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Estimating sectoral demands for electricity using the pooled mean group method

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HIGHLIGHTS

- We estimate sectoral electricity demand in the Northeastern U.S. using panel data.
- Cooling degree days have a positive effect in electricity demand in all three sectors.
- Long run own price elasticities are negative in residential and industrial sectors.
- Natural gas has long run substitution effect in residential and commercial sectors.
- Heating oil price has short run positive effect in residential and commercial sectors.

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ABSTRACT

This paper examines the demand for electricity in the residential, commercial, and industrial sectors of the Northeastern United States using state-level panel data over the period from 1997 to 2011. It applies panel unit root and cointegration tests and then estimates the parameters using the pooled mean group method. The panel unit root and cointegration tests show that the series are integrated of order one and cointegrated. The electricity demand for the residential sector is responsive to its own price in the long run, with own price elasticity being −0.11, but irresponsive to own price in the short run. The long run income elasticities of electricity demand for the residential, commercial, and industrial sectors are 0.93, 0.53, and 1.95, respectively. Higher income elasticity implies that energy efficient appliances and the regulation of housing structures might be effective policy tools to promote energy conservation. The short run impact of fuel oil price is significant in the residential and commercial sectors. Cooling degree days have significant positive effects on the demand for electricity in the residential and commercial sectors. The long run cross price elasticities for natural gas in the residential and commercial sectors are 0.095 and 0.105, respectively.

1. Introduction

Estimating the demand for electricity in the residential, commercial, and industrial sectors of the Northeastern United States over the period 1997-2011 is the primary focus of this study. Electricity is one of the major drivers of economic activities in the commercial and industrial sectors of the economy. Heating and cooling of buildings and homes is the single largest use of electricity, followed by water heating, lighting, and appliance use in the residential sector.

On the supply side, major determinants of electricity price are the price of fuel, power plant costs, costs for transmission and distribution, weather, and regulations; whereas, electricity demand is driven by own price, cross price, income, and weather factors. However, numerous studies related to the sectoral demand for electricity indicate a mixed intensity of price and income elasticities; such as electricity demand is highly price and income elastic [1–5], price inelastic [6], and income inelastic [7]. Thus, the estimation of price, income, and weather elasticities of electricity demand with an appropriate model specification would have greater policy implications regarding energy conservation and efficiency in different sectors.

Fell et al. [4] find residential electricity demand is price sensitive in the context of U.S. customers; Chang et al. [8] show that the variation in temperature affects electricity demand in the short run; and Lee and Chiu [9] demonstrate that the impact of temperature in electricity demand is more important compared to price and income effect. Many studies concerning sectoral energy consumption show mixed response to price and income over the time. In particular, electricity demand is price and income elastic as well as inelastic depending on geographical

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region, energy market structure, consumer type, estimation methods, type of data, and economic status of the study region. In our case, it would be reasonable to estimate the demand elasticities in new contexts so as to aid in policy formulation regarding the electricity demand-supply mechanism, energy conservation, and welfare implications. Although the same issue was previously studied for the Northeastern U.S. by Beierlein et al. [10], using the data over 1967–1977, much has changed concerning factors affecting electricity demand since last 40 years. This makes it imperative that we study this issue again in the changed context. Additionally, Beierlein et al. did not conduct unit root and cointegration tests and also did not incorporate the impact of cooling degree days, which is one of the most influential factors for electricity demand, as noted by many authors. For example, Shaik and Yeboah [11] find energy demand sensitivity to downside temperature in the Northeastern U.S; You et al. [12] note the significant impact of cooling degree days in household electricity demand in Singapore and Shanghai; and Gutiérrez-Pedrero et al. [13] find cooling degree days to be a major driver of electricity demand in the European region. While estimating with panel data, the possibility of unit roots and cointegration are important concerns, due to the fact that without addressing those, regression results could be spurious. This study uses the most appropriate techniques for panel unit testing, as proposed by Pesaran [14], and Maddala and Wu [15], cointegration testing as proposed by Pedroni [16] and Kao [17], and estimates the parameters using dynamic pooled mean group, mean group, dynamic fixed effect, and common correlated effect mean group methods.

