote statistical significance at the 1%, and 5% levels, respectively

#### **4.2.2** Panel cointegration test with structural breaks:

The conflicting result of Pedroni (1999) tests may be because of its restrictive assumption of cross-sectional independence and not considering of structural breaks. To overcome these shortcomings of the Pedroni (1999) tests we employed the Westerlund (2006) panel cointegration test with multiple structural breaks. We followed the same procedure as panel stationary tests to perform Westerlund (2006) *Z*(M) test of panel cointegration with fully modified (FMOLS) residuals. The results of two deterministic specifications with and without constant are reported in Table 5 (Panel A). Furthermore, considering cross-sectional dependence, we also used bootstrapped critical values as suggested by Westerlund (2006). The first, second and third row respectively report the test statistics, the asymptotic p-value, and the bootstrapped p-value. The results show that when cross-sectional dependence is ignored, the null of cointegration cannot be rejected. Thus the Pedroni (1999) and Westerlund (2006) tests provide evidence that NSDP and electricity consumption are related in the long run. The Westerlund (2006) test also reports the estimated breaks by using Bai and Perron (2003) technique, reported in Table 5(Panel B).

Table 5: Panel of	cointegration	test with structural	breaks	Westulund	(2006))
			~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~		

Model	Brea	ks
Test Statistics	in constant	in constant and trend
Value	8.531	53.188
P-value <sup>a</sup>	0.000	0.000

P-Value <sup>b</sup>	0.350	0.444
	Estimated breaks	
States	Break dates	
Andaman & Nicobar Islands	19	992, 2002
Andhra Pradesh		0
Arunachal Pradesh		0
Assam		0
Bihar		0
Delhi		2006
Goa		0
Gujarat		0
Haryana	19	992, 2006
Himachal Pradesh		1985
Jammu & Kashmir		1986
Karnataka	19	994, 2000
Kerala		0
Maharashtra		0
Manipur		0
Meghalaya	19	997, 2003
Madhya Pradesh		0
Nagaland		0
Odisha		0
Puducherry		0
Punjab	19	987, 1993
Rajasthan		0
Sikkim	19	990, 2003
Tamil Nadu		1985
Tripura		2005
Uttar Pradesh		0
West Bengal		0

Note: <sup>a</sup> The p-values based on the asymptotic normal distribution. <sup>b</sup>The p-values based on the bootstrapped distribution. $\Delta$  represents difference at first level. The maximum number of breaks allowed in break model is two

There are two statistically significant break points for some states and for others there is only one, while in case of some states there is no structural break. If we see historically, for most of the states break occurred in and around 1980, which seem very reasonable, as it is believed that the Indian government started adopting reform in 1980, which popularly known as reform by stealth. In other states, mostly break point coincided with the reform adopted in electricity regulation around 2000.

# 4.3 Panel Causality test:

As the results provide evidence that the NSDP and electricity consumption are cointegrated, it is appropriate in the next step, to examine the direction of causality. The panel causality test developed by Dumitrescu and Hurlin (2012) is employed. In panel context, one of the major issues is heterogeneity, which has been taken care by the Dumitrescu and Hurlin (2012) panel

Granger test. Further, critical values are reported after allowing cross-sectional dependence. The results of this test are presented in Table 6. First panel of the table shows statistics of the panel whereas; the lower panel gives state wise results.

