Review of Economic Analysis 17 (2025) 167-192 1973-3909/2025167

Does Relation between Energy and Economic Growth hold for all Indian States? Empirical Analysis using Hurlin-Venet Process.

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Electricity consumption is often regarded as a precondition for economic growth and any bottleneck in its production can severely hurt the growth prospects of an economy more specifically a developing one. Representing a strong case of its value, the causal relationship between energy consumption and economic growth is addressed by extending the Granger causality framework in a heterogeneous panel setup. Exclusively four different causal behaviours are examined: Homogeneous Non-Causality (HNC), Homogeneous Causality (HC), Heterogeneous Non-Causality (HENC), and Heterogeneous Causality (HEC). Both HNC and HC hypotheses are rejected in the causality direction from Economic growth to energy consumption thereby suggesting that the panel of Indian states is not homogeneous. Following this heterogeneous causality tests (HENC and HEC) are conducted for each Indian state to check the hypothesis of causality from economic growth to energy. For 8 out of 17 Indian states strong unidirectional causality is found while for 6 other states, there is no evidence of any causality in the stated direction. The remaining 3 states show weak evidence of causality. Thus, the results are suggestive of the fact that the central government cannot dictate policies at the state level rather state needs to frame regional policies in line with the situation that suits.

Keywords: Energy, Economic growth, India, Causality, Hurlin-Venet

JEL Classifications: C22, O13, O40, O53, Q43

1 Introduction

Energy is often regarded as a major input in the process of growth, and as such, its demand is expected to increase continuously. With ever-increasing demand for energy, the focus is not

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just on production but also on distribution. With better distribution channels, the consumption of energy is likely to improve and increase. As such, any obstacle in the supply of energy is likely to be reflected in terms of poor growth scenarios. Best and Burke (2018) also asserted that electricity availability is a precondition for faster economic growth, where a percentage more electricity consumption on average is associated with 0.006 percentage points of increase in growth in the subsequent decade.

The relationship between energy and economic growth is one of the most talked about and most researched topics, but unfortunately, no consensus has been reached until now. Whether energy precedes growth or growth precedes energy is still a major question hovering in the minds of researchers. Magazzino (2011) provides four hypotheses about the direction of causality between energy consumption and GDP. The first is the ***hypothesis of neutrality***, which holds that there is no causality (in either direction) between these two variables. The second is the ***conservation hypothesis***, which holds that there is evidence of unidirectional causality from growth to energy consumption. Under the third hypothesis, which is known as the ***growth hypothesis***, energy consumption drives GDP growth. The fourth hypothesis is the ***feedback hypothesis***, which suggests a bidirectional causal relationship between energy consumption and GDP growth. The pattern of causality can offer policy suggestions of varying importance. For instance, if the long-run pattern of causality is from energy to economic growth, that would imply that economies would have to drop the plans of going for energy conservation policies because that can severely detract from their growth trajectory. Given the situation of increasing population accompanied by industrialization and urbanization, the policy imperative of energy conservation certainly would not be the priority of the Indian government. On the other hand, if the direction of causality is from economic growth to energy, the economy can go ahead with energy conservation policies without having any adverse effect on its economic growth.

Table 1 elaborately provides evidence from the world over about the studies that have favored different hypotheses from time to time. Even Indian evidence is not sufficient to provide a unanimous result on the importance of the variable to validate what precedes the other.

India is a diverse country with some states producing energy in bulk and supplying it to other states, while some other states rely heavily on energy imports from other states. Some states enjoy domination of the agriculture sector, while others favor the flourishing industrial sector, and yet others favor the tertiary sector.

Table 1: Energy- Growth Causality Evidence (International as well as Indian Evidence)

Hypothesis	International Evidence[1]	Indian Evidence[2]
Growth Hypothesis (Energy→ Growth)	Lee (2005) 18 Developing countries Squalli (2007), OPEC countries Apergis and Payne (2009, 2010), American economies. Rufael (2014) Belarus and Bulgaria Arora and Kaur (2020) BRICS	Masih and Masih (1996) Asafu-Adjaye (2000) Gupta and Sahu (2009) Nain et al. (2012) Mohanty and Chaturvedi (2015)
Conservation Hypothesis (Growth→ Energy)	Al-Iriani (2006) Gulf Countries Mehrara (2007) 11 Oil exporting countries Lee and Chang (2008) 16 Asian countries Rufael (2014) Czech Republic, Latvia, Lithuania, and the Russian Federation Odhiambo (2016) South Africa	Cheng (1999) Soytas and Sari (2003) Ghosh (2002, 2009) Pradhan (2010) Abbas and Choudhry (2013) Kumari and Sharma (2016) Tiwari (2021)
Feedback Hypothesis (Growth↔Energy)	Narayan and Smyth (2009), 6 countries Belke (2011), OECD countries Omri (2013) MENA countries Campo and Sarmiento (2013), Latin American countries Rufael (2014) Ukraine Karanfil and Li (2015) 160 Countries Osman et al (2016) GCC countries Kirrikkaleli et al (2018) 35 OECD countries	Paul and Bhattacharya (2004) Ahmad et al (2016)
Neutrality Hypothesis	Acaravci and Ozturk (2010) 10 transition economies Rufael (2014) Albania, Macedonia, Moldova, Poland, Romania, Serbia, Slovak Republic and Slovenia	Murray and Nan (1996) Zhang (2011) Tiwari (2012)

For instance, as per the Energy statistics report prepared by the Government of India, Maharashtra enjoys the highest installed capacity of 42491.72 MW,[3] followed by the state of

[1] For detailed review on American economy refer Mahalingam and Orman (2018) and for that on China refer Akkemik (2012)

[2] For detailed literature review on Indian studies refer Tiwari (2020)

[3] States of India by installed power capacity - Wikipedia

Gujarat with a capacity of 38039.89 MW, while the northeastern state of Assam has the lowest capacity of 1823.69 MW. The differences exist not just for installed capacity, but even the consumption of electricity is highly different across Indian states. As of 2018-19, the Annual per capita consumption of electricity for Punjab was 1682.40 kWh, 1484.97 kWh for Gujarat, while on the other it had been as low as 195.18 kWh for the state of Bihar. Given this backdrop, it becomes imperative to not only understand but also address these regional differences to prepare policies that do not thwart the growing process by preparing regional policies in line with the situation that best describes them.