Unique regional factors are often lost due to aggregation in panel data. The importance of regional effects on total energy consumption and cost has been noted by several authors. For example, Taylor [18] provides the guidelines while estimating sectoral electricity demand, and Balestra and Nerlove [19] explains the importance in the case of natural gas demand. Beierlein et al. [10] estimate the sectoral electricity and natural gas demand in the Northeasten U.S. using 11 years of data. Hsing [20] estimates residential electricity demand for five southern states using data over the period 1981-1990 and finds the natural gas price insignificant in residential electricity demand; and Kalashnikov et al. [21] analyze the problem of finding a pooled regression formula relating the price and consumption demand of natural gas for each state in the United States. A regime shift analysis conducted by Sun et al. [22] in the U.S. electricity market shows the evolution of electricity prices correlation in residential, commercial, and industrial sectors, taking into account the uncertain influence of the fuel market. Their results indicate that electricity price correlation increased continually in all three sectors. It decreased in 2012, indicating its sensitivity to fuel price. Due to weather variations, more economic activities, higher income levels, and growing energy use, the Northeastern U.S. is a unique region to consider for electricity demand estimation.

Intuitively, people use more electricity for cooling during hot days. Consumers tend to adjust electricity demand based on temperature variations. In that sense, the impact of cooling degree days (CDD) in electricity demand estimation cannot be ignored. Shaik and Yeboah [11] examine the effects of climate change on US sectoral energy demand using state level panel data from 1970 to 2014. They find that the Northeast, Central, and the Southern region of the U.S. are sensitive for energy demand to downside temperature. Residential and industrial energy use in these regions go up with the rise of downside deviation from the mean temperature. The commercial sector is least affected, because it uses the least energy due to improved technological change. They find technological advancement leads to significant saving in energy consumption. Monthly household electricity demand analysis in conjunction with temperature variation conducted by You et al. [12] in Singapore and China indicates that a one degree increase in monthly temperature is significantly associated with a 13.6% increase in the monthly electricity consumption for Singapore, and a 30 degree days increase in heating and cooling degree days is associated with a 24.9% increase in monthly electricity consumption in Shanghai in the long run. In this nexus, the inclusion of temperature variables is very important when estimating electricity demand. Okajima and Okajima [23] find a significant effect of severe weather on household electricity consumption in Japan.

The previous study in the Northeastern U.S. did not include the impact of CDD. Therefore, we include CDD to model the dynamics of electricity demand, especially to account for short run impact in energy demand as noted by Chang et al. [8] in the Korean electricity market. This study reveals new findings due to the fact that it incorporated an extended sample period, took into account an important variable, adopted the latest model specification methods, and used more effective estimation techniques. The finding concerning short run substitutability between electricity and heating fuel oil price has policy implications from the environmental perspective.

Numerous authors have estimated the demand for electricity using different approaches in different geographical regions. However, the results concerning price and income elasticities of electricity demand for a particular sector are not uniform. The elasticity of electricity demand varies from region to region. Paul et al. [24] estimate the demand for electricity in the U.S. using a fixed effect model, paying particular attention to regional, seasonal, and sectoral variations. The estimated results show that the electricity demand is price inelastic in the short run, but varying by region, season, sector, and customer classes in the long run. Alberini et al. [1] investigate the demand for electricity and natural gas for households/dwellings in the 50 largest metropolitan areas in the United States using data over the period 1997-2007. Their findings indicate that the household electricity demand is strongly responsive to its own prices both in the short run and long run. However, price elasticity of electricity demand declines with income. Jamil and Ahmad [25] estimate demand for electricity using an error correction model with annual data over the period 1961-2008. They find that the residential electricity demand is highly elastic to price and income in the long run. Gutiérrez-Pedrero et al. [13] analyze the drivers of the intensity of electricity consumption in non-residential sectors in Europe and find that the cooling degree days have a significant impact on increased electricity intensity. However, they find negligible price impact on electricity demand. Salari and Javid [26] estimate residential electricity demand in the U.S. using state level data over the period 2005-2013. Estimated results using both static and dynamic panel methods indicate that the sociodemographic information, such as per capita income, household size, and educational level, have a significant impact on electricity demand in the residential sector. Burke et al. [27] estimate aggregate short run and long run price elasticity of electricity demand in the U.S. using data over the period 2003-2015. Estimated results using the instrumental variable method indicate that the electricity demand is irresponsive to price in the short run, but the long run demand is highly responsive to price, with a maximum price elasticity around -1 in the industrial sector and a minimum value around -0.3 in the commercial sectors. These values are very high compared with most of the existing literature.

