PETROLEUM CONSUMPTION AND ECONOMIC GROWTH RELATIONSHIP: EVIDENCE FROM THE INDIAN STATES

*Seema Narayan, Thai-Ha Le, Badri Narayan Rath and Nadia Doytch**

This paper reveals that over the period 1985-2013, the wealthier states of India experienced a prevalence of the feedback hypothesis between real gross domestic product growth and petroleum consumption in the short run and the long run. Over the short term, the whole (major) 23 Indian state panels show support for the conservative hypothesis. Regarding the panels comprising low- and middle-income Indian states, although there appeared to be significant bidirectional effects in the long run, none of the results suggest that energy consumption increases economic growth. This implies that growth in energy demand can be controlled without harming economic growth. The results, however, indicate that for the low- and middle-income states, increases in petroleum consumption could adversely affect economic activity in the short and long run. These findings relate to the aggregate data on petroleum. Examining the short-run and long-run energy-growth linkages using disaggregated data on petroleum consumption reveals that only a few types of petroleum products have stable long-run relationships with economic growth. In fact, with disaggregated petroleum data, the vector error correction model (VECM) and cointegration results support the neutral hypothesis for high-incomes states. For the low- and middle-income groups, while the conservation effect is found to prevail in the short run and the long run, higher economic growth appears to reduce consumption of selected types of petroleum products.

JEL classification: O13, Q43, C33

Keywords: petroleum consumption, economic growth, feasible generalized least squares (FGLS), cross-sectional dependence, Indian states

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I. INTRODUCTION

Energy is an inseparable component of economic development. Among the different energy sources, such as coal, oil, natural gas, electricity, solar, wind and nuclear energy, oil continues to play a vital role in a country's economy, supporting, for example, transportation, industries, and households. In this regard, India is no exception, however, oil is the largest energy source of the country, accounting for 31 per cent of primary energy consumption. In 2018, oil consumption in India was 239.1 million tons oil equivalent, an increase of 5.3 per cent compared to the previous year, and represented a 5.1 per cent share of total world oil consumption (British Petroleum, 2019, p. 21). In terms of barrels per day, the country consumed 5,156,000 barrels per day (bpd), increased by 5.9 per cent compared to the previous year, and accounted for 5.2 per cent of world oil consumption in 2018, according to British Petroleum (2019). India was the third largest consumer of crude oil in the world during the year, only behind the United States of America (20,456,000 million bpd) and China (13,525,000 million bpd) in terms of consumption (British Petroleum, 2019).

According to Reuters, in 2017, India became the third largest net oil importer in the world, with imports averaging 4.37 million barrels per day (Verma, 2018). Because of its fast growing economy, energy demand in India rose rapidly over the years, in terms of per capita energy consumption and oil consumption. This is attributable to the increased affordability of oil (on the back of the drop in the price of oil) for a large section of its population who previously could not afford it, as is evident in the motorization of the Indian economy (Sen and Sen, 2016).

In per capita terms, however, oil consumption in India remains relatively low in comparison to the world's largest consuming economies and to other non-Organization for Economic Cooperation and Development (OECD) countries (Sen and Sen, 2016). Interestingly, even though the population of India is 1.3 billion, the country still lags other emerging market powerhouses in oil consumption per capita, giving it room for rapid growth. In September 2014, a policy initiative, the "Make in India" programme, was launched by Prime Minister Narendra Modi.[1] The objective of the programme is to put manufacturing at the heart of the country's growth model. A government target of increasing the manufacturing sector's share of gross domestic product (GDP) from approximately 15 per cent to 25 per cent by the beginning of the next decade can be expected to equate to a significant increase in demand for energy, and higher oil consumption in manufacturing (Sen and Sen, 2016). Also of note, a programme involving infrastructure construction (roads and national highways), which is being partly funded through revenue from higher taxation of oil and oil products, is likely to support oil demand growth in the country.

[1] For more information on "Make in India" scheme, see www.makeinindia.com/about.

Against this background, for this paper, we use state-wise petroleum consumption and economic growth data for 23 Indian states. Our study relates to the voluminous literature that examines the role of the energy consumption (E) and economic growth (Y) nexus in the cases of a single country and multiple countries (Akarca and Long, 1980; Asafu-Adjaye, 2000; Fang and Le, forthcoming; Kraft and Kraft, 1978; Le, 2016; Le and Nguyen, 2019; Le and Quah, 2018; Lee and Chang, 2005; Apergis and Payne, 2009a; 2019b; Narayan, Narayan and Popp, 2010a; 2010b; Narayan, 2016; Oh and Lee, 2004; Proops, 1984; Rafiq and Salim, 2009; Stern, 1993; and Yang, 2000). The E-Y nexus is governed by four hypotheses: the growth hypothesis; the conservation hypothesis; the feedback hypothesis; and the neutrality hypothesis.[2]

A number of recent studies have analysed the relationship of oil consumption and economic growth in India. The E-Y literature on India has been based on gas (Akhmat and Zaman, 2013); oil (Akhmat and Zaman, 2013); nuclear energy (Akhmat and Zaman, 2013; Wolde-Rufael, 2010); coal (Govindaraju and Tang, 2013); electricity (Abbas and Choudhury, 2013; Akhmat and Zaman, 2013; Cowan and others, 2014; Ghosh, 2002; Nain, Ahmad and Kamaiah, 2015) and aggregate energy consumption (Pao and Tsai, 2010; Vidyarthi, 2013; Yang and Zhao, 2014) (table 1).

As indicated earlier, we examine the state data for 23 states as a panel and also divide the states by income in order to account for some heterogeneity that arises as a result of income (see section II). As explained by the International Energy Agency (IEA) (2015, p. 21), "(t)he widespread differences between regions and states within India necessitate looking beyond national figures because of the country's size and heterogeneity, in terms of demographics, income levels and resource endowments, and also because of a federal structure that leaves many important responsibilities for energy with individual states." While our study is predominantly based on aggregate data, we also check the robustness of our findings using disaggregated petroleum data[3] and have found the disaggregated data to be informative and useful because of the importance of each petroleum product tends to vary across states.

Foreshadowing our key results, in the long run, we find evidence in favour of the feedback effect for the all states panel in addition to all the subpanels of states at different income levels. In the short run, we find that while the all states panel shows support for the conservative hypothesis, all income panels seem to show the presence of the feedback effect. Regarding the signs of the effects, however, we find that while petroleum consumption and economic growth are positively related for the high-income

[2] The growth hypothesis indicates that E causes Y; the conservation hypothesis indicates that Y causes E; the feedback hypothesis treats both E and Y as leading each other; and the neutrality hypothesis relates no linkage between E and Y.

[3] We are thankful to an anonymous reviewer for the suggestion of introducing disaggregated data in the study.

states in the short run and the long run, they can be negatively linked for the middle- and low-income states. The use of disaggregated petroleum products data in the analysis reveals that cointegration between petroleum products and income is missing for the high-income states and only present for selected petroleum products in the case of low- and middle-income states.

The remainder of the study is organized as follows. Section II includes a review of the related literature with a focus on India. Section III contains an explanation of the aggregate petroleum consumption and economic growth patterns for 23 Indian states. In section IV, the econometric methods and models used to examine the four hypotheses associated with the petroleum consumption-economic growth nexus are presented. Section V includes a discussion of the key findings relating to the aggregate data on petroleum consumption, while section VI presents the results derived using the disaggregated data on petroleum consumption. Section VII provides a discussion on the key findings and their implications relating to aggregate and disaggregated data on petroleum consumption. Section VIII concludes the study with policy implications.

II. LITERATURE REVIEW

A handful of studies have investigated the link between energy consumption and economic growth in India (Paul and Bhattacharya, 2004; Vidyarthi, 2013; Tiwari, Shahbaz and Hye, 2013; Shahbaz and others, 2016; Nain, Bharatam and Kamaiah, 2017). Paul and Bhattacharya (2004) find the prevalence of *the feedback hypothesis* for the Indian economy over the period 1950-1996, when energy consumption leads to economic growth in the short run and economic growth leads to higher energy consumption in the long run. Vidyarthi (2013) shows evidence of the feedback effect for electricity consumption, although the casual effects in the short run and the long run were different from Paul and Bhattacharya (2004) (see table 1). Nasreen and Anwar (2014) find that the feedback effect is prevalent in the short run and long run over the period 1983-2011. Tiwari, Shahbaz and Hye (2013) examine the Environmental Kuznets Curve (EKC) hypothesis of India using aggregate coal consumption and economic growth data along with carbon dioxide (CO_2) emissions. They find feedback hypothesis between economic growth and CO_2 emissions. The same interpretation is drawn between coal consumption and CO_2 emissions.

Abbas and Choudhury (2013) concur when looking at electricity consumption in India and agricultural GDP over the period 1972-2008. Some authors find evidence of a unidirectional relationship relating to *the growth hypothesis*, which suggests that energy consumption drives economic growth in the long run (Pao and Tsai, 2010) and in the short run (Yang and Zhao, 2014; Nain, Ahmad and Kamaiah, 2015). Akhmat and Zaman (2013) suggest a unilateral link for electricity and gas consumption in India in the long run. Wolde-Rufael (2010) shows the same linkage for nuclear energy in the long run. Other studies on India show evidence of *the conservative hypothesis*, or a unidirectional link flowing from economic growth to energy consumption, for different sources of energy: electricity consumption (Ghosh, 2002 (in the short run); Abbas and Choudhury, 2013 (in the short run and the long run)); nuclear energy in the long run (Akhmat and Zaman, 2013); and coal consumption in India in the short run (Govindaraju and Tang, 2013). Similarly, Shahbaz and others (2016) examine the relationship between globalization and energy consumption in India and have found acceleration of globalization results in a decline in energy consumption, but economic growth increases energy demand in the long run.

In the literature, we find that there is also evidence in favour of the *neutrality hypothesis* for India. Akhmat and Zaman (2013), for instance, find a relationship between fuel and oil consumption and economic growth over the period 1975-2009. Similarly, Govindaraju and Tang (2013) find evidence supporting the neutrality hypothesis in the case of coal in the long run for the period 1965-2009; and Cowan and others (2014) find this for electricity consumption over the period 1990-2010.

Almost all these studies come up with short-term and long-term inferences from Granger causality tests drawing on the vector autoregressive (VAR) model or the vector error correction model (VECM), depending on whether a cointegration relationship between non-stationary variables, E and Y, is established. The key variations are in the datasets in terms of panel or time series (aggregate or disaggregated), and sample periods; and the techniques (cointegration and causality tests) (see table 1). Naser (2015) finds that a long-run impact of oil is associated with nuclear energy consumption on economic growth in India, along with China, the Republic of Korea and the Russian Federation. Bildirici and Bakirtas (2014) argue that for China and India, this relationship is bidirectional.