The literature reviewed above highlights several research gaps. These can be summarized as below: Though the research hitherto on the energy-growth nexus has been exhaustive, it has been inconclusive. Particularly taking the case of India (as Table 1 suggests), no consensus has been reached until now, and the debate about the causality still holds its strength. This lack of unanimity could be attributed to the choice of methodology, the time span of the study, and the choice of variables taken up. Secondly, while all the causality studies (particularly of Indian origin) strictly assume homogeneity among the cross sections, after which the causal relationship, if it exists, is treated as homogeneous. But a caveat here is that all cross-sections are likely to exhibit differences, thus imparting heterogeneity to them as well as to the patterns of causality within the panel framework. Thus, the issue of heterogeneity is more pertinent to panel studies (as is the present case). The lack of addressing the issue of heterogeneity presents a major methodological gap in Indian studies. Lastly, the research gap can be viewed from a geographical prism. The heterogeneous patterns of causality have been validated in the two most important economies of the world, namely the USA (Mahalingam and Orman, 2018) and China (Akkemik et al, 2012; Zhang and Xu, 2012). Thus, the same is expected for India as well, and the present research would seek to test homogeneous causality as against heterogeneous causality. For instance, in India, there was only a single study by Sethi and Kaur (2013) that dealt with two Indian states and worked out different patterns of causality. In addition, the case of heterogeneous causality has been well documented for Telecommunications and growth relationships in the case of Indian states (Arora and Kaur, 2021). Therefore, the need for the study is immense given the fact that sub-national differences have been validated in the case of other economies of the world and in the case of other infrastructures as well.

The purpose of the paper is to study the causality relationship between energy and economic growth for 17 Indian states for the period 1991-2017 by implicitly taking up the issue of heterogeneity. Given the recent importance of the energy sector in India, the results from the paper can have far-reaching implications. As far as the contribution that the study makes to the overall subject, these can be found along three major lines: Firstly, it is the first-ever study for

India, to the best of our knowledge, that distinguishes between homogeneous and heterogeneous causal patterns between energy and economic growth. Given the different ways in which we have defined both of our variables, imparting comprehensiveness as well as robustness to our research results. Secondly, the study is based on more recent econometric methodologies, which comprise first-generation and second-generation unit root tests, cross-section dependence tests, Westerlund cointegration tests, and Hurlin-Venet causal mechanisms. The application of nascent and more advanced econometric tools provides us with a more concrete analysis. The last and most important contribution that the present research makes is that it strongly engages with the ongoing methodological debate by presenting very strong evidence along the lines of heterogeneous causal patterns within India. Despite being a regional study, it offers its conclusions and findings to the international audience and researchers to validate such patterns within different economies of the world. Altogether, this can help to entirely start a new strand of literature that talks about heterogeneous patterns of causality, unlike the homogeneous patterns that have been the subject matter of an ample number of studies.

The rest of the paper is structured as follows: Section 2 talks about the data and its source from which the database is culled. Methodological details are presented in Section 3. Empirical Analysis is provided in Section 4, and the last section, i.e., Section 5, concludes and provides relevant policy implications.

2 Database

Because the research emphasizes the relationship between economic growth and energy, we used various definitions to represent our variables of interest. The representation of variables in different forms helps check the sensitivity and robustness of our results. The variables representation and the data source that is accessed to compile data are presented in the adjoining Table 2. Data on economic growth variables are given in lakhs and are measured at constant 2011-12 prices for comparison.

The data are collected for the period running from 1991-2017 for 17 Indian states. These states are Andhra Pradesh, Assam, Bihar, Gujarat, Assam, Haryana, Himachal Pradesh, Jammu & Kashmir, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. Four Indian states experienced bifurcation during this period. These were Uttar Pradesh, Bihar, and Madhya Pradesh in 2000 and Andhra Pradesh in 2014. But for comparative purposes, the states originally (before bifurcation) have been retained in the analysis.

Table 2: Definition of Variables and the Source of Data

Variables	Definition	Data Source
Economic Growth	Per Capita Net State Domestic Product (Y) Gross Domestic Product (G) Net State Domestic Product (N)	Economic and Political Weekly Research Foundation
Energy	Per Capita Electricity Consumption (in KWh) (E) Index of Energy[4] (Per Capita Electricity Consumption and Installed capacity per one thousand population) (E.I.)[5]	Statistical Abstract Series

3. Methodology

3.1 Cross-Section Dependence Tests

Panel data studies have hitherto focused on the assumption that cross-sectional units that form part of the study are independent of one another. But this assumption lately has been criticized by researchers, particularly when we are dealing with country samples. Keeping in mind the possibility of both dependence as well as independence among the cross sections, the unit root and cointegration literature is available in two forms:

The first-generation unit root tests (Levin et al., 2002, Im et al., 2003) and subsequently the first-generation co-integration tests (Pedroni, 1999) both of which presume cross-sectional independence.

On the contrary, the second-generation unit root test (Pesaran, 2007) and cointegration tests (Westerlund, 2007) assume cross-section dependence.

Given the different lines of procedure based on cross-section dependence (or independence), the test must precede the testing procedure of unit root and cointegration tests.

There are two most often applied tests for checking cross-section dependence in the panel data Breusch-Pagan LM test (1980) and Pesaran's test of independence (2007).

3.2 Unit root tests

At the outset, it is important to check the time series properties of the individual variables before proceeding to the next stage to avoid any spurious estimates at a later stage. The results of unit root tests will guide the future strategy of econometric techniques. The CIPS test statistic developed by Pesaran (2007) can be expressed as follows:

[4] The methodology for construction of Energy index is presented in the Appendix (A 1)

[5] For the purpose of construction of energy index, a constant value is added to make the values positive after which logarithmic values are taken.

$$\text{CIPS (N, T)}=\frac{1}{N}\sum_{i=1}^{N} t_i(\text{N,T})$$

where t_i (N, T) is nothing but the value of our variable of interest.