Panel Statistics	LEC do	es not cause	LNSDP	LNSDP does not cause LEC		
Tests/Lag orders	K=1	K=2	K=3	K=1	K=2	K=3
Wbar statistic	1.193	1.957	4.060	4.335	5.441	6.021
Zbar statistic	0.709	-0.225	6.747*	12.254*	17.881*	19.224*
Zbar tild statistic	0.395	-0.440	1.432	10.597*	7.342*	4.897*
	Indiv	idual Wald S	Statistics			
States/Lag order	K=1	K=2	K=3	K=1	K=2	K=3
Andaman & Nicobar Islands	2.885	4.629***	5.317	0.551	1.985	0.449
Andhra Pradesh	0.618	1.789	2.499	8.513*	6.988**	11.679*
Arunachal Pradesh	0.464	2.315	3.833	0.694	8.639**	14.648*
Assam	0.010	0.199	1.741	6.643**	5.653***	5.516
Bihar	0.120	0.237	1.893	0.004	2.037	2.467
Delhi	0.297	0.585	1.766	2.116	2.429	1.858
Goa	1.450	6.808**	12.488*	1.586	4.939	5.485
Gujarat	4.678**	1.714	3.163	4.402**	6.325**	3.939
Haryana	0.038	1.001	2.730	7.261**	9.082*	8.288**
Himachal Pradesh	1.355	4.135	2.802	2.873***	5.664***	6.506***
Jammu & Kashmir	1.080	0.594	0.617	5.342**	5.688***	5.480
Karnataka	0.953	0.767	0.915	5.398**	4.440	3.816
Kerala	0.044	0.633	4.887	6.659*	7.926**	6.319***
Maharashtra	0.001	2.523	3.912	5.976**	10.409*	10.894**
Manipur	0.071	0.017	1.905	1.735	2.365	3.921
Meghalaya	0.832	1.379	1.112	8.996*	5.371***	5.738
Madhya Pradesh	2.465	4.444	7.297***	1.236	3.754	3.749
Nagaland	0.009	0.212	0.276	3.945**	2.716	3.704
Odisha	0.166	0.559	4.426	7.251*	8.364**	9.719**
Puducherry	0.716	3.821	3.773	0.480	4.356	10.385
Punjab	1.098	1.422	5.484	8.562*	5.809***	4.848
Rajasthan	3.564***	1.260	2.876	2.652	3.279	5.675
Sikkim	4.742**	5.977**	5.764	5.052**	4.568	2.707
Tamil Nadu	0.157	3.040	15.469*	1.990	3.918	8.981
Tripura	4.081**	1.734	7.931**	7.328*	6.558**	5.521
Uttar Pradesh	0.018	0.022	0.873	6.850*	9.735*	7.277***
West Bengal	0.298	1.014	3.878	2.956***	3.914	2.991

Table 6	5:	Panel	Granger	causality	tests
	••		<u> </u>		

\*,\*\*, and \*\*\* denote statistical significance at the 1%, 5% and 10% levels, respectively

The Wbar statistic corresponds to the cross sectional average of the N standard individual Wald statistics of Granger non causality tests. The Zbar tiled statistic corresponds to the standardized statistic (for fixed T sample). We compute all these statistics for one, two and three lags for completeness and robust inference.

Both Zbar and Zbar tiled statistics are significant at 1% level there by rejecting the null of homogenous non-causality from output (NSDP) to electricity consumption irrespective of the number of lags included. But the null of homogenous non-causality from electricity consumption to output (NSDP) can be rejected only for the lag three at 1% level of significance. Overall, the results indicate that output has more impact on energy consumption the than energy consumption on output. Thus the results suggest that there exists heterogeneous causality between energy consumption and output across the states, and hence it is necessary to look more closely at the individual state level.

Looking at individual Wald statistics it reveals that, out of twenty seven states, in sixteen states there is uni-directional causality running from output to electricity consumption. Out of these sixteen states, in seven states the null of non-causality from output to electricity consumption can be rejected irrespective of lag length. For states like Assam, Meghalaya, and Punjab, the null of non-causality from output to electricity consumption can be rejected at lag one and two and for Karnataka and West Bengal at lag one. For Tamil Nadu the null of non-causality can be rejected at lag two and three respectively. Whereas for the states of Andaman and Nicobar, Goa, Madhya Pradesh and Rajasthan causality runs from electricity consumption to output. While there is feedback causal relationship in the states of Gujarat, Sikkim and Tripura.

The heterogeneity of causal results may be easily understood in the context of the situation in the power generation and demand across the states. India till 2014 was divided into five regional grids namely Western, Northern, eastern, Southern and North-eastern, which now have been integrated. Eastern region, which includes the states with less industrialization, has less demand, on the other hand southern region with more industrialization and base of IT/ITEs industries always has more demand and therefore facing power shortage. Similarly, western region with industrial states always has more demand than supply. The gap between the supply and demand may also be attributed to the heterogeneous relationship across the states. Apart from the two above cited reason for the heterogeneity, the different economic development of the different states may seem to also drive the heterogeneous causal relationship between economic growth and energy consumption across the states.