Regarding the cointegration tests, several studies have used the time series Engle-Granger univariate cointegration approach (see, for instance, Paul and Bhattacharya, 2004); others have used the time series Johansen multivariate cointegration method (Paul and Bhattacharya, 2004). Furthermore, to address the issue of a small sample, some authors use the autoregressive distributed lag (ARDL) bounds test (such as Nain, Bharatam and Kamaiah, 2017); others have tackled the small sample problem by including more countries in the study. This gives them the benefit of taking advantage of a larger dataset and using panel-based cointegration methods, such as the Pedroni (1999; 2004) cointegration test, the Kao (1999) test, or the Johansen/Fisher test, to derive results from a larger dataset (Nasreen and Anwar, 2014; Pao and Tsai, 2010). Instead of applying the standard Granger causality test, Kónya (2006) employs the bootstrap panel causality approach to allow for cross-section dependence and heterogeneity within the panel. Yang and Zhao (2014), in place of the usual in-sample Granger causality tests, apply an out-of-sample Granger causality test to better gauge the out-of-sample forecasting performance of models. Wolde-Rufael (2010)

Table 1. A summary of recent literature on Indian energy consumption and economic growth

Study	Sample	Data	Technique	Variables	Result
Paul and Bhattacharya (2004)	1950-1996	Time series	Engle-Granger cointegration and Granger causality; Johansen multivariate cointegration	Energy consumption; GDP; gross capital formation; population	LR: Y-> E; SR: E-> Y
Nasreen and Anwar (2014)	1980-2011	Panel data: 15 Asian countries	Pedroni conintegration	Energy consumption, PGDP; trade openness; energy prices	LR and SR: E<->Y
Tiwari (2011)	1970-2007	Time series	Granger causality (VAR); Dolado and Lütkepohl approach		LR: Y->E
Energy consumption with carbon emissions and other variables					
Pao and Tsai (2010)	1971-2005	Panel including BRIC nations (Brazil, Russian Federation, India and China)	Kao, Johansen/Fisher; Pedroni cointegration; Granger causality	Energy consumption; real GDP; carbon emissions	LR: E->Y
Yang and Zhao (2014)	1970-2008	Time series/aggregate	Out-of-sample Granger causality tests and directed acyclic graphs (DAG)	Energy consumption; real GDP; carbon emissions; trade openness	SR: E-> Y and CO2; trade openness->E
Vidyarthi (2013)	1971-2009	Time series/aggregate	Johansen approach; Granger causality	Energy consumption; real GDP; carbon emissions	LR:E->Y; SR: Y->E

Table 1. *(continued)*

Study	Sample	Data	Technique	Variables	Result
Ahmad and others (2016)	1971-2014	Time series/aggregate	ARDL (autoregressive distributed lag bounds)	Total energy, gas, oil, electricity and coal consumption; RGDP; carbon emissions	E-> CO2; Y<-> CO2
Electricity					
Abbas and Choudhury (2013)	1972-2008	Time series – aggregate - GDP and per capita GDP (PGDP); and disaggregate - agriculture GDP (AGDP)	Johansen approach	Electricity consumption and GDP; PGDP; AGDP	Aggregate: GDP - LR: Y-> E; SR: Y-> E; PGDP - LR: E ≠Y; SR: Y->E. Disaggregate: AGDP - LR: Y<->E; SR: Y<->E
Akhmat and Zaman (2013)	1975-2010	Time series – aggregate - GDP and per capita GDP (PGDP); and disaggregate - agriculture GDP (AGDP)	Granger causality (VAR)	Electricity, PGDP growth	LR: E->Y
Ghosh (2002)	1950-1997	Time series/aggregate	Engle and Granger (1987); Granger causality	Electricity consumption and economic growth (per capita)	LR: Y->E
Cowan and others (2014)	1990-2010	Panel – BRICS/ aggregate	Bootstrap panel causality approach; Kónya (2006)	Electricity, GDP growth, CO2	LR: E ≠Y

Table 1. *(continued)*

Study	Sample	Data	Technique	Variables	Result
Nain, Ahmad and Kamaiah (2015)	1971-2011	Time series/aggregate and disaggregate: sectoral	ARDL bounds test; Toda and Yamamoto (1995)	Sectoral and aggregate electricity consumption; RGDP	Aggregate - LR: E ≠ Y; SR: E->Y; disaggregate: agriculture - E ≠ Y; industrial - LR: E ≠ Y; SR: E->Y; domestic and commercial - LR and SR: Y->E
Coal					
Govindaraju and Tang (2013)	1965-2009	Time series/aggregate	Bayer and Hanck (2009) cointegration test; Granger causality	Coal consumption; real GDP per capita	LR: E ≠ Y; SR: Y->E
Nuclear energy					
Akhmat and Zaman (2013)	1975-2010	Time series/aggregate - PRGDP; and disaggregate - agriculture GDP (AGDP)	Granger causality	Coal consumption; real GDP per capita	LR: Y->E
Wolde-Rufael (2010)	1969-2006	Time series/aggregate	ARDL bounds tests; Toda and Yamamoto (1995)	Nuclear energy; RGDP per capita; real gross fixed capital formation	LR: E->Y

Table 1. *(continued)*

Study	Sample	Data	Technique	Variables	Result
Oil					
Akhmat and Zaman (2013)	1975-2010	Time series/aggregate - per capita GDP (PGDP); and disaggregate - agriculture GDP (AGDP)	Granger causality	Oil consumption	LR: Y ≠ E
Gas					
Akhmat and Zaman (2013)	1975-2010	Time series/aggregate - per capita GDP (PGDP); and disaggregate - agriculture GDP (AGDP)	Granger causality	Gas consumption	LR: E->Y
Combination of different energy sources					
Bildirici and Bakirtas (2014)	1980-2011	Time series/aggregate	ARDL (autoregressive distributed lag bounds)	Coal, natural gas and oil consumption; RGDP	LR: E<->Y (for coal and oil)
Naser (2015)	1965-2010	Time series/aggregate	Johansen cointegration technique	Oil consumption, nuclear consumption; RGDP	LR: E->Y

Notes: E, energy consumption; Y, economic growth; GDP, gross domestic product; PGDP, per capita gross domestic product; RGDP, real gross domestic product; LR, long run; SR, short run.

apply the multivariate Toda and Yamamoto (1995) approach, which is often employed in the case of a small sample.

A sectoral perspective on the manufacturing sector of India suggests that the three dominant and highly energy-intensive manufacturing industries are steel, aluminium and cement. Dutta and Mukherjee (2010) suggest that unless these sectors innovate in the way they are using energy, India will lose global competitiveness in related industries.

Innovation in the energy sector of India is also necessary because of the impact of oil and gas energy consumption on CO2 emissions. Ahmad and others (2016) find that energy consumption from oil and gas, electricity and coal consumption contributes to carbon emissions in India. The question of energy consumption in the country as a determinant of growth is inevitably intertwined with the issue of raising CO2 emissions. A series of papers that examine various scenarios for future energy consumption indicate that none of the traditional sources of energy, oil, gas, coal, hydrocarbon, nuclear, hydrogen, hydro and renewables, will be sufficient to meet the future energy demands and that India would have to rely on imports for a significant portion of its energy supply (Parikh and others, 2009; Parikh and Parikh, 2011). At the same time, the most feasible scenario for CO2 emissions reduction is to cut energy demand and boost energy efficiency in production and consumption. That would make it possible to meet environmental conservation goals without compromising on economic development and future growth (Parikh and Parikh, 2011).

While the overall energy consumption of the country is estimated to rise sharply in the next decade, energy inequalities in the country are rampant. Saxena and Bhattacharya (2018) examine the role of caste, tribe, and religion as determinants of energy inequality in India. Using data at the household level for 2011-2012, the authors estimate the energy inequalities stemming from differential access to liquid petroleum gas and electricity, focusing on disadvantaged groups, such as castes, tribes, and religious denominations, and find that these factors are relevant to energy access. Even though the above-mentioned social inequalities in energy access exist, residential energy consumption in India is expected to quadruple in the next decade because of lifestyle changes related to the county’s recent economic growth (Bhattacharyya, 2015). Urbanization, a fast-growing middle class and western-style consumerism are factors behind the expected overbearing residential energy consumption expansion in the near future. A large part of the energy supply burden on liquefied petroleum gas is expected to fall (Bhattacharyya, 2015). This makes the unveiling of the link between petroleum consumption and economic growth in the context of India even more pressing.

The expected rapid growth in energy consumption, in conjunction with the above described energy inequalities and contribution to carbon emissions, make India a prime candidate for the development of renewable energy technologies (Singh, 2018). In addition to coping with the energy deficits, transitioning to renewables would reduce the exposure of India to variations in the price of crude oil. A recent study by Mallick, Mahalik and Sahoo (2018) finds that crude oil price reduces significantly private investment, whereas economic growth and globalization tend to boost it. Economic growth and urbanization are the key factors pushing energy demand higher in the long run, Shahbaz and others (2016) argue that transitioning to renewables would allow for supporting raising energy demand without the negative side effects on pollution and of energy access inequality in India.

III. DATA

Our study covers 23 Indian states,[4] which in total encompasses approximately 95 per cent of the national area. We collected the petroleum consumption and its by-products consumption data for the states from the States of India database, a comprehensive compilation of state-level statistics published by the Centre for Monitoring Indian Economy. The only problem with this is related to the state-wise population data for each year spanning from 1985/86 to 2013/14. The petroleum product-wise data referred to in each state over the sample period are available in the absolute value (in thousand tonnes). Therefore, in order to convert the data to per capita term, we have collected state-wise population data from the Economic and Political Weekly Research Foundation database for the same period and then divided the aggregate petroleum consumption and the various by-products by the population for each state. Furthermore, we note that this is an unbalanced panel data, as there are missing observations for a number of states. All of the per capita variables (petroleum products and the by-products consumption) that we converted are in kilograms. For the by-products of the petroleum data not available for some states for different years, the per capita term becomes zero for those observations.

State-wise income per capita is defined as real per capita net state domestic product at factor cost data, with a base year of 2004/05 and is sourced from the Reserve Bank of India.[5] We divided these 23 states into three panels based on their level of income. For this classification, we calculated the average per capita income of each state over the study period 1985-2013 and categorized the states by high, middle, and low income, presented in table 2.[6]

[4] Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Delhi, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Nagaland, Odisha, Punjab, Rajasthan, Tamil Nadu, Tripura, Uttar Pradesh, and West Bengal.

[5] Real gross domestic product (RGDP) data are extracted from Indiastat. Available at Indiastat.com.

[6] Our classification of the Indian states by income closely follows Narayan, Rath and Narayan (2012) for at least 15 states.