For comparison's sake, the study also employs the Augmented Dickey-Fuller (ADF) test using the Levine-Lin-Chu (LLC) method (2002) and the Im-Pesaran-Shin (IPS) method (2003) to check the stationarity properties of the variables. Here, the null hypothesis of the unit root is tested. The test follows the estimation using the following equation:

$$\Delta Y_t = \alpha_i + \beta_i Y_{it-1} + \sum_{j=1}^{p} \beta_{ij} \Delta Y_{it-j} + \delta_i t + \varepsilon_{it}$$

where i= 1,2,3……N; t= 1, 2 .T; Δ = first difference operator;

3.3 Cointegration Testing Procedure

After having checked the order of integration or stationary properties of our variables, the next step is to check for long-term relationships among them. For this, a cointegration test is performed. For that, Westerlund's (2007) testing procedure is applied. Under this, four test statistics are developed. Two of which are group statistics, and the other two are panel statistics. The group statistics (G_a and G_t) are based on a weighted average of the individually estimated short-run coefficients and their t-ratios, respectively. On the contrary, P_a and P_t test statistics pool information over all the cross-sectional units to test the null hypothesis of non-cointegration for all cross-sectional entities. All these test statistics are normally distributed. The test essentially evaluates whether cointegration exists or not by determining if an error correction is present for the individual panel groups and the panel. The tests are based on the following error correction model:

$$\Delta y_{it} = \alpha_i + a_{0i}(y_{i,t-1} - b_i x_{i,t-1}) + \sum_{j=1}^{K1i} a_{1ij}\Delta y_{i,t-j} + \sum_{j=-K2i}^{K3i} a_{2ij}\, \Delta x_{i,t-j} + \mu_{it}$$

where a_{0i} is the error correction term, which also provides estimates of the speed of adjustment toward the long-run equilibrium for group i. Thus, the panel and group hypotheses are formulated as follows:

3.4 Hurlin Venet Causality Process

The process of Granger causality is quite problematic when applied to panel data. The problems arise on account of heterogeneity across the cross-sectional units, which is not addressed under the Granger causality framework. The heterogeneity among the cross-sectional data arises on two accounts: the first type of cross-sectional variation arises due to distinctive intercepts of each unit, and the other type of heterogeneity is on account of differences in regression coefficients. Keeping in mind these shortcomings, Hurlin and Venet (2001) suggested an alternative causality process. To test for the causality in a heterogeneous panel setup, the following two regression equations will be applied

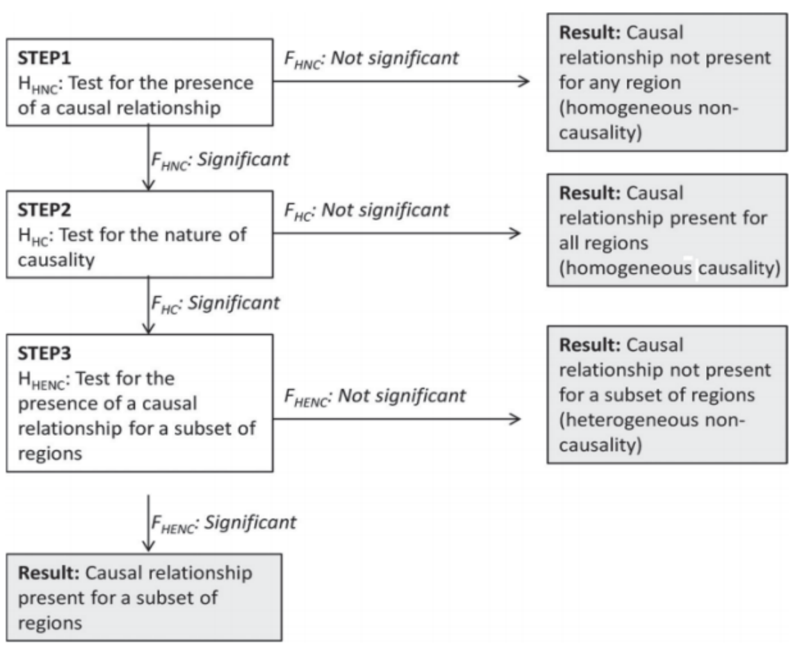
$$\ln E_{it} = \sum_{l=1}^{n} \gamma^{l} E_{i,t-j} + \sum_{l=1}^{n} \beta_{i}^{l} {}_{\neq} \ln Y_{i,t-l} + u_{i,t}, \qquad u_{i,t} = \alpha_i + \varepsilon_{i,t} \tag{1}$$

$$\ln Y_{it} = \sum_{l=1}^{n} \gamma^{l} Y_{i,t-j} + \sum_{l=1}^{n} \beta_{i}^{l} \ln E_{i,t-l} + u_{i,t}, \qquad u_{i,t} = \alpha_i + \varepsilon_{i,t} \tag{2}$$

Here I refer to the individual cross sections (which in our case are Indian states), t denotes the time, l is the number of lags, α, β and γ These are the parameters that are to be estimated. Here, the slope coefficients $\beta's$ are assumed to be constant over some time but vary across cross sections. The first equation tests for causality from growth to energy, while the second equation tests for the other causality direction.

Not going into the technical details of the methodology of the causality process here, a brief overview is provided in the subsequent diagram. As far as the technicalities of each hypothesis of the causal process are concerned, Appendix (A2) should be studied.

Figure 1. The process of Hurlin-Venet Causality



Source: Mukkala and Tervo (2013)

According to Hurlin and Venet (2001), four causality relationships emerge in a panel framework. These are Homogeneous causality (HC), Homogeneous Non-Causality (HNC), Heterogeneous causality (HEC), and Heterogeneous Non-Causality (HENC). As far as other causality studies, specifically of Indian origin, are concerned, the homogeneity assumption is taken to be implicit, and as a result, homogeneous causality is studied, but the method proposed by Hurlin and Venet studies a heterogeneous perspective of causality. The procedure to go about testing homogeneous (or heterogeneous causality is provided in figure 1 above.

4. Empirical Results

As already mentioned, the cross-section dependence test is a prerequisite for running integration and cointegration tests. The results from the Breusch-Pagan and Pesaran CD tests are presented in Table 3. The significance of test statistics vehemently supports the need to go for second-generation testing procedures of stationarity and cointegration.