Wang and Mogi [28] estimate residential and industrial electricity demand in Japan using annual data over the period 1989-2014. The income elasticities in both sectors are stable over the study period. However, consumers become less sensitive to price after the electricity deregulation and financial crisis and more sensitive to price after the Fukushima Daiichi crisis. The price elasticity in the residential sector is much higher than in the industrial sector, so they suggested that price and environmental taxation can be better policy tools in the residential sector. Atalla and Hunt [29] estimate residential electricity demand in six Persian gulf countries and find that electricity demand is irresponsive to price. Arisoy and Ozturk [30] estimate price and income elasticity of electricity demand in residential and industrial sectors in Turkey using data over the period of 1960-2008. They find income elasticities of electricity at 0.97 and 0.95 for industrial and residential sectors. But, the electricity demand is price inelastic in both sectors. Lee and Lee [7] estimate the demand for electricity and total energy in OECD countries using data over the period 1978-2004. Estimated results using panel unit root tests and cointegration tests indicate that the total energy demand is irresponsive to price and income. Blázquez et al. [3] estimate the residential demand for electricity in the residential sector for Spanish provinces using data over the period 2000-2008. The estimated results using a dynamic partial adjustment approach indicate that the residential electricity demand is price elastic in both the long run and short run. Lim et al. [31] examine the demand for electricity in the Korean service sector using the data covering the period 1970-2011. Estimated results using error correction model show that the price and income elasticities are highly significant in both the long run and short run. They suggest that a pricing policy would be more effective than direct regulation of electricity demand to stabilize the demand in the long run.

Household characteristics, such as income level, age of the building, household size, technology, and education may have varying impacts in residential electricity consumption behavior. In sectoral energy demand analysis, rural and urban areas could behave differently in energy consumption. Likewise, the type of utility involved in electricity distribution might impact the consumer behavior in energy demand as well. A meta-analysis conducted by Labandeira et al. [32] to identify the main factors affecting short run and long run elasticity of energy (electricity, natural gas, and other petroleum products) demand, notes varying degrees of elasticity based on the type of data, method used, regions, economic status of the countries, geographical regions, and type of consumer groups. In this thread, Saha and Bhattacharya [33] estimate price and income elasticities of electricity demand for four consumer categories: agricultural, commercial, industrial, and residential (for both public and private utilities) in West Bengal, India using annual data over the period 2000-2015. They find that the demand for electricity is price inelastic for all four categories. But the public sector utility in the industrial sector is more price inelastic than other categories. The income elasticity in the industrial sector is higher than in other sectors. They point out the implication of highly priced inelastic electricity demand as a rent seeking behavior and suggest regulating authorities adopt appropriate policy tools to counter the rent seeking behavior of the utilities to ensure competitiveness in the market. Schulte and Heindl [34] estimate the price and expenditure elasticities of residential energy demand using official expenditure data from 1993 to 2008 and find price elasticity of electricity demand to be -0.43 and expenditure elasticity to be 0.39. They also note that the behavioral response to price change is weaker for low income households and stronger in high income households. Silva et al. [35] estimate the residential electricity demand in urban and rural areas of Portugal using data over the period 1989-2010. They find that the rural households are more sensitive to price change than urban consumers. The potential reason they indicated is that the rural households may have more substitute energy sources to switch to if the price of electricity increases. They did not find much difference in income elasticity in either area. In another context, income quantile analysis conducted by Silva et al. [36] in Portugal shows significant differences in price elasticities of electricity demand, depending on the household income group. They find electricity and natural gas are substitute goods. Price increase tends to show a decrease in electricity consumption. Du et al. [37] analyze household electricity consumption after the reform of tiered pricing for household electricity in China using household survey data. They find that the electricity consumption of 82% of surveyed households was not affected by tiered pricing. They find that energy price, household income, and demographic attributes have a significant impact on residential electricity consumption.