Table 2. Panels by income

	High-income states	Middle-income states	Low-income states
States	Delhi, Gujarat, Haryana, Maharashtra, Punjab, Tamil Nadu	Andhra Pradesh, Arunachal Pradesh, Himachal Pradesh, Jammu and Kashmir, Karnataka, Kerala, Nagaland, Tripura, West Bengal	Assam, Bihar, Madhya Pradesh, Manipur, Meghalaya, Odisha, Rajasthan, Uttar Pradesh,

The preliminary observations indicate a strong positive correlation between income and energy consumption, at least in the average data in per capita terms. In table 3, we display the average per capita income and per capita energy consumption. Note that for the high-income states, which are also the most industrially developed ones (Delhi, Gujarat, Haryana, Maharashtra, Punjab, and Tamil Nadu) the average per capita income is 36,997 Indian rupee (Rs) (US$537) and their average petroleum consumption stands at 173 kg of oil equivalent per capita, which is also the highest. The middle-income states (Andhra Pradesh, Arunachal Pradesh, Himachal Pradesh, Jammu and Kashmir, Karnataka, Kerala, Nagaland, Tripura, and West Bengal) have an average per capita income of Rs24,451 and petroleum consumption is the second largest on average at 71.2 kg of oil equivalent per capita. The low-income states (Assam, Bihar, Madhya Pradesh, Manipur, Meghalaya, Odisha, Rajasthan, and Uttar Pradesh) on average show a per capita income of Rs15,281 and consume the least amount of petroleum

Table 3. Descriptive statistics

	All states		High-income states		Middle-income states		Low-income states	
	PEC	PRGDP	PEC	PRGDP	PEC	PRGDP	PEC	PRGDP
Mean	92.4	24 534.1	173.1	36 996.8	71.2	24 450.8	55.7	15 280.8
Median	70.7	20 711.0	159.6	30 808.2	62.3	22 376.9	48.8	14 333.0
Maximum	399.3	118 411.0	399.3	118 411.0	189.5	58 961.0	159.3	37 154.0
Minimum	18.8	2 728.0	72.8	12 736.7	18.8	8 275.4	24.4	2 728.0
Std. dev.	63.6	15 109.5	63.0	19 815.8	33.1	10 456.4	26.1	6 170.1
Skewness	1.5	2.1	0.9	1.6	0.8	0.9	1.9	0.5
Kurtosis	5.5	10.3	3.8	6.2	3.3	3.3	7.0	3.9
Jarque-Bera	437.5*	1 984.9*	29.2*	150.0*	30.9*	35.4*	295.8*	17.8*
Observations	667	667	174	174	261	261	232	232

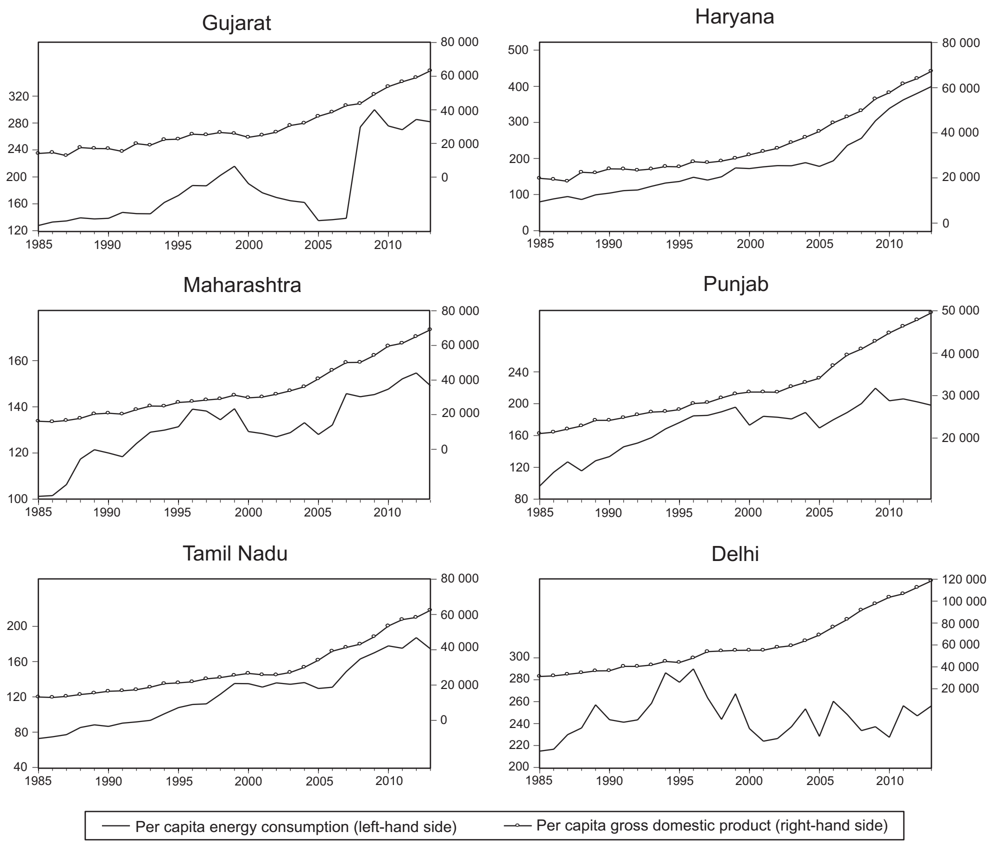
Notes: *Normality is rejected at the 1 per cent level. The mean values of the per capita real GDP (PRGDP) are in Indian rupees while petroleum is measured in terms kg per capita; PEC, per capita energy consumption.

(56 kg of oil equivalent per capita) in comparison to the other two income groups (see figure 1).

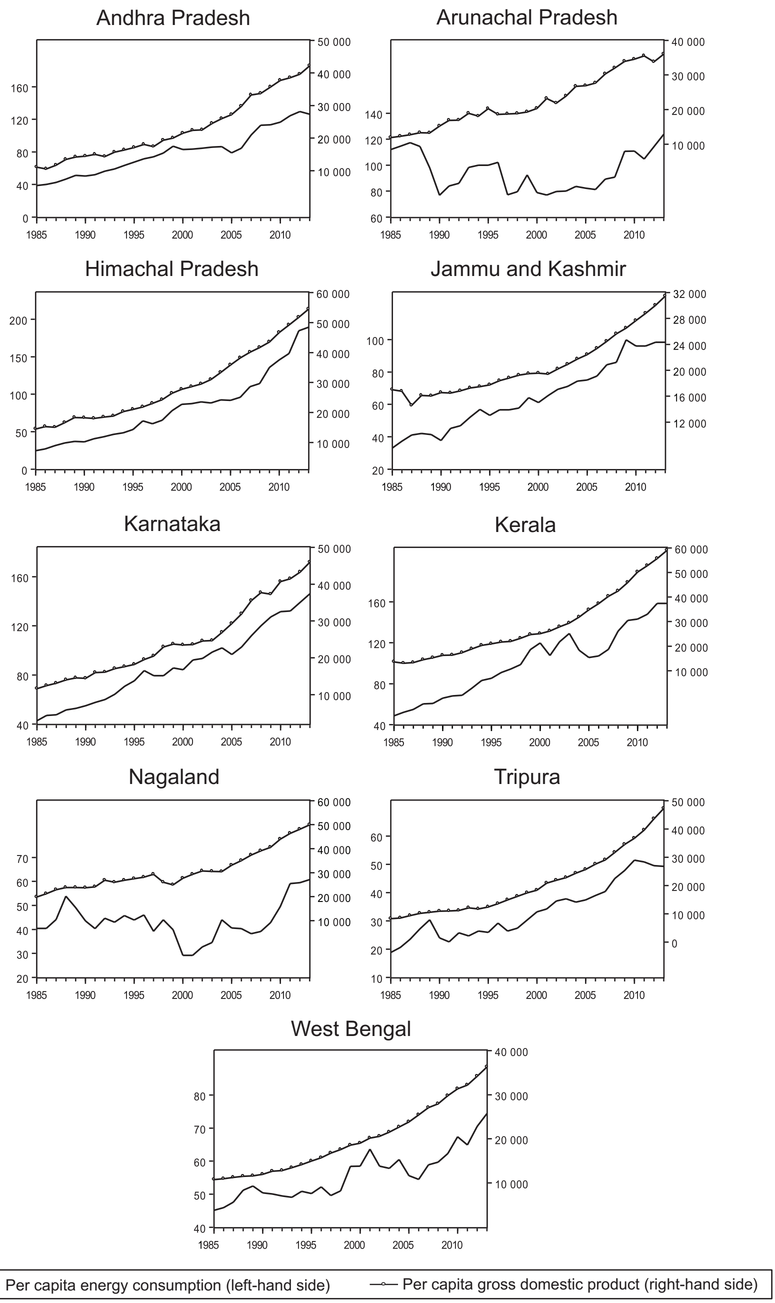
In the figure, we display energy consumption and real gross domestic product (RGDP) in per capita terms. For the high-income states (with the exception of Delhi), per capita RGDP is closely tracked by petroleum consumption per capita and thus this relationship seems to be positive. We find a similar pattern for middle- and low-income panels, with the exception of a few states. For instance, for the middle-income states, including Arunachal Pradesh, Nagaland, Kerala, and West Bengal, and more recently Jammu and Kashmir, the plots show a decline in petroleum consumption amid steady growth in income per capita. Of the low-income states, for Bihar, an agriculture-based state and the third largest in terms of population, a significant decline in petroleum consumption per capita in the 2000s is shown even though per capita income has been increasing steadily. For other low-income states, including Assam, Madhya Pradesh, Manipur, and Uttar Pradesh, similar relationships are shown on a year-to-year basis, although the long-term trend is upward.

Figure 1. Per capita energy consumption and real gross domestic product by state

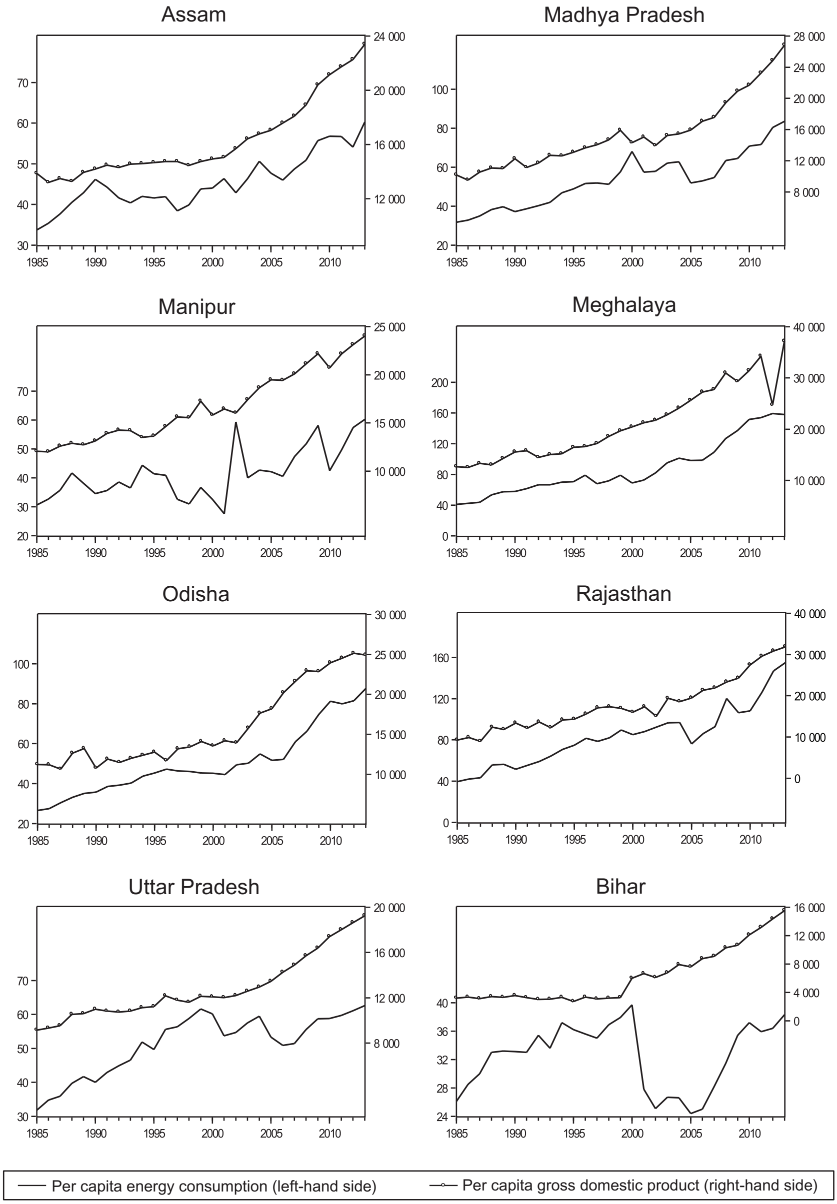
High-income states



Middle-income states



Low-income states



IV. EMPIRICAL METHODS

Our models for long-run inferences are as follows:

$$LPEC_{i,t} = \alpha_{1i} + \delta_{1i}t + \beta_1 LPGDP_{i,t} + \varepsilon_{1,it} \quad (1)$$

$$LPGDP_{i,t} = \alpha_2 + \beta_2 LPEC_{i,t} + \varepsilon_{2,it} \quad (2)$$

where i = 1,...,N for each country in the panel and t = 1,...,T refers to the time period. The parameters αi and δi allow for country-specific fixed effects and deterministic trends, respectively. Deviations from the long-run equilibrium relationship are represented by the estimated residuals, ε_{it}, LPEC and LPGDP are petroleum consumption per capita and economic growth per capita, respectively, expressed in log form.