We perform unit root tests for the different series of our variables, which are *ln Y, ln E, ln G, ln N, and ln E.I.*

The results from unit root tests are presented in Table 4. The conclusions drawn from both tests are similar in the sense that our variables are non-stationary at the level. When we take the first difference of the variables, they attain stationarity. This means that the order of integration of our variables is I (1).

Table 3: Cross-Section Dependence Test Statistics

Cross Section Dependence Test→ Models↓	Breusch–Pagan LM	Pesaran CD	The average absolute value of the off-diagonal elements
PCNSDP – Energy Consumption	700.348***	9.026***	0.378
PCNSDP- Index of Energy	997.307***	9.067***	0.459
GDP- Energy Consumption	758.338***	8.517***	0.387
GDP- Index of Energy	1139.175***	11.553***	0.497
NDP – Energy Consumption	759.142***	8.315***	0.390
NDP- Index of Energy	1135.138***	11.614***	0.495

Note: PCNSDP means per capita Net State Domestic Product; GDP means Gross Domestic Product; NDP means Net Domestic Product

Table 4: Unit root results

Variables	Level		First Difference	
	Individual intercept	Individual intercept + trend	Individual intercept	Individual intercept + trend
PCNSDP (Y) CIPS CADF	-2.435 -2.127*	-3.003 -2.756**	-5.292* -3.677***	-5.581 -3.782***
Elect (E) CIPS CADF	-1.354 -1.582	-2.064 -2.341	-4.646 -3.436***	-4.680 -3.463***
GDP CIPS CADF	-2.434 -2.164**	-3.218* -2.971***	-5.378* -3.783***	-5.716* -3.912***
NDP CIPS CADF	-2.524 -2.198	-3.126 -2.976***	-5.233* -3.499***	-5.593* -3.607***
E.I. CIPS CADF	-1.301 -1.723	-2.240 -2.733***	-4.103 -3.831***	-4.118 -3.865***

Note: All variables are expressed in logarithmic form; *** means significant at a 1 percent level.

After checking the stationarity properties of the variables, we go ahead to check whether the variables share any long-term relationship. For this, Westerlund's cointegration testing procedure is applied. Multiple models are run to check for long-term relationships between the variables. The results of cointegration are given in Table 5. From the test, we can say that in none of the models, the hypothesis of no cointegration is rejected, which implies that in our case, there is no long-term relationship between the variables of energy and economic growth, irrespective of how we define them. The absence of any long-run relationship between the two variables is also found in Kumari and Sharma (2016) and Tiwari (2020).

After having checked stationarity and the long-term relationship between our variables, we now proceed toward finding out the direction of the relationship between our variables of interest. There are two causality relationships to be tested: one is from Economic growth to energy, and the other is from energy to economic growth. To measure economic growth as well as energy variables, we have resorted to multiple definitions. To represent economic growth, we have three variables, namely per capita Net State Domestic Product (PCNSDP), Gross Domestic Product (GDP), and Net Domestic Product (NDP). As far as the energy variable is concerned, two notations have been used. The first one is the per capita consumption of electricity, and the second one is the index of energy, comprising of Annual per capita consumption of electricity (in KWh) and the installed capacity per thousand of the population (in MW). Table 6 presents the results from different combinations of bivariate relationships between the two variables.

Table 5: Westerlund Cointegration Test

Statistic	Value	Z-value	P-value
Model 1: PCNSDP – Energy Consumption			
G_t	-0.572	5.532	1.000
G_a	-2.703	3.362	1.000
P_t	-0.794	5.204	1.000
P_a	-0.468	3.494	1.000
Model 2: PCNSDP- Index of Energy			
G_t	-0.063	7.869	1.000
G_a	-1.398	4.350	1.000
P_t	0.206	6.211	1.000
P_a	0.146	4.065	1.000
Model 3: Gross Domestic Product- Energy Consumption			
G_t	-0.194	7.270	1.000
G_a	-1.747	4.087	1.000
P_t	0.595	6.602	1.000
P_a	0.331	4.236	1.000
Model 4: Gross Domestic Product- Index of Energy			
G_t	0.377	9.887	1.000
G_a	-0.339	5.153	1.000
P_t	2.486	8.504	1.000
P_a	1.551	5.369	1.000
Model 5: Net Domestic Product – Energy Consumption			
G_t	-0.264	6.947	1.000
G_a	-1.604	4.195	1.000
P_t	-0.132	5.870	1.000
P_a	-0.075	3.859	1.000
Model 6: Net Domestic Product- Index of Energy			
G_t	0.144	8.820	1.000
G_a	-1.046	4.618	1.000
P_t	1.492	7.504	1.000
P_a	0.949	4.811	1.000

Note: To determine the optimal lag/lead length, the AIC criterion is used, and the width of the Bartlett-Kernel is set at one. A model involving only a constant and no deterministic trend is used. Bootstrapped robust p-values are given due to the existence of cross-section dependence

Table 6: Test results for Homogeneous Non-Causality (HNC Hypothesis)

Causality From Economic Growth To Energy						
Lags	Y→ E	Y→ EI	GDP→E	GDP→E.I	NDP→E	NDP→E.I
1	35.04***	30.63***	33.50***	30.33***	33.49***	29.23***
2	19.92***	17.60***	19.49***	17.90***	19.17***	17.00***
3	12.84***	11.84***	12.94***	12.37***	12.96***	11.98***
Causality From Energy To Economic Growth						
Lags	E→ Y	E.I→ Y	E→GDP	E.I→ GDP	E→NDP	E.I → NDP
1	0.60	0.31	0.07	0.73	0.01	0.13
2	0.22	1.23	1.29	3.35**	1.02	2.67*
3	0.26	0.49	0.79	1.09	0.61	1.09

***, **, * imply significance levels of 1 percent, 5 percent, and 10 percent. E means electricity consumption, Y means Per capita Net State Domestic Product, energy index, GDP Gross Domestic Product, and NDP =Net Domestic Product.

We do not choose any lags according to the popular lag selection criteria, such as that of Akaike Information Criteria or Schwarz Information Criteria; rather, we present the results for up to three lags. This helps to verify the sensitivity and robustness of our test statistics. All causality equations are estimated as fixed effects equations.