The U.S. Energy Information Administration (EIA)[1] reports that the share of electricity consumption in 2016 by the residential, commercial, and industrial sectors was 38%, 37%, and 25%, respectively. About 34% of U.S. electricity is generated by using natural gas. In 2010, 3.3 billion gallons of heating oil was sold to residential customers in the Northeastern U.S., and it was 85% of the total heating fuel oil sales of the U.S. These numbers indicate that the prices of natural gas and heating oil might have a significant impact on electricity consumption in this region. Additionally, the Northeastern U.S. experiences far more heating degree days than cooling degree days.[2] This means that the Northeastern region has relatively cool climate that requires more energy for heating purposes rather than for cooling. The lower ranking of per capita electricity consumption is a reflection of this fact. However, the change in income, own price, cross price, and temperature variation influence the electricity demand. In those circumstances, estimating electricity demand in response to change in own price, heating oil price, natural gas price, income, and CDD variation can provide valuable information which could have useful policy implications in energy conservation and efficiency. This study will address a number of shortcomings in previous research regarding model specification and sample period. The findings of this study would be beneficial for those who are directly or indirectly associated with the electricity market and policy makers.

The remainder of this paper is organized as follows: Section 2 incorporates the methodological aspects concerning unit root and cointegration tests and empirical model specification. It also provides a brief comparison regarding the relevance of the PMG method over alternative estimators: mean group (MG), dynamic fixed effect (DFE), and common correlated effect mean group (CCEMG) in estimating sectoral demand for electricity in the Northeastern United states. Section 3 provides data sources and data description. Section 4 presents empirical results and interpretation of major findings. Finally, Section 5 provides concluding remarks and discussion of the study.

2. Methods

2.1. Empirical model

Electricity demand is separated by end users: residential (R), commercial (C), and industrial (I) sectors. Electricity demand equations for each sector are estimated separately by using PMG, MG, DFE, and CCEMG methods. Our approach is consistent with Blackburne and Frank [38], who estimated nonstationary heterogeneous panels with large N and T with annual aggregated consumption data for OECD countries. For model specification, we consider the long run electricity consumption function as:

$$QE_{it} = \alpha_0 + \alpha_1 PN_{it} + \alpha_2 PE_{it} + \alpha_3 PO_{it} + \alpha_4 YI_{it} + \alpha_5 CDD_{it} + v_{it} \quad (1)$$

The autoregressive distributed lag (ARDL) (1, 1, 1) dynamic panel specification of Eq. (1) can be expressed in the following form as used by Pesaran et al. [39]:

$$\begin{aligned} QE_{it} = {} & \mu_i + \theta_{10i} PN_{it} + \theta_{11i} PN_{i,t-1} + \theta_{20i} PE_{it} + \theta_{21i} PE_{i,t-1} + \theta_{30i} PO_{it} \\ & + \theta_{31i} PO_{i,t-1} + \theta_{40i} YI_{it} + \theta_{41i} YI_{i,t-1} + \theta_{50i} CDD_{it} + \theta_{51i} CDD_{i,t-1} \\ & + \lambda_i QE_{i,t-1} + \varepsilon_{it}, \end{aligned} \quad (2)$$

The error correction re-parameterization of Eq. (2) is obtained as[3]:

$$\begin{aligned} \Delta \mathrm{QE_{it}} = {} & \phi_i (QE_{i,t-1} - \alpha_{0i} - \alpha_{1i} PN_{it} - \alpha_{2t} PE_{it} - \alpha_{3t} PO_{it} - \alpha_{4t} YI_{it}) - \theta_{11i} PN_{it} \\ & - \theta_{21i} PE_{it} - \theta_{31i} PO_{it} - \theta_{41i} YI_{it} - \theta_{51i} CDD_{it} + \varepsilon_{it} \end{aligned} \quad (3)$$

[1] U.S. Energy Information Administration Report. (http://www.eia.gov/energyexplained/index.cfm?page=heating_oil_use) https://www.eia.gov/energyexplained/index.cfm?page=electricity_use.

[2] Environmental Protection Agency (EPA) https://www.epa.gov/sites/production/files/2016-08/documents/print_heating-cooling-2016.pdf.

[3] All the variables are in natural logarithm. Hence, the coefficients represent elasticity.