Our estimation of short-run models consists of two steps. The first step relates to the estimation of the residual from the long-run relationship as in equations (1) and (2). Incorporating the residual as a right-hand side variable, the short-run error correction model is estimated at the second step. We then get the dynamic error correction model of our interest for estimation. Specifically, causality (short-run) inferences are made by estimating the parameters of the following VECM equations.

$$DLPEC = \alpha_3 + \sum_{K=1}^{m} \beta_{31k} DLPEC_{t-k} + \sum_{K=1}^{m} \beta_{32k} DLPGDP_{t-k} + \beta_{33} Z_{3,t-1} + \varepsilon_{3,it} \quad (3)$$

$$DLPGDP = \alpha_4 + \sum_{K=1}^{m} \beta_{41k} DLPEC_{t-k} + \sum_{K=1}^{m} \beta_{42k} DLPGDP_{t-k} + \beta_{43} Z_{4,t-1} + \varepsilon_{4,it} \quad (4)$$

where *DLPEC* and *DLPGDP* denote petroleum consumption per capita and economic growth per capita, expressed in log-first-difference form and $Z_{3,t-1}$ and $Z_{4,t-1}$ are the error correction terms which are the lagged residual series of the cointegrating vector (1) and (2), respectively.

From equation (4), the null hypothesis that LPEC does not Granger-cause LPGDP is rejected, therefore supporting the growth hypothesis, if the set of estimated coefficients on the lagged values of LPEC is jointly significant. Furthermore, in instances where LPEC appears in the cointegrating relationship, the growth hypothesis is also supported if the coefficient of the lagged error correction term is significant. Changes in an independent variable may be interpreted as representing the short-run causal impact, while the error correction term provides the adjustment of LPEC and LPGDP towards their respective long-run equilibrium. The vector error correction model (VECM) representation, therefore, allows us to differentiate between the short- and long-run dynamic relationships.

Models (1), (2), (3) and (4) are estimated using the feasible generalized least squares (FGLS). In cross-sectional analysis, the error variance is likely to vary across the groups affecting the consistency of the estimators. Using the generalized least squares (GLS) method in the estimation could solve this issue. The proposed analysis nested within the GLS model can be stated as the following:

$$Y_{it} = \alpha + X'_{it}\beta + \delta_i + \gamma_i + \varepsilon_{it} \quad (5)$$

where $i = \overline{1,N}$, $t = \overline{1,T}$, Y is a dependent variable (*LPEC* or *LRGDP*), α is a constant, X is a vector of explanatory variables, β represents a vector of coefficients to be estimated, ε_{it} represents the residual terms, δ_i and γ_i are the cross-section and, respectively period fixed or random effects, the GLS estimator is based on the following moments:

$$g(\beta) = \sum_{i=1}^{M} g_i(\beta) = \sum_{i=1}^{M} Z'_i \hat{\Omega}^{-1} \varepsilon_i(\beta) \quad (6)$$

where Z'_i is the instrument matrix for the i-th cross-section, $\varepsilon_i(\beta) = (Y_{it} - \alpha - X'_{it}\beta)$ and $\hat{\Omega}$ is a consistent estimation of the variance-covariance matrix Ω. In cross-sectional analysis, the error variance may vary across the groups, affecting the consistency of the estimators. GLS in the estimation can solve this issue, although other sources of variance variability may still exist.

To explore the FGLS model with the best fitted error process for the data, we test for heteroskedasticity using the modified Wald test proposed by Greene (2008). This has a null hypothesis in that there is homoskedasticity in the error term. The results reported in table 4 confirm the rejection of this null hypothesis at a 1 per cent significance level

Table 4. Evidence of heteroskedasticity

DPEC = f(DPGDP)						
Test name	Error process	Test statistic	(1) All states	(2) High-income states	(3) Middle-income states	(4) Low-income states
Modified	Heteroskedasticity	Chi(2)	720.92***	194.01***	115.84***	378.32***
DPGDP = f(DPEC)						
Test name	Error process	Test statistic	(1) All states	(2) High-income states	(3) Middle-income states	(4) Low-income states
Modified	Heteroskedasticity	Chi(2)	5 942.32***	531.06***	506.85***	1 680.17***

Notes: The modified Wald statistic for group-wise heteroskedasticity in the residuals of a fixed effect model is calculated following Greene (2008, p. 598). The most likely deviation from homoskedastic errors in the context of pooled cross-section time-series data (or panel data) is likely to be error variances specific to the cross-sectional unit. xttest3 tests the hypothesis that H_0: sigma(i)^2 = sigma^2 for all i, N_g, where N_g is the number of cross-sectional units. The resulting test statistic is distributed Chi-squared(N_g) under the null hypothesis of homoskedasticity. ***, ** and * indicate rejection of the null hypothesis at 1 per cent, 5 per cent and 10 per cent significance levels.

for all the panels, including those with the dependent variables as petroleum consumption per capita (PEC) and as economic growth per capita (PGDP).

Next, we apply the Pesaran (2004) test that examines the null hypothesis of cross-sectional independence for the PEC and PGDP models (Pesaran, Ullah and Yamagata, 2008). We present the cross-sectional dependence statistics for the PEC and PGDP models, respectively, in panels 1 and 2 in table 5. The hypothesis that the innovations relating to energy consumption or economic growth equations are cross-sectionally independent is rejected for all panels. Not surprisingly, the all states panel shows the greatest cross-sectional dependence. This is followed by the middle-income states in panel 1 and high-income states in panel 2. On the basis of this result, we proceed to use the FGLS model with an error process that assumes heteroskedasticity and panels that are cross-sectionally dependent. The econometric models were estimated using Stata.

Table 5. Evidence of cross-sectional dependence

Pesaran (2004)	Statistic	p-value
Panel 1: DPEC = f(DPGDP)		
All states	80.02***	0.0007
High-income states	18.81***	0.0004
Middle-income states	31.61**	0.0253
Low-income states	29.4***	0.0000
Panel 2: DPGDP = f(DPEC)		
All states	27.59***	0.0007
High-income states	15.26***	0.0004
Middle-income states	3.496**	0.0253
Low-income states	2.468***	0.0000

Notes: The Pesaran (2004) test was applied for the cross-sectional dependence (also see Pesaran, Ullah and Yamagata, 2008). H_0: cross-sectional independence. ***, ** and * indicate rejection of the null hypothesis at 1 per cent, 5 per cent and 10 per cent significance levels.

V. EMPIRICAL RESULTS

Panel unit root and cointegration tests and the vector error correction model

The panel unit root tests, namely, Im, Pesaran and Shin (2003); Levin, Lin and Chu (2002); and panel augmented Dickey-Fuller (ADF) (Maddala and Wu, 1999) are performed. These tests have the common null hypothesis of unit root. The test results are presented in table 6. Petroleum consumption per capita (PEC) and economic growth per capita (PGDP), expressed in log form, are integrated of order 1. This applies to all the panels.

Table 6. Unit root test results

	All states		High-income states		Middle-income states		Low-income states	
PEC	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
LLC - t*	-1.671	-14.369*	-0.845	-6.594*	-1.185	-9.315*	-0.839	-8.764*
	0.047	0.000	0.199	0.000	0.118	0.000	0.201	0.000
IPS - W-stat.	1.490	-13.390*	-0.248	-6.325*	1.592	-8.557*	1.052	-8.151*
	0.932	0.000	0.402	0.000	0.944	0.000	0.854	0.000
ADF - Fisher Chi-square	32.208	254.551*	15.555	60.761*	7.449	101.843*	9.204	91.948*
	0.939	0.000	0.213	0.000	0.986	0.000	0.905	0.000
PGDP	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
LLC - t*	5.750	-10.385*	2.856	-4.699*	3.749	-9.610*	4.351	-2.741*
	1.000	0.000	0.998	0.000	1.000	0.000	1.000	0.003
IPS - W-stat.	11.652	-12.868*	6.024	-6.121*	7.359	-9.071*	6.736	-6.896*
	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
ADF - Fisher Chi-square	1.550	245.771*	0.183	59.088*	0.847	108.921*	0.520	77.762*
	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000

Notes: The table covers the Im-Pesaran-Shin (IPS) (Im, Pesaran and Shin, 2003); Levin-Lin-Chu (LLC) (Levin, Lin and Chu, 2002); and augmented Dickey-Fuller (ADF) (Maddala and Wu, 1999) test results. * suggests statistical significance at 1 per cent level. PEC is the petroleum consumption in kilogram of oil equivalent per capita; PGDP is the real per capita net state domestic product at factor cost data with a base year of 2004/05.

As the panels comprise I(1) variables, they all are fit for three panel cointegration tests: Kao (1999), Pedroni (1999; 2004), and the Fisher type-test from Maddala and Wu (1999). The test of Pedroni (1999; 2004) is a panel cointegration test that extends the Engle and Granger method to a system of multivariate independent variables for homogeneous and heterogeneous properties across individuals for the panel data. The Kao (1999) test is a residual-based panel test that applies the Dickey-Fuller and augmented Dickey-Fuller type tests and considers homogeneous properties across individuals. The Kao (1999) test focuses on both strict endogenous regressors and strict exogenous regressors.

The Pedroni tests, unlike those of Kao, allow for heterogeneity among individual units of the panel and no exogeneity requirements are imposed on the regressors in the cointegrating regressions. The Maddala and Wu (1999) test is a different method that applies the combination test from Fisher (1932) to derive the test statistics for panel estimation. The combination statistic is constructed from various individual statistics, this combination statistic follows the Chi-square distribution rule, in which individual test statistic is computed by Johansen (1988).

Of these tests, the Pedroni (1999; 2004) test allows for cross-sectional dependence. Such test uses the fully modified ordinary least squares (FMOLS) estimator that deals with possible autocorrelation and heteroskedasticity of the residuals, taking into account the presence of nuisance parameters, which is asymptotically unbiased and deals with potential endogeneity of regressors. As our panel is burdened by all these three problems, we take this as the superior test of cointegration.