Overall, our results suggest that there is evidence for the causal relationship between energy consumption and output and it is heterogeneous across states. Out of twenty seven states, sixteen states show the presence of strong causality from output to energy consumption and in four states causality is the other way around. In three states there is bi-directional causality between energy consumption and output. The findings suggest that economic growth has more impact on energy consumption than what energy consumption has on economic growth.

In Table 7<sup>1</sup>, summary of causality results of the present paper along with other studies in Indian context is reported. The results of the present study and the earlier studies is comparable, as earlier studies has considered only the national coverage and this study covers states. Moreover, in the previous studies, alternative methods of time series has been applied, whereas in the present study we have employed panel techniques. However, we find a bidirectional causality, though causality from output to electricity consumption is more common among the states. This result is in line with Ahmad et al. (2016) and Nain et al. (2014). Most of the previous studies affirmed the "conservation hypothesis" that is causality runs from economic growth to

<sup>&</sup>lt;sup>1</sup> To the best of our knowledge there is no panel study for Indian state in this direction

electricity consumption. We also find that at individual state level for most of the states causality runs from output to electricity consumption.

Author(s)	Geographical Coverage	Sample period	Methodology	Conclusions (s)
Present Study	Regional	1980-2012	Panel Cointegration and Panel Causality	$Y \rightarrow ELC \text{ (strong)}$ ELC $\rightarrow Y \text{ (Weak)}$
Cheng (1999)	National	1952-1995A	Johansen-Juselius, VEC; Granger causality	Y→ELC
Ghosh (2002)	National	1950-1997A	Johansen-Juselius; cointegration; VAR	Y→ELC
Paul and Bhattacharya (2004)	National	1950-1996A	Johansen-Juselius; VEC; Granger causality	Short run: $Y \rightarrow CEU$ ; Long run: $CEU \rightarrow Y$
Ghosh (2009)	National	1970–2006A	ARDL bounds test;	Y→ELS
Tiwari (2011a)	National	1971-2005	Cointegration, VECM	Y→ELC
(Tiwari 2011b)	National	1971-2010	Johansen-Juselius, Granger-causality: VAR	ELC→Y
Nain et al. (2012)	National	1970-71 to 2009-10	ARDL, MWALD	ELC→Y
Ahmad et al. (2014)	National	1970-71 to 2009-10	ARDL, ECM	$Y \leftrightarrow ELC$
Yang and Zhou (2014)	National	1970-2008	DAG, Causality test	EC→Y
Nain et al. (2015)	National	1970-2011	ARDL, TY causality test	ELC→Y
Tang et al. (2016)	National	1971-2012	Cointegration, GVDC	Y→EC
Kumari and Sharma (2016)	National	1974-2014	JJ Cointegration, Causality	Y→ELC
Ahmad et al. (2016)	National	1971-2014	ARDL, VECM	$Y \leftrightarrow EC$

Table 7: Comparison of causality test results with other recent studies for India

Notes: definitions of notation:  $\rightarrow$ ,  $\leftrightarrow$  and  $\neq$  represent unidirectional, bi-directional causality and no causality, respectively. Abbreviations defined as follows: ELC=electricity consumption; ELS=electricity supply; CEU=commercial electricity; Y=real or nominal GDP or GNP; Alternative methodologies other than standard Granger-causality tests: Engle-Granger (1987); Johansen-Juselius (JJ) (1988, 1990); Pesaran et al. (2001) ARDL bounds test (ARDL); Abbreviations for models: VAR=vector autoregressive model and VEC=vector error correction model; DAG= Directed acyclic graph; GVDC= Generalised Variance Decomposition; MWALD= Modified Wald Statitic

The major findings are summarized as follows: first, there is a heterogeneous causal relationship between economic growth and energy consumption across the states. For most of the states, causality runs from output to energy consumption and for some states causality is other way. Whereas for few states, there is bidirectional causality between NSDP and electricity consumption which indicates that both the variables are interdependent. The interdependence between electricity consumption and output show that energy policies designed to reduce electricity intensity is appropriate. At the same time, this relationship also indicates that electricity supply shock may have a large impact on economic growth. (Herrerias et al., 2013). Second, the results also highlight that in the Indian context, it is the demand model that can at best be specified. The results suggest that Indian policy makers may implement the energy conservation policies, as it is the economic growth that appears to be more dominant than energy consumption. At the same time, policy makers should also keep in mind that the bidirectional interdependence between energy consumption and economic growth for other states may not give free hand on such policy adoption in respect of these states. Therefore, it is suggested that in such a situation, India should not adopt an integrated policy for all states, rather than state specific policies will be more appropriate. Along with conservation policies

India should also promote the adoption of renewable energy sources so that it will be easier to bypass the economic cost incurred by conservative energy policy in specific states.