Here, ϕ_i is the parameter of error correction speed of adjustment, andα_i's are the long run coefficients associated with the variables. The sign associated with ϕ_i is supposed to be negative if the variables exhibit a return to long run equilibrium. If the variables are I(1) and cointegrated, then the error correction term would beI(0). If$\phi_i = 0$, then there would be no long run relationship. The requirement for estimating Eq. (3) using the PMG method is that the series should be [I(1)] in levels and cointegrated. It implies the responsiveness of variables to any deviation from long run equilibrium. In Eq. (3), parameters ϕ_i and α_i can be defined as: $\phi_{\rm i} = -(1-\lambda_{\rm i})$, $\alpha_{0\rm i} = \frac{\mu_{\rm i}}{1-\lambda_{\rm i}}$, $\alpha_{1\rm i} = \frac{\theta_{10\rm i}+\theta_{11\rm i}}{1-\lambda_{\rm i}}$, $\alpha_{2\rm i} = \frac{\theta_{20\rm i}+\theta_{21\rm i}}{1-\lambda_{\rm i}}$, $\alpha_{3\rm i} = \frac{\theta_{30\rm i}+\theta_{31\rm i}}{1-\lambda_{\rm i}}$, $\alpha_{4\rm i} = \frac{\theta_{40\rm i}+\theta_{41\rm i}}{1-\lambda_{\rm i}}$, and $\alpha_{5\rm i} = \frac{\theta_{50\rm i}+\theta_{51\rm i}}{1-\lambda_{\rm i}}$.

Variables used in Eq. (3) are defined as follows:

QE = per capita consumption of electricity in KWh unit,
PN = average real price $U.S. per 1,000 therms of natural gas,
PE = average real price $U.S. per KWh of electricity,
PO = average real price $U.S. per gallon of heating fuel oil,
YI = per capita income in $U.S. (Household per capita for household sector, per capita retail sales for commercial sector, and value added by manufacturing per industry for industrial sector),
CDD = cooling degree days[4], and $\varepsilon_{\rm it}$ = error term.

We estimate Eq. (3) using PMG method proposed by Pesaran et al. [39]. The robustness of the PMG method would be tested by comparing the estimated results obtained from alternative methods: MG and DFE proposed by Pesaran & Smith [40] and CCEMG proposed by Pesaran [41]. In traditional DFE method, each group is pooled and only the intercepts are allowed to differ across groups. It is too restrictive due to the fact that it constrains long run coefficients to be equal across the group. It also restricts the speed of adjustment coefficients and short run coefficients to be equal. In MG method, model can be fitted separately for each group, and a simple arithmetic average of the coefficients is calculated. More importantly, the intercepts, slope coefficients, and error variances are allowed to differ across groups. The MG estimator is more flexible compared to DFE. In contrast, the PMG method is an intermediate (neither too restrictive as in DFE, nor too flexible as with MG) estimator that adopts some of the features of the DFE and MG methods. It allows the intercepts, short run coefficients, and error variance to differ across the groups as in MG but constrains the long run coefficients to be equal across groups as in DFE [38]. Pesaran et al. [39] developed a maximum likelihood method to estimate the parameters for those models. In the case of the CCEMG method, it allows coefficients to vary across the states and uses a simple average of the individual states. In this method, unobserved common factors are eliminated and augmented by a weighted cross section average of the dependent variable.

We expect to have a negative sign on the own price, and a positive sign on income, cross price, and CDD respectively. Additionally, based on the most aggregated consumption theories, we hypothesized that the long run income elasticities of electricity demand in all sectors are unitary.

2.2. Testing for unit root and cointegration

Different approaches to panel unit root tests have been proposed by several authors [7,15,42–45]. These approaches have both strengths and weaknesses depending on the characteristics of the data. The problem associated with LLC is that it is biased, and the bias correction process causes a severe loss of power. In the dynamic panel set up, a downward bias known as Nickel bias may exist due to the fixed effect, as pointed out by Nickell [46]. This bias is not affected by cross section dimensions. In order to correct the Nickell bias, Breitung & Meyer [47] introduced an approach of subtracting initial observations rather than taking the average in step 0 of LLC. Breitung [48] proposed alternative statistics, however; it has a low power when the trend parameters are heterogeneous across units. Maddala & Wu [15] pointed out some drawbacks of the IPS test, which is based on the average of an ADF test. In order to use IPS and LLC tests correctly, one would have to re-simulate the standardization factor due to the fact that the critical values of IPS and LLC tests are simulated only for common K_i and T_i. In this context, Maddala and Wu proposed an alternative approach that has some distinct advantages, such as: (1) does not require a balanced panel, (2) allows completely heterogeneous specifications, (3) can be used on any individual unit root test, and (4) does not require simulating adjustment factors that are specific to the sample size and specification.