Concerning the causality direction from economic growth to energy, we see that all the test statistics related to homogeneous non-causality hypotheses are statistically significant at a 1 percent level that too for all combinations of variables and at all lags. This means that there does exist a causal relationship between economic growth and energy for at least one of the states. Now, whether that causality is homogeneous or heterogeneous will be worked out with the help of subsequent statistics.

For other causal relationships, that as from energy to economic growth, the evidence is not sufficient to reject the null hypothesis of no causality. It is only partial. There are two combinations of variables where the null hypothesis is rejected. One is from the energy index to Gross Domestic Product, which is significant at a 5 percent level, and the other one is again from the energy index to Net Domestic Product, with the level of significance being 10 percent. Both the significant hypotheses are found at two lags. The rejection of the null hypothesis in both cases calls for moving on to the next stage of the testing procedure.

The rejection of the Homogeneous noncausality hypothesis implies that a causality pattern does exist between the variables. The pattern of causality could be homogeneous or heterogeneous. Firstly, we will check the hypothesis of homogeneous causality. Following the rejection of homogenous causality, the heterogeneous causality will be tested. The results for the Homogeneous causality hypothesis are presented in Table 7.

Table 7: Test Results for Homogeneous Causality (HC Hypothesis)

Causality From Economic Growth To Energy						
Lags	Y→ E	Y→ EI	GDP→E	GDP→E.I	NDP→E	NDP→E.I
2	1.36	0.23	2.49	0.98	1.84	0.44
3	1.57	0.18	2.51*	0.54	2.39*	0.47
Causality From Energy To Economic Growth						
	E→ Y	E.I→ Y	E→GDP	E.I→ GDP	E→NDP	E.I→ NDP
2	0.28	1.48	0.66	0.68	0.55	2.24
3	0.39	0.71	0.80	0.78	0.66	1.20

*** 1 percent, ** 5 percent, * 10 percent. E means electricity consumption, Y means Per capita Net State Domestic Product, energy index, GDP Gross Domestic Product; NDP =Net Domestic Product

Concerning the causality pattern from energy to economic growth, we are not able to reject the null hypothesis (as evident from the non-significance of our test statistics). This means that in none of the combinations, the resulting F statistic is greater than the critical F values, which is why the null hypothesis cannot be rejected. Non-rejection of our null hypothesis means that if causality exists between the variables, nature is homogeneous.

Moving on to the causality pattern from economic growth to energy, though most of our combinations are not strong enough to reject the null hypothesis of homogeneous causality, we do spot two significant combinations where the calculated F statistics are greater than the tabulated F statistics. With two significant test statistics (NDP to energy and GDP to energy) we go ahead with testing of heterogeneous noncausality hypothesis on the sample of our 17 Indian states.

HENC hypothesis is tested for each Indian state to arrive at a state-based causal pattern, and this is only run for the growth to energy model given the fact that the other hypothesis is not rejected at the earlier stage (HC Statistics). To check the HENC hypothesis, model 1 is run twice, separately for each 17 cross sections. In the first case, the model is run in an unrestricted mode without involving any restrictions, while in the second case, is run after restricting the nullity of the regression coefficient $\beta_i^l = 0$. The results from HENC for each Indian state are presented in Table 8. Our conclusion about the existence of causality is based upon a level of significance of 5 percent or less.

Table 8: Results from Heterogeneous Causality (HENC) between Growth and Energy Consumption

States↓	GDP→Energy			NDP→Energy		
Lags→	1	2	3	1	2	3
Andhra Pradesh	9.02***	6.74***	3.98**	9.82***	7.21***	5.60***
Assam	5.87**	5.50**	3.58**	5.79**	5.36**	4.04**
Bihar	0.55	1.62	1.41	0.55	1.57	1.54
Gujarat	3.98*	1.57	0.87	4.07*	1.67	1.02
Haryana	10.14***	5.70**	3.12*	10.68***	5.36**	3.01*
Himachal Pradesh	1.31	1.70	1.77	2.65	0.91	0.87
Jammu and Kashmir	3.79*	1.46	2.71*	3.23*	1.21	2.67*
Karnataka	4.60**	2.25	1.43	4.39**	2.11	1.29
Kerala	6.90**	3.21*	4.49**	7.69**	3.48*	4.26**
Madhya Pradesh	2.16	1.43	1.41	1.96	1.44	1.38
Maharashtra	3.37*	1.48	2.90*	3.33*	1.45	2.29
Odisha	0.02	0.10	0.39	0.04	0.15	0.48
Punjab	7.74**	4.70**	3.52**	7.34**	4.55**	3.44**
Rajasthan	7.86**	3.15*	2.68*	9.08***	3.22*	2.49*
Tamil Nadu	1.30	0.95	1.09	1.07	0.72	0.97
Uttar Pradesh	1.68	1.37	1.14	1.88	1.43	1.15
West Bengal	5.81**	4.45**	3.88**	5.54**	4.42**	4.01**

*** 1 percent, ** 5 percent, * 10 percent

We see that the states that depict causality are scattered over the country rather than being concentrated in the high-income regions of the coastal areas. Interestingly, we find out that the high-income state of Gujarat fails to produce any significant causality for itself, while on the other hand, we also see that low-income states of Bihar, Madhya Pradesh, Odisha, and Uttar Pradesh could not register significant causality.

Categorization of States:

Based on unidirectional causality that exists between growth and energy, the Indian states can be grouped under three heads:

1. Strong Unidirectional Causality: this set includes those states where the magnitude of causality is very strong between growth and energy consumption. Here, growth, whether represented by Gross Domestic Product or Net Domestic Product, favors a strong

unidirectional causality. The states that form part of this group are Andhra Pradesh, Assam, Haryana, Jammu and Kashmir, Kerala, Punjab, Rajasthan, and West Bengal.