The results from the three cointegration tests are captured in table 7, panels 1-3. Pedroni test results (panel 1) suggest at least one cointegrating relationship for all panels. When compared against the Kao and Fisher test results, we find that the results for all Indian states and the middle- and low-income states are the same.[7]

The relationship between petroleum and economic growth within the long-run models and vector error correction models (VECMs)

Next, we estimate the long-run models and VECMs for the all states and income-based panels. This approach differs from the literature on the long run and VECM in that we estimate the long run and VECM nested within the FGLS model relating to petroleum consumption and economic growth. The long-run results are presented in table 8. The influence of income on petroleum consumption on per capita is examined in panel 1 and the impact of petroleum consumption on per capita real income is examined in panel 2. In the long run, we see signs of a feedback effect for the Indian states at the higher end of the income spectrum. In this regard, our findings are consistent with only two out of 16 studies on energy-economic growth that support the feedback hypothesis.

Per capita real income is found to have a positive and significant influence on petroleum consumption for all the states in the long run (table 8, panel 1). Petroleum consumption positively affects per capita income of the high-income states (table 8, panel 2). However, for the all states panel, and the middle- and low-income Indian states, we find that petroleum consumption reduces per capita real income in the long run. Hence, while the bilateral link exists between the two variables, it is clear that we fail to find evidence on the feedback hypothesis in its true form.

[7] Before the estimation, we conduct the Di Iorio and Fachin (2007) test for breaks in cointegrated panels to examine the stability of the relationship between our variables of interest. The results support the acceptance of the null hypothesis of no break. That is, the relationship among the investigated variables is stable and not subject to structural breaks during the investigation period. The results are not presented here to conserve space, but they are available upon request.

Table 7. Cointegration results

	All states		High-income states		Middle-income states		Low-income states	
Panel 1: Pedroni residual cointegration test	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Panel v	4.242*	0.000	2.665*	0.004	2.347*	0.010	2.431*	0.008
Panel rho	-4.905*	0.000	-2.099*	0.018	-1.723*	0.043	-4.251*	0.000
Panel PP	-5.616*	0.000	-2.274*	0.012	-2.091*	0.018	-4.734*	0.000
Panel ADF	-3.393*	0.000	-1.898*	0.029	-1.987*	0.023	-2.070*	0.019
	W. Stat.	Prob.	W. Stat.	Prob.	W. Stat.	Prob.	W. Stat.	Prob.
Panel v	3.686*	0.000	2.080*	0.019	2.596*	0.005	1.754*	0.040
Panel rho	-4.173*	0.000	-1.841*	0.033	-2.077*	0.019	-3.178*	0.001
Panel PP	-5.389*	0.000	-2.341*	0.010	-2.648*	0.004	-4.147*	0.000
Panel ADF	-3.476*	0.000	-1.590*	0.056	-2.531*	0.006	-1.866*	0.031
	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Group rho	-2.056*	0.020	-0.621*	0.267	-0.577	0.282	-2.336*	0.010
Group PP	-4.940*	0.000	-1.942*	0.026	-2.215*	0.013	-4.344*	0.000
Group ADF	-3.070*	0.001	-1.087	0.138	-2.083*	0.019	-2.054*	0.020
Panel 2: Kao residual cointegration test	t-Stat.	Prob.	t-Stat.	Prob.	t-Stat.	Prob.	t-Stat.	Prob.
ADF	-1.643*	0.050	-0.327	0.372	-2.579*	0.005	-0.262	0.397
Panel 3: Fisher statistics	Trace test	Prob.	Trace test	Prob.	Trace test	Prob.	Trace test	Prob.
None	87.130*	0.000	15.740	0.204	34.450*	0.011	36.950*	0.002
At most 1	53.890	0.198	12.990	0.370	21.160	0.271	19.740	0.232
	Max-eigen test	Prob.	Max-eigen test	Prob.	Max-eigen test	Prob.	Max-eigen test	Prob.
None	81.740*	0.001	15.320	0.225	32.050*	0.022	34.360*	0.005
At most 1	53.890	0.198	12.990	0.370	21.160	0.271	19.740	0.232

Notes: The table presents the results from three cointegration tests: Pedroni, Kao, and Fisher. For the Pedroni test, the first eight statistics refer to homogenous test – the alternative hypothesis: common AR coefficients (within-dimension) while the last three statistics refer to heterogeneous test with the alternative hypothesis: individual AR coefficients (between-dimension). * suggests statistical significance at the 1 per cent level.

Table 8. Long-run models

	(1) All states	(2) High-income states	(4) Middle-income states	(5) Low-income states
Panel 1: *LPEC = f(LPGDP)*				
LPGDP	0.812***	0.556***	0.650***	0.550***
	(0.028)	(0.036)	(0.057)	(0.038)
Observations	667	174	261	232
Number of crossid	23	6	9	8
Panel 2: *LPGDP = f(LPEC)*				
LPEC	-0.682***	1.030***	-0.511***	-0.867***
	(0.024)	(0.067)	(0.045)	(0.06)
Observations	667	174	261	232
Number of crossid	23	6	9	8

Notes: Using the feasible generalized least squares (FGLS) methodology, we estimate the long-run relationship between petroleum consumption and economic growth. Standard errors are reported in the parentheses. ***, ** and * indicate rejection of the null hypothesis at 1 per cent, 5 per cent and 10 per cent significance levels.

Next, we report the results on VECMs selected using the usual selection criteria between models with one to six lags. The VECM results relating to per capita petroleum consumption and economic growth models are presented, respectively, in tables 8 and 9.

The key findings are as follows. First, the error correction model (ECM) has the expected negative sign and is significant for all the models with petroleum consumption (or economic growth) as the dependent variable. The implications are twofold. First, there is a two-way long-run relationship, or a feedback effect, between economic growth and petroleum consumption, as suggested by the preliminary observations. Second, after a shock related to economic growth (petroleum consumption), petroleum consumption (economic growth) bounces back towards equilibrium.

Furthermore, the VECM results point towards a bidirectional association between economic growth and petroleum consumption in the short run for all the panels, except the all states panel. For the high-income Indian states, the feedback hypothesis in its true form is found for the short run as well. This implies that higher petroleum consumption predicts higher economic growth, and in return past economic growth encourages petroleum consumption in the following year. However, for the middle-income states, while a previous year's economic growth is a precursor for a positive change in petroleum consumption in the following year, a previous year's increase in petroleum consumption does not mean higher economic growth in the following year.

Table 9. State-wise economic growth and petroleum consumption: feasible generalized least squares (FGLS) results

Variables	Dependent variable:				Dependent variable:			
	(1) All States	(2) High-income States	(3) Middle-income States	(4) Low-income States	(1) All States	(2) High-income States	(3) Middle-income States	(4) Low-income States
$DLPGDP_{t-1}$	**-0.0471**	**0.0348*** **	**0.366*** **	**-0.140**	-0.187***	-0.244**	-0.00776	-0.295***
	(0.0665)	**(0.0114)**	**(0.121)**	**(0.0893)**	(0.0440)	(0.0774)	(0.0634)	(0.0707)
$DLPGDP_{t-2}$	**-0.0217**			**-0.234** **	0.121***			0.0828
	(0.0683)			**(0.0953)**	(0.0453)			(0.0760)
$DLPGDP_{t-3}$	**0.245*** **			**0.120**	0.0457			0.0567
	(0.0650)			**(0.0939)**	(0.0430)			(0.0749)
$DLPGDP_{t-4}$	**0.112* **				0.141***			
	(0.0650)				(0.0430)			
$DLPGDP_{t-5}$	**0.0930**				-0.0373			
	(0.0641)				(0.0423)			
$DLPEC_{t-1}$	-0.0972**	0.0760	0.0685	-0.234***	**-0.00431**	**0.0299*** **	**-0.0182*** **	**-0.0288*** **
	(0.0425)	(0.0780)	(0.0622)	(0.0719)	**(0.0277)**	**(0.0052)**	**(0.00322)**	**(0.00548)**
$DLPEC_{t-1}$	-0.0657			-0.130*	**0.0206**			**0.0162**
	(0.0423)			(0.0716)	**(0.0276)**			**(0.0553)**
$DLPEC_{t-1}$	0.00278			-0.0315	**-0.0393**			**-0.0367**
	(0.0412)			(0.0690)	**(0.0270)**			**(0.0540)**
$DLPEC_{t-1}$	-0.0288				**-0.0347**			
	(0.0417)				**(0.0273)**			
$DLPEC_{t-1}$	0.0561				**-0.0358**			
	(0.0420)				**(0.0275)**			
ECM_{t-1}	-0.0213**	-0.0624**	-0.0256**	-0.0189**	-0.0950***	-0.0258**	-0.0333***	-0.0205***
	(0.00930)	(0.0286)	(0.0129)	(0.0053)	(0.00500)	(0.01433)	(0.0076)	(0.0015)
Observations	529	162	243	200	529	162	243	200
No. of crossid	23	6	9	8	23	6	9	8

Notes: Using the feasible generalized least squares (FGLS) methodology, we estimate the short-run relationship between petroleum consumption and economic growth. Lag length selection for each panel is based on Akaike information criterion (AIC) and Bayesian information criterion (BIC). ***, ** and * indicate rejection of the null hypothesis at 1 per cent, 5 per cent and 10 per cent significance levels. Standard errors are reported in the parentheses.

In addition, for the low-income states, higher growth in previous years predicts reduced demand for petroleum consumption. What is puzzling is that higher petroleum consumption predicts a fall in the short-term real income growth. Unsurprisingly, for the all states panel, we find an unidirectional link in the short run, with the effect running from economic growth to petroleum consumption. This supports the prevalence of the conservative hypothesis for the short run. The finding suggests that a reduction in the use of petroleum and a switch to cleaner and cheaper alternatives will not harm economic growth.

VI. THE ENERGY CONSUMPTION AND ECONOMIC GROWTH (E-Y) CONNECTIONS WITH DISAGGREGATED PETROLEUM

We examine the relationship between state-wise data on petroleum consumption and income using the disaggregated data on petroleum consumption by state. We classified the different types of petroleum consumption into six energy sources: (a) liquefied petroleum gas (LPG); (b) petrol (PET); (c) superior kerosene oil (SKO); (d) diesel/high speed diesel (HSD); (e) furnace oil (FO); and (f) naptha; aviation turbine fuel; light diesel oil; low sulphur heavy stock/hot heavy stock; lubes and greases; itumen; others (OTHERS). The disaggregated petroleum consumption data are sourced from the States of India database. The disaggregated petroleum consumption data are converted into per capita terms using population data on the Indian states attained from the Economic and Political Weekly Research Foundation database. We conducted the same tests for the aggregate data and the disaggregated data. The results for the disaggregated data are presented in the appendix.

We begin with the descriptive statistics in appendix table A.1. Notice that, with the exception of HSD, the petroleum disaggregates vary in terms of importance for each state. Out of all petroleum products, the average consumption of HSD is consistently the strongest type of consumption in all states. In the high-income states, the consumption of HSD is followed by PET, SKO, LPG, and FO. In the middle-income states, HSD consumption is trailed by SKO, PET, LPG, and FO. In the low-income states, consumption of SKO, PET, LPG, and FO are, on average, lower than that of HSD.