The size of a panel unit root test can be affected by the presence of cross-sectional error correlation. In order to reduce the size distortion, MW suggested a bootstrap method. This method has an advantage over the Im et al. approach in the sense that it does not depend on different lag lengths in individual ADF regression. To address the case of cross-sectional dependence more spesifically, Pesaran [14] has proposed a cross-sectionally augmented IPS known as the CIPS method, which follows the common correlated effects approach. In this method, cross section dependence is filtered out by augmenting the ADF regressions separately for each state with cross-section averages, as explained by Cavalcanti et al. [49]. For this study, we employ two methods of panel unit tests: MW and CIPS.

In order to establish the long run relationship among the variables, we use two methods for cointegration tests proposed by Pedroni [16] and Kao [17]. The Pedroni test includes asymptotic and finite-sample properties of the test statistics to examine the null hypothesis of no cointegration in the panel. This approach allows for the possibility of unit–specific fixed effects and deterministic trends. It considers both pooled within the dimension tests and group mean between dimension tests. It also allows for heterogeneity among individual members of the panel in both the long run and short run. Pedroni [16] has suggested two types of panel cointegration tests. The first one is based on within dimension, known as "weighted statistics," which consists of four statistics: panel v-statistic, panel rho-statistic, panel PP-statistic and panel ADF-statistic. The second test is based on group statistics, namely: group rho-statistic, group PP-statistic and group ADF- statistics. Another approach of cointegration tests proposed by Kao [17] is a generalization of an augmented Dickey Fuller (ADF) test. It uses the t-statistic for panel data to test the null hypothesis of no cointegration. As in the time series case, the limiting distribution is affected by serial correlation of the error and the non exogeneity of the regressors, which induces bias. To remove the influence of these parameters, estimates of the long run covariance are needed. Kao [17] uses the bias corrected test where the variance of innovations is the same in all cross-section units. Generally, time series data of a longer period is expected for cointegration tests to establish long run relationships among the variables. However, some authors [50–51] have established a cointegration test using small sample (T = 16 and T = 18 respectively).

3. Data description

We use several different data sources for this study. We utilize state level annual data over the period from 1997 to 2011 for the Northeastern United States, encompassing nine states (Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont). Due to some missing variables, we are able to utilize data from 1997 to 2011 which is the most recent available data from the Energy Information Administration

[4] CDD is used for electricity demand in short run estimation because change in cooling degree days influence immediate adjustment in electricity demand. In that sense, it is more realistic to include CDD in short run estimation of electricity demand.