2. No Causality: Bihar, Himachal Pradesh, Madhya Pradesh, Odisha, Tamil Nadu, and Uttar Pradesh are those states where no evidence of causality is found, irrespective of how we have defined growth.
3. Weak Unidirectional Causality: under this group are the states where the causality exists when growth is proxied by Gross Domestic Product or Net Domestic Product, and even if it's presented, the level of significance is as high as 10 percent. Gujarat, Karnataka, and Maharashtra fall under this group. These three are industrially advanced states. The growth impulses in these states are derived from the industrial sector. But because the industrial sector has already flourished well, that would mean that no more growth in that sector is expected. As a result, the energy consumption needs for this sector will not be as intense as in other states of India.

The different causal patterns observed for different Indian states are very much in line with the works of Sethi and Kaur (2013) who exclusively considered two Indian states that are geographically placed together but found out that the sectoral mix of every state economy presents an exceptional ground for varying causal behaviour patterns in the economy. The agriculturally dominated states of India, like Punjab, Haryana, Rajasthan, West Bengal, Andhra Pradesh and Jammu and Kashmir all display unidirectional causality from GDP to energy consumption, largely because these are all growing on the backs of the agricultural sectors' performance. For instance, in the case of Andhra Pradesh, which is popularly known as the 'rice bowl of India' requires an average of 2,800 litres of water for cultivating a kilogram of rice and this is entirely sourced from pump set irrigation (WaterAid 2019). Also, the sector contributes 34 percent to the state's income.

Additionally, the inadequate reach of the irrigation coverage compels the state to depend on groundwater irrigation. The energy-driven pump sets are the single most important factor that guides high energy requirements in these states. Given the data on the total area under irrigated crops, the research showed that in 1970-71, a 10 percent increase in electricity consumption was associated with only a 0.8 percent increase in agricultural growth in 1970-71, this increased to 1.8 percent by 2014-15 (Tiwari et al., 2020). This suggests that the Indian agriculture sector is largely driven by groundwater irrigation that relies on energy consumption.

The states that do not display any significant causality from GDP to energy, like Gujarat, Maharashtra, Karnataka, and Tamil Nadu, have different reasons behind this kind of segregated results. But in simple terms, because these are all industrially driven states (refer to Appendix 3), the intensiveness to contribution to energy consumption is low in comparison to that of agriculture-driven states. For instance, the electricity intensity in India's industrial sector has been declining from 1970-71 to 2014-15. In 1970-71 a 10 percent increase in electricity consumption was responsible for a 10.1 percent increase in industrial growth, which reduced to 0.97 percent by 2014-15. This decline in elasticity over some time could be attributed to numerous reasons, like high electricity costs to the industrial sector on account of cross-subsidization and increased usage of energy-efficient technology emanating from forces of globalization and foreign competition. The need to introduce energy-efficient technology for the industrial sector becomes even more relevant given the extent of peak power outages faced by the industry in these states. For instance, the figures for electricity shortages during peak time for the state of Karnataka was 11.2 percent (Central Electricity Authority, 2017).

For the state of Karnataka, Tamil Nadu it is well well-accepted and well-known fact that their economy is largely driven by less electricity-hungry industries like information technology, e-commerce, and finance. This explains well why no significant causal results were produced for these two states.

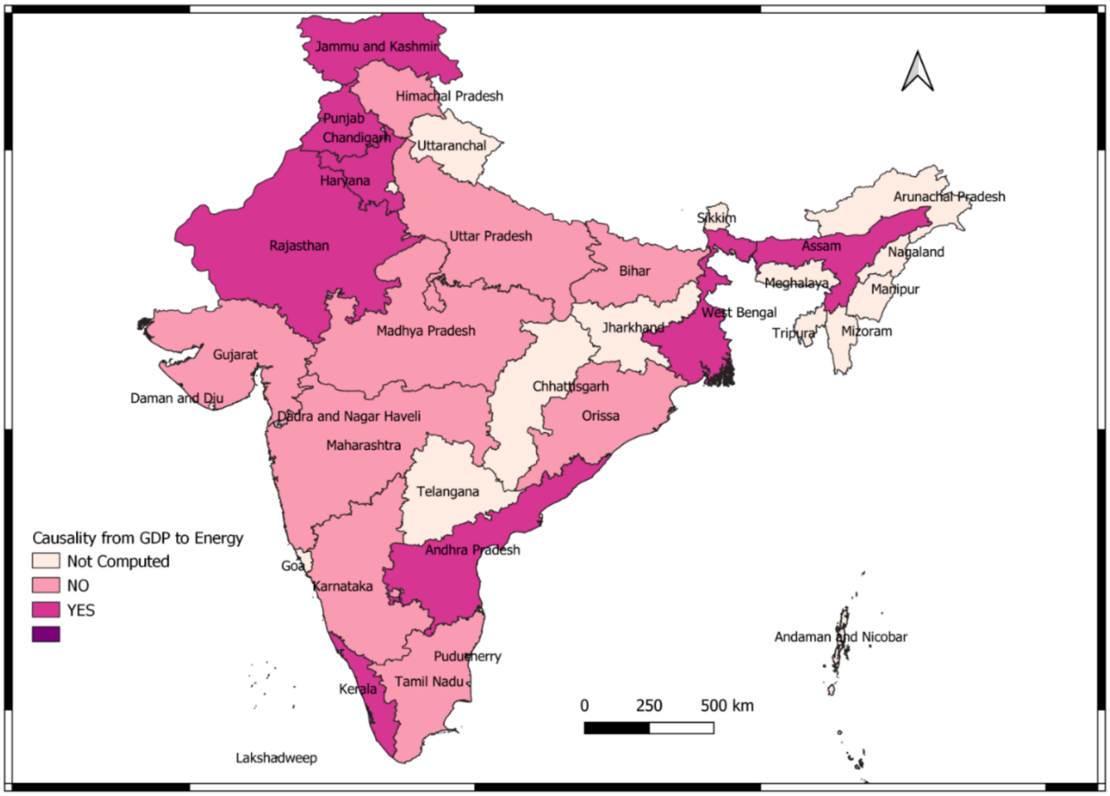
Mahalingam and Orman (2018) and Akkemik et al (2012) too verified different causality results for USA and China respectively. These works too discussed the varied causal patterns attributing those to different geographical characteristics and sectoral importance under each of their provinces or states.