The unit root tests of the disaggregated petroleum data are presented in appendix table A.2. As the disaggregated petroleum types are found to be stationary at I(1), we proceed with the cointegration tests. The cointegration test results indicate rather limited cases of cointegration between the disaggregated petroleum types and economic growth. The full sample, comprising of all the Indian states, indicates that petroleum disaggegates SKO and OTHERS, possibly having a stable long-run association with income (appendix table A.3). For the high-income states panel, none of the petroleum types are cointegrated with the state income (appendix table A.4). For the middle-income Indian states panel, PET, LPG, and OTHERS may have stable long-run relations with income (appendix table A.5). For the low-income states panel, only LPG has a possible cointegration link with income (appendix table A.6).

The causal relationships and the direction of the causation between these cointegrated relationships are examined using VECMs (appendix table A.7). Estimation methods were similar to those discussed in the previous sections. For VECM, when the state-wise economic growth is the dependent variable, we find VECM to be valid in two instances — the link between LPG and economic growth of the middle-income and low-income states (appendix table A.7, panel 1). The long-run linkage between these variables are positive and significant (appendix table A.8, panel 2). This means that LPG has a positive effect on income of the middle-income states and low-income states.

Returning to VECMs, when different petroleum types are alternated as dependent variables, all cointegrated relations produce valid VECMs (appendix table A.7, panel 2). These findings imply that LPG and economic growth of the low-income states have a bidirectional or a feedback relationship. However, the rest of the valid relationships discussed here satisfy the conservative hypothesis. In the conservative hypothesis, economic growth is a good predictor of use of petroleum disaggegates, namely, SKO, and OTHERS (for the full sample); PET (for the middle-income sample); and LPG (for the low-income sample).

While in the long run economic growth is predicted to have a positive effect on the disaggregated energy consumption, in the short run economic growth is found to reduce consumption of SKO (for the all states panel) and LPG (for the low-income states panel).

VII. FURTHER DISCUSSIONS

This study shows different results regarding the nexus between energy consumption and economic growth across the 23 selected Indian states grouped in different panels based on their income level. This suggests that an appropriate approach for India should be to adopt state-specific policies in lieu of an integrated policy for all states.

For the high-income (and most industrialized) states of India, we find a prevalence of the feedback effect in the long and short run using aggregate petroleum data. This finding implies that energy supply shock may have a significant impact on economic growth (and vice versa). As such, adopting a general energy conservation policy may have a detrimental impact on the economic growth process in high-income states in India. Energy policy targeted towards higher petroleum usage is critical for the economic growth of these states. In this regard, it is suggested that the Government of India encourages the use and development of more advance and eco-friendly technologies by providing an array of energy tax credits as incentives for use of alternative energy resources. By so doing, it can minimize the energy supply shock effect on the output and reduce the unfavourable effects on the environment.

The Government of India has achieved significant milestones in building nuclear power plants. For instance, the Russian Federation-backed 2,000 megawatt Kudankulam Nuclear Power Plant in Tamil Nadu was completed in 2013; it has become the single largest nuclear power station in India. In addition, India also signed the Civil Nuclear Cooperation Agreement with the United States in 2008. This initiative is expected to foster the growth of the country’s civil nuclear sector and consequently enhance its energy security. India would greatly benefit from a stable clean energy source for its large and rapidly growing economy, which also would have favourable environmental effects. Our use of disaggregated data indicates insignificant effects of short-term and long-term linkages between petroleum and economic growth. This suggests that the use of aggregate data is more appropriate for modelling the linkages between petroleum consumption and income in high-income states.

For the middle- and low-income states, we are unable to find a feedback effect between petroleum consumption and economic growth in the aggregate data. For the middle-income states, economic growth is able to predict higher petroleum consumption but past increases in petroleum consumption does not predict future economic growth. We find this to be the case in the short run and in the long run. However, when we consider disaggregated petroleum consumption data, we find that LPG and economic growth show the feedback effect.

For the low-income state panel, in the long run, economic growth increases aggregate petroleum consumption, but increased aggregate petroleum consumption reduces economic growth. In the short run, economic growth reduces petroleum demand and lower petroleum consumption translates into higher economic growth. For the all states panel, there is a prevalence of the unidirectional link, with the effect running from economic growth to aggregate petroleum consumption. This supports the conservative hypothesis for the short run. These findings suggest that a reduction in the use of petroleum and switching to cleaner and cheaper alternatives (here, abundant and cheap labour should not be ruled out) will not harm economic growth. In fact, in the case of low- (and middle-) income states, economic growth is encouraged, with a reduction in petroleum usage. Our study of the disaggregated petroleum consumption suggests that petroleum products relating to superior kerosene oil and others are also influenced by economic growth.

While our analysis gives strong support for the feedback hypothesis for the richer states of India, our results also show two points of interest to policymakers: (i) petroleum is affecting growth negatively in the middle- and low-income states in India; and (ii) economic growth can be promoted even with lower petroleum consumption. These results have not been observed in the Indian literature or any other study to date.

VIII. CONCLUDING REMARKS

We examined the energy consumption and economic growth (E-Y) nexus for a panel of 23 Indian states and the subpanels of these Indian states classified by high, middle, and low income on the basis of their average per capita real GDP over the period 1985-2013. Upon finding the presence of cross-sectional dependence in the panels and heteroskedasticity in the relationships, we use the FGLS methodology to examine the long-run and short-run relationships.

Our key findings are as follows. For the country's high-income (and most industrialized) states, we find evidence of the feedback effect in the long run and the short run. For the middle- and low-income states, however, we do not find this feedback effect between petroleum consumption and economic growth in neither the short run nor the long run. Similarly, for the low-income state panel, in the long run, economic growth appears to increase petroleum consumption but higher petroleum usage seems to reduce economic growth. In the short run, we find that economic growth reduces petroleum demand while lower petroleum consumption leads to higher economic growth. For the all states panel, there is evidence of the unidirectional effect running from economic growth to petroleum consumption in the short run. This supports the prevalence of the conservative hypothesis. These results are also confirmed by using disaggregated data on petroleum consumption.

Some of the distortions we notice may be because the economies of the middle- and low-income Indian states have been chiefly informal and therefore statistically unaccounted for. A large part of agriculture, construction and manufacturing are comprised of informal sectors that consume petroleum but are largely missing in the GDP statistics.

At play here could be other features of the poorer states that do not show clear E-Y linkages. For instance, the informal sectors rely heavily on unskilled labour. We suspect that increased use of imported and expensive petroleum in place of abundant unskilled workers is to some degree also leading to a misallocation of resources in these poorer states. However, exploring this issue is not within the scope of the study. We leave this as part of a future research agenda.

Appendix

Table A.1. Descriptive statistics

This table provides the descriptive statistics for the petroleum types (in log form): furnace oil (FO); diesel/high speed diesel (HSD); liquefied petroleum gas (LPG); Petrol (PET); superior kerosene oil (SKO); and naptha; aviation turbine fuel; light diesel oil; low sulphur heavy stock/hot heavy stock; lubes and greases; bitumen; others (OTHERS).

Income groups	High income						Middle income						Low income					
Petroleum types	FO	HSD	LPG	PET	SKO	OTHERS	FO	HSD	LPG	PET	SKO	OTHERS	FO	HSD	LPG	PET	SKO	OTHERS
Mean	2.30	4.086	2.34	2.52	2.45	3.69	1.08	3.57	1.76	1.97	2.17	2.37	0.88	3.12	1.00	1.16	1.99	1.95
Standard deviation	0.90	0.433	0.73	0.67	0.52	0.56	1.17	0.47	0.86	0.59	0.29	0.68	1.07	0.48	0.81	0.58	0.25	0.61
Coefficient of variation	0.39	0.11	0.31	0.27	0.21	0.15	1.08	0.13	0.49	0.30	0.14	0.29	1.21	0.15	0.80	0.49	0.12	0.31

Table A.2. Unit root test: disaggregate petroleum variables

This table covers the Im, Pesaran and Shin (2003); Levin, Lin and Chu (2002); and ADF (Maddala and Wu, 1999) test results.

Variable	Method	Full sample				Income group 1				Income group 2				Income group 3			
		I(0)		I(1)		I(0)		I(1)		I(0)		I(1)		I(0)		I(1)	
		Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
PET	Levin, Lin and Chu t*	2.895	0.998	-3.261	0.001	0.897	0.815	0.017	0.507	1.307	0.905	-3.352	0.000	2.076	0.981	-2.061	0.020
	Im, Pesaran and Shin W-stat.	6.265	1.000	-6.634	0.000	2.906	0.998	-3.408	0.000	3.142	0.999	-4.329	0.000	3.407	1.000	-3.699	0.000
	ADF - Fisher Chi-square	18.099	1.000	125.143	0.000	4.625	0.969	32.191	0.001	9.098	0.695	41.579	0.000	3.592	0.999	41.230	0.001
LPG	Levin, Lin and Chu t*	-7.445	0.000	-6.412	0.000	-3.151	0.001	-4.563	0.000	-3.627	0.000	-5.481	0.000	-5.571	0.000	-0.496	0.310
	Im, Pesaran and Shin W-stat.	-1.836	0.033	-8.151	0.000	-0.767	0.222	-3.685	0.000	-0.703	0.241	-4.848	0.000	-1.619	0.053	-3.636	0.000
	ADF - Fisher Chi-square	72.278	0.008	153.116	0.000	17.957	0.117	34.952	0.001	21.699	0.041	45.363	0.000	27.199	0.039	40.626	0.001
HSD	Levin, Lin and Chu t*	-0.060	0.476	-4.045	0.000	0.317	0.625	-0.782	0.217	-0.650	0.258	-2.155	0.016	0.239	0.595	-2.790	0.003
	Im, Pesaran and Shin W-stat.	2.767	0.997	-6.057	0.000	1.399	0.919	-2.352	0.009	1.685	0.954	-3.540	0.000	1.481	0.931	-4.032	0.000
	ADF - Fisher Chi-square	28.975	0.977	115.876	0.000	5.435	0.942	23.681	0.023	8.277	0.763	34.057	0.001	11.338	0.788	45.479	0.000
SKO	Levin, Lin and Chu t*	3.657	1.000	-4.481	0.000	4.890	1.000	-1.501	0.067	1.098	0.864	-1.712	0.044	-0.770	0.221	-2.646	0.004
	Im, Pesaran and Shin W-stat.	3.075	0.999	-6.150	0.000	5.240	1.000	-1.825	0.034	0.705	0.760	-2.872	0.002	0.410	0.659	-4.212	0.000
	ADF - Fisher Chi-square	32.392	0.936	118.349	0.000	0.755	1.000	19.526	0.077	8.698	0.729	28.624	0.005	13.990	0.600	46.729	0.000
FO	Levin, Lin and Chu t*	-0.906	0.182	-6.645	0.000	-1.995	0.023	-8.318	0.000	1.098	0.864	-1.712	0.044	-0.770	0.221	-2.646	0.004
	Im, Pesaran and Shin W-stat.	-0.082	0.467	-9.380	0.000	-1.101	0.135	-8.036	0.000	0.705	0.760	-2.872	0.002	0.410	0.659	-4.212	0.000
	ADF - Fisher Chi-square	45.063	0.200	171.720	0.000	16.867	0.155	76.997	0.000	8.698	0.729	28.624	0.005	13.990	0.600	46.729	0.000
OTHERS	Levin, Lin and Chu t*	0.460	0.677	-9.812	0.000	2.096	0.982	-5.370	0.000	0.394	0.653	-5.050	0.000	-0.902	0.184	-5.370	0.000
	Im, Pesaran and Shin W-stat.	0.870	0.808	-12.293	0.000	0.692	0.756	-6.051	0.000	2.026	0.979	-6.291	0.000	-0.565	0.286	-7.145	0.000
	ADF - Fisher Chi-square	36.513	0.840	231.107	0.000	11.495	0.487	58.144	0.000	3.573	0.990	60.335	0.000	15.505	0.488	78.994	0.000

Notes: PET, petrol; LPG, liquefied petroleum gas; HSD, diesel/high speed diesel; SKO, superior kerosene oil; FO, furnace oil; OTHERS, naptha, aviation turbine fuel, light diesel oil, low sulphur heavy stock hot heavy stock, lubes and greases, itumen, and others.