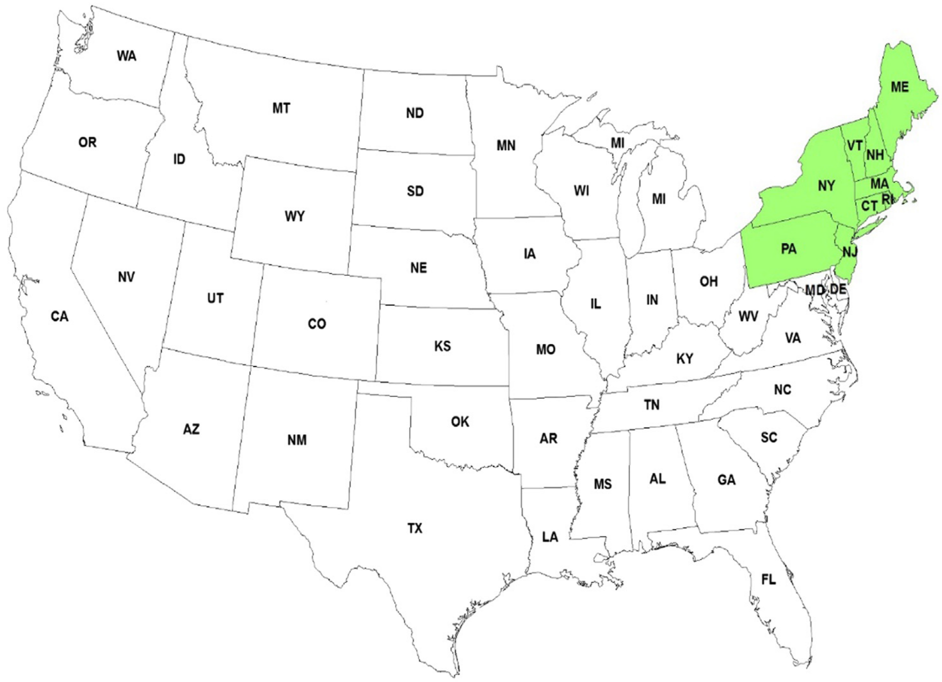

Fig. 1. Study area - Northeastern U.S. states highlighted in green color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(EIA). Fig. 1 shows the study area considered in this paper.

We collected data on total electricity consumption, electricity prices, and the number of customers of electricity in the residential, commercial, and industrial sectors from the EIA. Substitute energy prices, such as heating fuel oil (distillate and residual type) and natural gas prices, are gathered from the same source, the EIA. The cooling degree days for each state are obtained from the National Oceanic and Atmospheric Administration (NOAA), consumer price index (CPI), and producer price index (PPI) from the U.S. Department of Labor. Aditionally, we obtained the gross domestic product by state, gross retail sales by state, and disposable personal income for each state from the U.S. Department of Commerce, Bureau of Economic Analysis. We use value added by manufacturing per industry by state as income for the industrial sector, gross retail sales for the commercial sector, and disposable household per capita income of each state as an income factor for the residential sector.

In order to maintain a consistency in unit of measurement, we converted the data into compatible units by employing appropriate conversions. Per capita electricity consumption is measured in KWH. The average price of natural gas, electricity, and fuel oil are measured in dollars per KWH, dollars per 1000 therms, and dollars per gallon respectively. To adjust for inflation, prices and per capita disposable household income are divided by CPI and per capita disposable retail sales, and per capita disposable industrial income is divided by PPI. Final data sets in natural logarithm include the following:

QE = per capita electricity consumption (KWH),
PN = avg. real price of natural gas ($/ 1000 therm.),
PE = avg. real price of electricity ($/KWH),
PO = average real price of fuel oil ($/ gallons),
CDD = cooling degree days, and
YI = real disposable per capita income in dollars (household per capita income for the residential sector, per capita retail sales for the commercial sector, and per capita value added by manufacturing for the industrial sector).

Table 1 provides descriptive statistics of the variables used in this study. Figs. 2, 3, and 4 provide the demand trend for electricity in the residential, commercial, and industrial sectors of the study region, respectively.

Table 1
Descriptive Statistics of variables used in the estimation.

SECTOR	STAT.	QE	PN	PE	PO	YI	CDD
Residential	Mean	7589.4	638.8	0.070	0.94	41,713	551.5
	Max	10,535	869.6	0.094	1.54	54,401	1149
	Min	5746.0	391.2	0.050	0.46	25,389	135
	SD	1155.0	115.0	0.009	0.32	8209.0	231
Commercial	Mean	63,676	643.8	0.074	0.98	31,941	551.5
	Max	95,179	983.7	0.102	1.96	52,065	1149
	Min	36,240	252.1	0.044	0.37	21,972	135
	SD	16,335	165.0	0.010	0.45	6819.0	231
Industrial	Mean	$1.4 * 10^6$	520.9	0.057	0.98	$21 * 10^6$	551.5
	Max	$6.6 * 10^6$	918.3	0.089	1.94	$79 * 10^6$	1149
	Min	$0.46 * 10^6$	190.8	0.032	0.31	$6.1 * 10^6$	135
	SD	$1.2 * 10^6$	186.0	0.013	0.31	$1.7 * 10^6$	231

Note: Variable definitions are QE = per capita electricity consumption (KWH), PN = avg. real price of natural gas ($/1000 therm.), PE = avg. real price of electricity ($/KWH)
PO = average real price of fuel oil ($/ galloons), CDD = cooling degree days, YI = real disposable per capita income in dollars (household per capita income for residential sector, per capita retail sales for commercial sector, and per capita value added by manufacturing for industrial sector).