Also, the states that depict some forms of causality are geographically clustered together. This gives credence to the possibility of spatial dependence or autocorrelation that is observed among regions, as has been postulated by Anselin (2001). This means that in the case of the presence of some magnitude positive spatial autocorrelation, regions with similar growth rates would cluster together in the same space, while in the case of the presence of negative spatial autocorrelation, regions with dissimilar rates of growth would cluster together. But this largely is a presumption that requires further testing using Global spatial autocorrelation (Moran's I) statistics, Moran scatter plot (distribution of Moran's I), and Exploratory Spatial Data Analysis. However, the present testing of spatial autocorrelation is out of the scope of the present work. But this can certainly suggest why clustering is observed in the case of causality patterns in the case of Indian states.

The set of states can be well illustrated through a geographical map (see Figure 2) .

After finding out the states that show heterogeneous patterns of causality, which in our case are 8 in number, we move onto the second step of HENC hypothesis testing. In this, we jointly take up these 8 states and we test for no causality in them by restricting the nullity of the regression coefficient, i.e., $\beta_i^l = 0$ for them as a group. The results of this test are presented in Table 8 for both cases. The results pinpoint that the HENC hypothesis stands rejected, given the fact that calculated F statistics are greater than the critical value of F. Columns 2 and 3 of Table 9 prove that there does exist heterogeneous causality for the selected 8 states when they are studied as a single group.

Figure 2: Heterogeneous Causality Map of Indian States[6]



Source: Author's Presentation

Table 9: Tests of heterogeneous Non-Causality

Lags	GDP→Energy	NDP→Energy
1	57.90***	55.67***
2	37.72***	35.93***
3	16.66***	16.15***

*** 1 percent

[6] The map is required to be printed in coloured format. The states which show not computed direction of causality are actually the ones which are either bifurcated ones (Uttarakhand, Chhattisgarh, Jharkhand and Telangana) or are those which do not form part of the study due to data constraints namely the union territories.

Conclusion and Policy Implications

The present paper examined the causality behaviour between energy and economic growth by taking up 17 Indian states for the period 1991-2017. The variables of our interest are defined in multiple ways to arrive at robust results that are free from definition bias. Unlike the previous studies which focus on cointegration and conventional Granger causality techniques, the present research has made use of a novel technique that accounts for heterogeneity among the cross-sectional units which the conventional Granger process ignores.

The results can be summarized as follows:

The energy-led economic growth hypothesis is outrightly rejected in our case and even if the relationship holds it is homogeneous. This means the growth hypothesis as given in the literature stands completely rejected in our case because there is no evidence of causality running from energy to economic growth. Heterogeneous causality and non-causality tests for the causality running from growth to energy hold for 8 of the Indian states and the remaining 9 states show no heterogeneous causality. Given the nature of causality that holds in some states while not in other states, the results suggest that the Indian government needs to incorporate a regional perspective at the time of formulating energy policies rather than going in by single energy policy framed at the central level. For the states with strong causality running from economic growth to energy (Andhra Pradesh, Assam, Haryana, Jammu and Kashmir, Kerala, Punjab, Rajasthan, and West Bengal), which are 8 in number, these states can easily implement energy conservation policies to a greater extent without hurting their growth. The energy conservation policies will also correct the pollution problems to a greater extent. Also, it is easy to conserve energy rather than produce new energy by way of added electric power generation capacity.

Rather than a single hypothesis validating in the case of the entire panel, we see that multiple hypotheses suit different states of India. While for some it is a conservation hypothesis while for others it is a neutrality hypothesis. Bihar, Himachal Pradesh, Madhya Pradesh, Odisha, Tamil Nadu, and Uttar Pradesh show a lack of causality in the direction of growth to energy. This implies that here in these states, energy policies and economic growth are not intertwined with one another but are rather independent of each other.

Thus, heterogeneous causal patterns between economic growth and energy suggest that because Indian states differ on account of development, population, natural resources, consumption patterns, and many other factors, the causality patterns were likely to be different. Largely, it is suspected that states that derive their state income from the agriculture sector are the ones that favour a presence of significant causality from GDP to Energy, while the states whose economy is driven by the industrial sector or service sector are the majorly missing the link between GDP to energy.

In short, we can say that the one policy fits approach is what does not apply to India at the subnational level given the heterogeneous pattern of causality.

Though the present research unveils the heterogeneous pattern of causality it is not entirely free from limitations. The future course of research could be carried out by considering different energy sources. Also, disaggregate perspectives could be researched from a sectoral viewpoint as well. Thus, future research in this domain could emphasize these two points.

Appendix

A1. Energy Index

KMO and Bartlett Criteria

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	780.871
	df	1
	Sig	0.000

Eigenvalues and variance explained by the selected components after PCA

Component	Eigen Value	Variance	Cumulative
1	1.905	95.256	95.256
2	0.095	4.744	100.00

A2. Hurlin- Venet Process of Granger

$$\ln E_{it} = \sum_{l=1}^{n} \gamma^{l} E_{i,\,t-j} + \sum_{l=1}^{n} \beta_{i}^{l}{}_{\neq} \ln Y_{i,\,t-l} + u_{i,\,t}\,, \tag{1}$$

$$\ln Y_{it} = \sum_{l=1}^{n} \gamma^{l} Y_{i,\,t-j} + \sum_{l=1}^{n} \beta_{i}^{l} \ln E_{i,\,t-l} + u_{i,\,t}\,, \tag{2}$$

Homogeneous Non Causality

In this Homogeneous Non causality test, the null hypothesis states that for none of the cross sections there exists a causality relationship:

$$\text{For all } i,\ E(\ln E_{i,t} \mid \ln E_{i,\,t}, \alpha_i) = E(\ln E_{i,t} \mid \ln E_{i,\,t}, \ln Y_{i,t}, \alpha_i) \tag{3}$$

The Null and alternative hypothesis for HNC can be written as :

$$H_0\colon \beta_i^l = 0 \text{ for all } i \in [1, N] \text{ and for all } l \in [1, n] \tag{4}$$

$$H_1 = \beta_i^l \neq 0$$

The F statistic for the HNC test is given as

$$F_{HNC} = \frac{(RSS2 - RSS1)/Nl}{RSS1/[NT - N(1+l) - l]} \tag{5}$$

where RSS_2 is the sum of squared residuals which are obtained under H_0 and RSS_1 is the unrestricted sum of squared residuals. T is the number of periods, N is the number of cross-section units and l is the number of lags. If we reject the HNC hypothesis, we then proceed to test the homogeneous causality hypothesis.