Table A.3. Cointegration test results: disaggregate energy data (full sample)

The table presents results from three cointegration tests: Pedroni, Kao, and Fisher. For the Pedroni test, the first eight statistics refer to homogeneous test –- the alternative hypothesis: common autoregressive (AR) coefficients (within-dimension) while the last three statistics refer to heterogeneous test with the alternative hypothesis: individual AR coefficients (between-dimension).

Variable		Pedroni				ADF		Fisher				
		Stat.	Prob.	W. Stat.	Prob.	Stat.	Prob.		Trace	Prob.	Max-eigen	Prob.
PET	Panel v	-1.560	0.941	-0.338	0.632	-0.616	0.269	None	92.070	0.000	78.540	0.002
	Panel rho	1.172	0.879	-0.460	0.323			At most 1	73.060	0.007	73.060	0.007
	Panel PP	0.691	0.755	-1.399	0.081							
	Panel ADF	2.086	0.982	0.269	0.606							
	Group rho	-1.267	0.103									
	Group PP	-2.855	0.002									
	Group ADF	-1.521	0.064									
LPG	Panel v	0.135	0.446	0.526	0.300	-4.018	0.000	None	57.400	0.121	62.580	0.052
	Panel rho	-0.260	0.398	-0.308	0.379			At most 1	25.450	0.994	25.450	0.994
	Panel PP	-2.135	0.016	-1.856	0.032							
	Panel ADF	-0.282	0.389	0.056	0.522							
	Group rho	1.278	0.899									
	Group PP	-1.349	0.089									
	Group ADF	1.086	0.861									
HSD	Panel v	2.885	0.002	3.003	0.001	-1.483	0.069	None	59.510	0.087	55.590	0.157
	Panel rho	-2.219	0.013	-2.433	0.008			At most 1	53.110	0.219	53.110	0.219
	Panel PP	-3.401	0.000	-3.583	0.000							
	Panel ADF	-0.944	0.173	-0.916	0.180							
	Group rho	-0.854	0.197									
	Group PP	-3.094	0.001									
	Group ADF	-0.588	0.278									

Table A.3. *(continued)*

Variable		Pedroni				ADF		Fisher				
		Stat.	Prob.	W. Stat.	Prob.	Stat.	Prob.		Trace	Prob.	Max-eigen	Prob.
SKO	Panel v	2.723	0.003	0.132	0.448	-1.331	0.092	None	113.300	0.000	93.170	0.000
	Panel rho	1.241	0.893	0.433	0.668			At most 1	88.920	0.000	88.920	0.000
	Panel PP	2.292	0.989	-0.607	0.272							
	Panel ADF	-1.007	0.157	-1.934	0.027							
	Group rho	1.768	0.961									
	Group PP	0.218	0.586									
	Group ADF	-1.825	0.034									
FO	Panel v	1.607	0.054	0.728	0.233	1.327	0.092	None	48.420	0.081	45.360	0.136
	Panel rho	-1.905	0.028	-0.630	0.265			At most 1	43.160	0.192	43.160	0.192
	Panel PP	-1.354	0.088	-0.278	0.391							
	Panel ADF	-0.288	0.387	-0.505	0.307							
	Group rho	0.570	0.716									
	Group PP	-0.169	0.433									
	Group ADF	-0.680	0.248									
OTHERS	Panel v	4.245	0.000	2.866	0.002	-0.419	0.338	None	79.960	0.001	76.460	0.003
	Panel rho	-7.587	0.000	-6.739	0.000			At most 1	56.150	0.145	56.150	0.145
	Panel PP	-6.478	0.000	-5.936	0.000							
	Panel ADF	-3.705	0.000	-4.106	0.000							
	Group rho	-3.292	0.001									
	Group PP	-4.354	0.000									
	Group ADF	-2.990	0.001									

Notes: ADF, augmented Dickey-Fuller (Dickey and Fuller, 1979); PP, Phillips-Perron (Phillips and Perron, 1988). PET, petrol; LPG, liquefied petroleum gas; HSD, diesel/high speed diesel; SKO, superior kerosene oil; FO, furnace oil; OTHERS, naptha, aviation turbine fuel, light diesel oil, low sulphur heavy stock hot heavy stock, lubes and greases, itumen, and others.

Table A.4. Cointegration test results: disaggregate energy data (high-income group)

The table presents results from two cointegration tests: Pedroni, and Kao. For the Pedroni test, the first eight statistics refer to homogenous test – the alternative hypothesis: common autoregressive (AR) coefficients (within-dimension) while the last three statistics refer to heterogeneous test with the alternative hypothesis: individual AR coefficients (between-dimension).

Variable		Pedroni				ADF	
		Stat.	Prob.	W. Stat.	Prob.	Stat.	Prob.
PET	Panel v	0.016	0.494	0.016	0.494	0.117	0.453
	Panel rho	-0.002	0.499	-0.002	0.499		
	Panel PP	0.259	0.602	0.259	0.602		
	Panel ADF	0.990	0.839	0.990	0.839		
	Group rho	0.504	0.693				
	Group PP	0.676	0.751				
	Group ADF	1.545	0.939				
LPG	Panel v	0.338	0.368	0.338	0.368	-1.064	0.144
	Panel rho	-1.212	0.113	-1.212	0.113		
	Panel PP	-1.096	0.137	-1.096	0.137		
	Panel ADF	0.073	0.529	0.073	0.529		
	Group rho	-0.624	0.266				
	Group PP	-0.932	0.176				
	Group ADF	0.455	0.676				
HSD	Panel v	1.521	0.064	1.521	0.064	-0.187	0.426
	Panel rho	-0.917	0.180	-0.917	0.180		
	Panel PP	-0.807	0.210	-0.807	0.210		
	Panel ADF	-0.070	0.472	-0.070	0.472		
	Group rho	-0.350	0.363				
	Group PP	-0.589	0.278				
	Group ADF	0.286	0.613				
SKO	Panel v	-0.695	0.757	-0.695	0.757	2.252	0.012
	Panel rho	0.749	0.773	0.749	0.773		
	Panel PP	0.922	0.822	0.922	0.822		
	Panel ADF	0.999	0.841	0.999	0.841		
	Group rho	1.203	0.886				
	Group PP	1.464	0.928				
	Group ADF	1.555	0.940				

Table A.4. *(continued)*

Variable		Pedroni				ADF	
		Stat.	Prob.	W. Stat.	Prob.	Stat.	Prob.
FO	Panel v	-0.055	0.522	-0.055	0.522	0.014	0.495
	Panel rho	-0.257	0.398	-0.257	0.398		
	Panel PP	-0.728	0.233	-0.728	0.233		
	Panel ADF	0.649	0.742	0.649	0.742		
	Group rho	0.265	0.605				
	Group PP	-0.495	0.310				
	Group ADF	1.139	0.873				
OTHERS	Panel v	1.310	0.095	1.310	0.095	0.214	0.415
	Panel rho	-1.135	0.128	-1.135	0.128		
	Panel PP	-0.888	0.187	-0.888	0.187		
	Panel ADF	-1.103	0.135	-1.103	0.135		
	Group rho	-0.553	0.290				
	Group PP	-0.685	0.247				
	Group ADF	-0.940	0.174				

Notes: ADF, augmented Dickey-Fuller (Dickey and Fuller, 1979); PP, Phillips-Perron (Phillips and Perron, 1988). PET, petrol; LPG, liquefied petroleum gas; HSD, diesel/high speed diesel; SKO, superior kerosene oil; FO, furnace oil; OTHERS, naptha, aviation turbine fuel, light diesel oil, low sulphur heavy stock hot heavy stock, lubes and greases, itumen, and others.

Table A.5. Cointegration test results: disaggregate energy data (middle-income group)

The table presents results from three cointegration tests: Pedroni, Kao, and Fisher. For the Pedroni test, the first eight statistics refer to homogeneous test – the alternative hypothesis: common autoregressive (AR) coefficients (within-dimension) while the last three statistics refer to heterogeneous test with the alternative hypothesis: individual AR coefficients (between-dimension).

Variable		Pedroni				ADF		Fisher				
		Stat.	Prob.	W. Stat.	Prob.	t-Stat.	Prob.		Trace	Prob.	Max-eigen	Prob.
PET	Panel v	1.732	0.042	2.679	0.004	-0.822	0.206	None	38.450	0.000	33.860	0.001
	Panel rho	-1.053	0.146	-1.880	0.030			At most 1	23.500	0.024	23.500	0.024
	Panel PP	-1.783	0.037	-2.403	0.008							
	Panel ADF	-2.218	0.013	-3.053	0.001							
	Group rho	-1.092	0.137									
	Group PP	-2.332	0.010									
	Group ADF	-3.607	0.000									
LPG	Panel v	0.220	0.413	0.464	0.322	-3.067	0.001	None	23.780	0.022	26.240	0.010
	Panel rho	-0.111	0.456	-0.072	0.471			At most 1	3.865	0.986	3.865	0.986
	Panel PP	-1.093	0.137	-0.678	0.249							
	Panel ADF	-0.937	0.174	-0.423	0.336							
	Group rho	0.719	0.764									
	Group PP	-0.479	0.316									
	Group ADF	-0.334	0.369									
HSD	Panel v	1.388	0.083	1.546	0.061	-0.386	0.350	None	23.630	0.023	24.080	0.020
	Panel rho	-0.898	0.185	-0.921	0.179			At most 1	9.203	0.686	9.203	0.686
	Panel PP	-1.804	0.036	-1.691	0.045							
	Panel ADF	-0.870	0.192	-0.695	0.244							
	Group rho	-0.781	0.217									
	Group PP	-2.119	0.017									
	Group ADF	-1.133	0.129									

Table A.5. *(continued)*

Variable		Pedroni				ADF		Fisher				
		Stat.	Prob.	W. Stat.	Prob.	t-Stat.	Prob.		Trace	Prob.	Max-eigen	Prob.
SKO	Panel v	0.095	0.462	-0.127	0.550	-1.112	0.133	None	18.15	0.1113	16.12	0.1858
	Panel rho	0.163	0.565	0.265	0.605			At most 1	15.64	0.2081	15.64	0.2081
	Panel PP	-0.853	0.197	-0.784	0.217							
	Panel ADF	-1.174	0.120	-0.731	0.232							
	Group rho	1.140	0.873									
	Group PP	-0.391	0.348									
	Group ADF	-0.497	0.310									
FO	Panel v	3.176	0.001	2.395	0.008	-0.005	0.498	None	5.795	0.8322	4.53	0.9203
	Panel rho	-1.286	0.099	-0.246	0.403			At most 1	12.24	0.269	12.24	0.269
	Panel PP	-0.768	0.221	0.235	0.593							
	Panel ADF	-0.866	0.193	-0.736	0.231							
	Group rho	0.755	0.775									
	Group PP	0.907	0.818									
	Group ADF	-0.080	0.468									
OTHERS	Panel v	3.275	0.001	2.151	0.016	-0.902	0.184	None	26.06	0.0105	24.05	0.02
	Panel rho	-3.074	0.001	-3.348	0.000			At most 1	15.92	0.1947	15.92	0.1947
	Panel PP	-2.590	0.005	-2.828	0.002							
	Panel ADF	-1.670	0.047	-2.345	0.010							
	Group rho	-1.922	0.027									
	Group PP	-2.449	0.007									
	Group ADF	-2.016	0.022									

Notes: ADF, Augmented Dickey-Fuller (Dickey and Fuller, 1979); PP, Phillips-Perron (Phillips and Perron, 1988). PET, petrol; LPG, liquefied petroleum gas; HSD, diesel/high speed diesel; SKO, superior kerosene oil; FO, furnace oil; OTHERS, naptha, aviation turbine fuel, light diesel oil, low sulphur heavy stock hot heavy stock, lubes and greases, itumen, and others.