# 5. Conclusion

This paper examines the co-movement and causal relationship between energy (electricity) consumption and economic growth in Indian states for the period 1980 to 2012. To the best of our knowledge, this is the first study that provides a deep empirical insight on the relationship between electricity consumption and output for the Indian states under panel structural break framework. Further, the advanced panel techniques employed which not only are taking care of heterogeneity but also the cross-sectional dependence and structural breaks. The panel cointegration and panel causality tests are conducted to answer the questions of co-movement and causal relationship among electricity consumption and economic growth respectively. Our results suggest that there is a long-run steady-state equilibrium relationship between economic growth measured by NSDP and energy (electricity) consumption for states, allowing state heterogeneity. These results are also robust to cross-section dependence between states as well as to structural breaks. Further, the results provide evidence of causality between energy (electricity) consumption and economic growth for the panel, but it is heterogeneous across the states. Overall, the results suggest that though there is bi-direction causal relationship between energy (electricity) consumption and economic growth, economic growth has more impact on the energy consumption than the other way round. Our findings are is contrary to most of the earlier studies for India at aggregate level, such as by Cheng (1999), Ghosh (2002, 2009), and Chen et al. (2007) as they have reported unidirectional causality running from economic growth to energy (electricity) consumption. This implies that energy consumption and economic growth is interdependent. This further implies that that a general energy conservation policy may not be very effective for economic growth process in Indian states and a slow growth in Indian states may have detrimental impact on the demand for energy. In light of this, we suggest that governments should formulate state specific policies and should also encourage use and development of more advance and eco-friendly technologies by giving tax incentives or any other benefits, so that it can avoid the energy supply shock effect on the output and mitigate the environmental issues also. The completion of nuclear reactor in Tamil Nadu with the help of Russia and Civil Nuclear Agreement with USA are steps taken by the Indian government is seen in this regard.

# Acknowledgment

The authors would like to thank Dr. Wasim Ahmad, Taufeeq Ajaz, Sajjad Ahmad and Anjuman Shaheen for their help.

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  - Footnotes

<sup>&</sup>lt;sup>1</sup> See Kumar and Managi, (2009) for detailed analysis of resources, environmental issues and regulation, regional disparities and policies across the Indian states.

<sup>&</sup>lt;sup>2</sup> Per Capita Income is measured at 2004-05 constant prices and accessed from Planning Commission of India.

<sup>&</sup>lt;sup>3</sup> Mukherjee (2008) examined the efficiency in the use of electrical power at state level and Sen and Jamasb (2012) analyzed the determinants and impact of electricity reform, giving special regard to its political economy and regional diversity across the states. Another interesting study by Kumar and Managi (2011) argues to fix the responsibility at the firm level to reduce the pollution for various pollutants.

<sup>&</sup>lt;sup>4</sup> See for recent and comprehensive literature survey Lee (2005, 2006); Yoo (2006); Payne (2009, 2010a, 2010b); Ozturk (2010); Bo (2011); Omri (2014).

<sup>&</sup>lt;sup>5</sup> Electricity accounted for about 57.57% of the total energy consumption (in peta joules) during 2011-12(CSO, 2013)

<sup>9</sup> If T is small, the individual Wald statistics  $W_{i,t}$  does not converge to a chi-squared distribution. Consequently,

the average Wald statistics  $W_{N,T}^{HNC}$  in equation (6) no longer has asymptotic property like (7) holds.

<sup>10</sup> Further, this can also be applied for unbalanced panel data. For formal discussion see Dumitrescu and Hurlin (2012)

 <sup>&</sup>lt;sup>6</sup> The electricity consumption is measured in Kilo Watt per Hour and NSDP is in Rs. billion.
 <sup>7</sup> To save the space Pedroni (1999) test not described, interested reader may consult the reference
 <sup>8</sup> See basher and Westerlund (2009) for details.