Homogeneous Causality (HC)

The test of Homogeneous Causality implies that there are individual causality relationships:

$$\text{For all i, } E(\ln E_{i,t} \mid \ln E_{i,\,t}, \alpha_i) \neq E(\ln E_{i,t} \mid \ln E_{i,\,t}, \ln Y_{i,t}, \alpha_i) \tag{6}$$

The Null (H_0) and alternative (H_1) hypothesis for HC can be written as:

$$H_0\text{: } \beta_i^l = \beta^l \text{ for all i} \in [1, N] \text{ and for all l} \in [1, n] \tag{7}$$

$$H_1 = \beta_i^l \neq \beta_k^l$$

The F statistic for the HC test is given as

$$F_{HC} = \frac{(RSS3 - RSS1)/(N-1)n}{RSS1/[NT - N(1+2n) + n]} \tag{8}$$

where RSS_3 is the sum of squared residuals obtained when the restriction of homogeneity is imposed for each lag j of the coefficients associated with the variable $\ln Y_{i,\,t-1}$ (dependent variable of our interest). Rejection of the HC hypothesis means that the causality relationship does not hold for at least one cross-section in the panel and we then proceed to test the heterogeneous non-causality hypothesis.

Heterogeneous Non-Causality (HENC)

The test of Heterogeneous Non-Causality means testing the hypothesis that there is at least one and at most *N-1* equalities as follows:

$$\text{For all i, i} \in [1, N]\text{, } E(\ln E_{i,t} \mid \ln E_{i,\,t}, \alpha_i) \neq E(\ln E_{i,t} \mid \ln E_{i,\,t}, \ln Y_{i,t}, \alpha_i) \tag{9}$$

The Null (H_0) and alternative (H_1) hypothesis for HENC can be written as:

H_0: $\beta_i^l = 0$ for all i ϵ [1, N] and for all l ϵ [1, n]

H_l= $\beta_i^l \neq 0$ for all i ϵ [1, N] and for all l ϵ [1, n]

The F statistic for the HENC test is calculated in two steps as follows: First, we test the hypothesis. $\beta_i^l = 0$ for all $l\in[1, n]$ and compute the following set of F statistics:

$$F_{HENC}^{i} = \frac{(RSS2,i - RSS1)/n}{RSS1/[NT - N(1+2n)+n]} \tag{11}$$

where $RSS_{2,\,i}$ is the sum of squared residuals obtained from Eq. (1) when the homogeneity restriction $\beta_i^j = 0$ is imposed for all i and all $l\in[1, n]$. In this test the n coefficients attached to the variable $\ln Y_{i,\,t-1}$ are all equal to 0, i.e., they are excluded from Eq. (1). The n tests allow for testing individuals that exhibit no causality relationships.

The second step of the F test is a test of the joint hypothesis that there is no causality relationship for a subgroup of cross-sections. Denoting the subgroup that exhibits causal relationships as I_c and that does not as I_{nc}, the following model is run for all periods $t\in[1, T]$:

$$ln\ E_{it} = \sum_{l=1}^{n} \gamma^l E_{i,\,t-j} + \sum_{l=1}^{n} \beta_i^{\,l}\ ln\ Y_{i,\,t-l} + u_{\,i,\,t}, \tag{12}$$

$$u_{\,i,\,t} = \alpha_i + \varepsilon_{i,\,t} \text{ with } \beta_i^l = 0 \text{ for } i\in I_{nc} \text{ and } \beta_i^l \neq 0 \text{ for } i\in I_c$$

Denoting the dimensions of I_c and I_{nc} respectively as N_c and N_{nc}, the F statistic is then calculated as follows:

$$F_{HENC} = \frac{(RSS4 - RSS1)/Nnc\ n}{RSS1/[NT - N(1+n) - Ncn]} \tag{13}$$

where RSS_4 is the sum of squared residuals obtained when the restriction $\beta_i^l = 0$ is imposed for all $i\in I_{nc}$. If we fail to reject the HENC hypothesis, there is Granger causality from lnE to lnY only for a sub-sample of countries.

Heterogenous Causality (HEC)

This means that we are testing that there is at least one individual causality relationship and at most the number of cross-section units, N, and also that individual predictors are heterogeneous:

$$\exists i \ \epsilon\ [1, N],\ E(lnE_{i,t} \mid ln\ E_{i,\,t}, \alpha_i) \neq E\ (lnE_{i,t} \mid ln\ E_{i,\,t}, lnY_{i,t}, \alpha_i) \tag{14}$$

$$\exists (i,\ k)\ \epsilon\ [1, N],\ E(lnE_{i,t} \mid ln\ E_{i,\,t}, , lnY_{i,t}, \alpha_i) \neq E\ (lnE_{k,t} \mid ln\ E_{k,\,t}, lnY_{k,t}, \alpha_k)$$

A3: Manufacturing share across different points in time

Share of Manufacturing Sector of Indian states in NSDP (in percent)

States	1991	2001	2011	2017
Andhra Pradesh	18.55	12.06	11.67	9.68
Assam	9.81	9.05	9.85	13.61
Bihar	7.39	7.20	5.54	7.78
Gujarat	16.17	19.09	20.99	28.22
Haryana	19.87	20.05	16.42	17.72
Himachal Pradesh	6.76	18.02	23.01	27.55
Jammu & Kashmir	7.52	5.04	9.27	10.44
Karnataka	15.52	13.93	15.03	15.66
Kerala	11.05	12.65	9.14	9.62
Madhya Pradesh	12.60	12.82	10.51	9.67
Maharashtra	21.94	18.83	18.35	19.44
Odisha	18.31	22.82	16.02	14.63
Punjab	8.41	9.85	12.29	12.63
Rajasthan	9.32	12.05	14.39	9.95
Tamil Nadu	20.83	19.32	18.03	20.39
Uttar Pradesh	12.81	11.06	10.72	13.02
West Bengal	11.64	13.12	12.21	13.50

Source: Author's calculation using data from Central Statistical Organisation

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