Table A.6. Cointegration test results: disaggregate energy data (low-income group)

The table presents results from three cointegration tests: Pedroni, Kao, and Fisher. For the Pedroni test, the first eight statistics refer to homogeneous test – the alternative hypothesis: common autoregressive (AR) coefficients (within-dimension) while the last three statistics refer to heterogeneous test with the alternative hypothesis: individual AR coefficients (between-dimension).

Variable		Pedroni				ADF		Fisher				
		Stat.	Prob.	W. Stat.	Prob.	t-Stat.	Prob.		Trace	Prob.	Max-eigen	Prob.
PET	Panel v	2.829	0.002	2.860	0.002	-0.531	0.298	None	24.660	0.076	16.580	0.413
	Panel rho	-2.520	0.006	-3.164	0.001			At most 1	29.810	0.019	29.810	0.019
	Panel PP	-3.046	0.001	-3.919	0.000							
	Panel ADF	-1.068	0.143	-1.119	0.132							
	Group rho	-2.597	0.005									
	Group PP	-4.277	0.000									
	Group ADF	-1.053	0.146									
LPG	Panel v	-0.178	0.571	-0.074	0.529	-2.009	0.022	None	16.090	0.447	17.460	0.357
	Panel rho	-0.263	0.396	-0.327	0.372			At most 1	10.910	0.815	10.910	0.815
	Panel PP	-1.601	0.055	-1.480	0.069							
	Panel ADF	0.527	0.701	0.893	0.814							
	Group rho	0.288	0.613									
	Group PP	-1.339	0.090									
	Group ADF	1.865	0.969									
HSD	Panel v	1.273	0.101	1.318	0.094	-0.891	0.187	None	18.080	0.319	15.440	0.493
	Panel rho	-2.080	0.019	-2.177	0.015			At most 1	22.290	0.134	22.290	0.134
	Panel PP	-3.077	0.001	-3.137	0.001							
	Panel ADF	-0.455	0.324	-0.312	0.377							
	Group rho	-1.131	0.129									
	Group PP	-2.851	0.002									
	Group ADF	0.054	0.522									

Table A.6. *(continued)*

Variable		Pedroni				ADF		Fisher				
		Stat.	Prob.	W. Stat.	Prob.	t-Stat.	Prob.		Trace	Prob.	Max-eigen	Prob.
SKO	Panel v	0.829	0.204	0.280	0.390	-0.046	0.482	None	28.940	0.024	23.990	0.090
	Panel rho	-0.627	0.266	-0.338	0.368			At most 1	27.090	0.041	27.090	0.041
	Panel PP	-1.440	0.075	-1.263	0.103							
	Panel ADF	0.057	0.523	-0.504	0.307							
	Group rho	-0.309	0.379									
	Group PP	-1.285	0.099									
	Group ADF	-0.646	0.259									
FO	Panel v	3.043	0.001	1.816	0.035	-0.090	0.464	None	17.720	0.125	16.910	0.153
	Panel rho	-2.980	0.001	-1.452	0.073			At most 1	14.010	0.300	14.010	0.300
	Panel PP	-3.105	0.001	-1.851	0.032							
	Panel ADF	-1.020	0.154	-1.011	0.156							
	Group rho	-0.760	0.224									
	Group PP	-1.641	0.050									
	Group ADF	-0.777	0.219									
OTHERS	Panel v	2.432	0.008	1.978	0.024	-0.444	0.328	None	23.470	0.102	22.640	0.124
	Panel rho	-4.425	0.000	-3.383	0.000			At most 1	18.960	0.271	18.960	0.271
	Panel PP	-4.107	0.000	-3.438	0.000							
	Panel ADF	-2.591	0.005	-2.169	0.015							
	Group rho	-2.050	0.020									
	Group PP	-3.066	0.001									
	Group ADF	-1.696	0.045									

Notes: ADF, Augmented Dickey-Fuller (Dickey and Fuller, 1979); PP, Phillips-Perron (Phillips and Perron, 1988). PET, petrol; LPG, liquefied petroleum gas; HSD, diesel/high speed diesel; SKO, superior kerosene oil; FO, furnace oil; OTHERS, naptha, aviation turbine fuel, light diesel oil, low sulphur heavy stock hot heavy stock, lubes and greases, itumen, and others.

Table A.7. State-wise economic growth and disaggregate energy consumption: feasible generalized least squares results

Using the feasible generalized least squares (FGLS) methodology, we estimate the short-run relationship between different types of petroleum consumption and economic growth that we found evidence of cointegration. Note that we found no evidence of cointegration for the group of high-income states. Lag length selection for each panel is selected based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Variables	Panel 1: Dependent variable: GDP per capita (DLPGDP)						Panel 2: Dependent variable: petroleum consumption (different types)					
	(1) All states	(2) All states	(3) Middle-income states	(4) Middle-income states	(5) Middle-income states	(6) Low-income states	(1) All states	(2) All states	(3) Middle-income states	(4) Middle-income states	(5) Middle-income states	(6) Low-income states
	SKO	OTHERS	OTHERS	PET	LPG	LPG	SKO	OTHERS	OTHERS	PET	LPG	LPG
$DLPGDP_{t-1}$	-0.118*** (0.045)	-0.094** (0.045)	-0.003 (0.067)	-0.030 (0.067)	-0.004 (0.065)	-0.209*** (0.070)	-0.078 (0.067)	-0.287 (0.230)	0.518 (0.458)	0.598*** (0.153)	-0.143 (0.197)	-0.209*** (0.081)
$DLPGDP_{t-2}$	0.119*** (0.045)	0.135*** (0.045)				0.050 (0.074)	-0.164** (0.067)	-0.187 (0.227)				-0.219*** (0.085)
$DLPGDP_{t-3}$	0.016 (0.043)	0.012 (0.043)				-0.054 (0.072)	0.006 (0.063)	0.400* (0.216)				0.101 (0.083)
$DLPGDP_{t-4}$	0.148*** (0.042)	0.152*** (0.042)					-0.039 (0.062)	0.231 (0.213)				
$DLPGDP_{t-5}$	-0.070* (0.041)	-0.061 (0.041)					-0.067 (0.062)	0.380* (0.213)				
$DLPEC_{t-1}$	0.036 (0.031)	0.016* (0.009)	0.10 (0.009)	0.046* (0.027)	-0.021 (0.022)	-0.034 (0.064)	-0.014 (0.050)	-0.294*** (0.049)	-0.349*** (0.063)	0.182*** (0.064)	-0.178*** (0.065)	-0.211** (0.083)
$DLPEC_{t-2}$	0.012 (0.034)	0.015 (0.010)				-0.126* (0.067)	0.162*** (0.049)	-0.115** (0.050)				0.228*** (0.081)
$DLPEC_{t-3}$	-0.068** (0.033)	0.008 (0.010)				-0.126* (0.064)	-0.038 (0.049)	-0.045 (0.054)				-0.037 (0.075)
$DLPEC_{t-4}$	-0.069** (0.032)	0.010 (0.010)					-0.018 (0.047)	-0.052 (0.054)				
$DLPEC_{t-5}$	-0.027 (0.032)	0.001 (0.010)					0.158*** (0.047)	-0.195*** (0.051)				

Table A.7. *(continued)*

Variables	Panel 1: Dependent variable: GDP per capita (DLPGDP)						Panel 2: Dependent variable: petroleum consumption (different types)					
	(1) All states	(2) All states	(3) Middle-income states	(4) Middle-income states	(5) Middle-income states	(6) Low-income states	(1) All states	(2) All states	(3) Middle-income states	(4) Middle-income states	(5) Middle-income states	(6) Low-income states
	SKO	OTHERS	OTHERS	PET	LPG	LPG	SKO	OTHERS	OTHERS	PET	LPG	LPG
ECM_{t-1}	0.004	-0.0002	-0.003	0.010	-0.030**	-0.038***	-0.045***	-0.055***	-0.087***	-0.026*	-0.058***	-0.041***
	(0.006)	(0.006)	(0.008)	(0.011)	(0.004)	(0.014)	(0.013)	(0.018)	(0.031)	(0.015)	(0.019)	(0.013)
Observations	478	476	221	223	221	177	455	453	212	214	212	168
No. of crossid	23	23	9	9	9	8	23	23	9	9	9	8

Notes: SKO, superior kerosene oil; PET, petrol; LPG, liquefied petroleum gas; OTHERS, naptha, aviation turbine fuel, light diesel oil, low sulphur heavy stock hot heavy stock, lubes and greases, itumen, and others. ***, ** and * indicate rejection of the null hypothesis at 1 per cent, 5 per cent and 10 per cent significance levels. Standard errors are reported in parentheses.

Table A.8. Long-run models with disaggregate energy sources

Using the feasible generalized least squares (FGLS) methodology, we estimate the long-run relationship between different types of petroleum consumption and economic growth that we found evidence of cointegration. Note that we found no evidence of cointegration for the group of high-income states.

	(1) SKO	(2) OTHERS	(3) PET	(4) LPG
PEC = f(PGDP)				
All states	0.051* (0.026)	0.944* (0.056)		
Observations	641	640		
Number of crossid	23	23		
Middle-income states		0.756*** (0.100)	1.259*** (0.066)	1.820*** (0.072)
Observations		250	251	249
Number of crossid		9	9	9
Low-income states				0.425*** (0.033)
Observations				221
Number of crossid				8
PGDP = f(PEC)				
All states	0.114* (0.059)	0.328* (0.019)		
Observations	641	640		
Number of crossid	23	23		
Middle-income states		0.247*** (0.033)	0.469*** (0.025)	0.395*** (0.016)
Observations		250	251	249
Number of crossid		9	9	9
Low-income states				0.425*** (0.033)
Observations				221
Number of crossid				8

Notes: PEC, per capita energy consumption; PGDP, per capita gross domestic product. SKO, superior kerosene oil; PET, petrol; LPG, liquefied petroleum gas; OTHERS, naptha, aviation turbine fuel, light diesel oil, low sulphur heavy stock hot heavy stock, lubes and greases, itumen, and others. ***, ** and * indicate rejection of the null hypothesis at 1 per cent, 5 per cent and 10 per cent significance levels. Standard errors are reported in parentheses.

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