4. Empirical results

4.1. Unit root and cointegration tests results

Before proceeding with parameter estimation, it is important to make sure that the series is I(1) and cointegrated, because our proposed estimators require I(1) and a cointegrated series. We employ two methods of panel unit root test procedures proposed by Maddala and Wu and Pesaran. The unit root test results for each sector are presented in Appendix Tables A1, A2, and A3. These provide the results with trend and without trend for three lags in each case. The results seem to

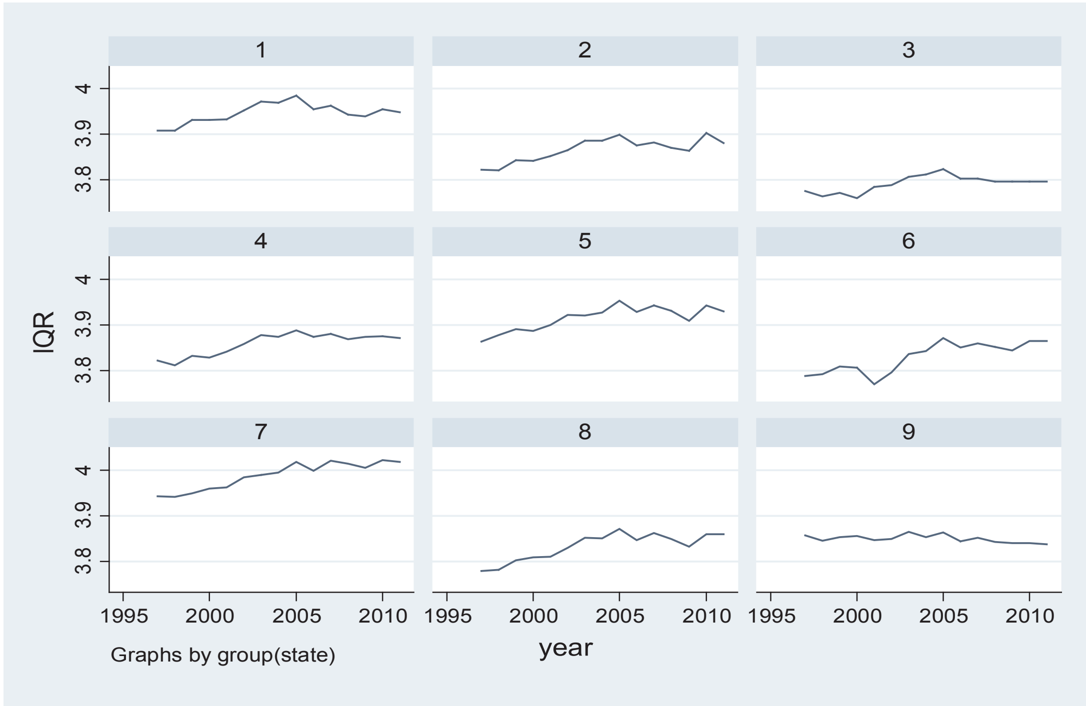

Fig. 2. Per capita electricity consumption (log value) in the residential sector of the study area (1997-2011). Here, the state number are as follows: CT = 1, ME = 2, MA = 3, NH = 4, NJ = 5, NY = 6, PA = 7, RI = 8, VT = 9.

be mixed; however, the majority of the test statistics indicate that the variables are non-stationary at level and stationary at first difference. Thus, we can generalize that the variables QE, PE, PN, PO, and YI are I (1).

In order to establish the existence of a long run relationship between energy consumption and its own price, cross price, income, and CDD, we use two methods of cointegration tests proposed by Kao [17] and Pedroni [16]. Table 2 displays the cointegration test results. In the Pedroni test, weighted panel PP stat indicates that the null of no cointegration is rejected at a 1% significance level in each sector. Likewise, group PP stat rejects the null hypothesis at a 1% significance level. Similarly, the Kao test rejects the null hypothesis at a 1% significance level. Thus, we can make a conclusion that there exists a long run relationship between the electricity demand and its own price, cross price, income, and cooling degree days. From unit root and cointegration test results, we are able to establish that the series is I(1) and

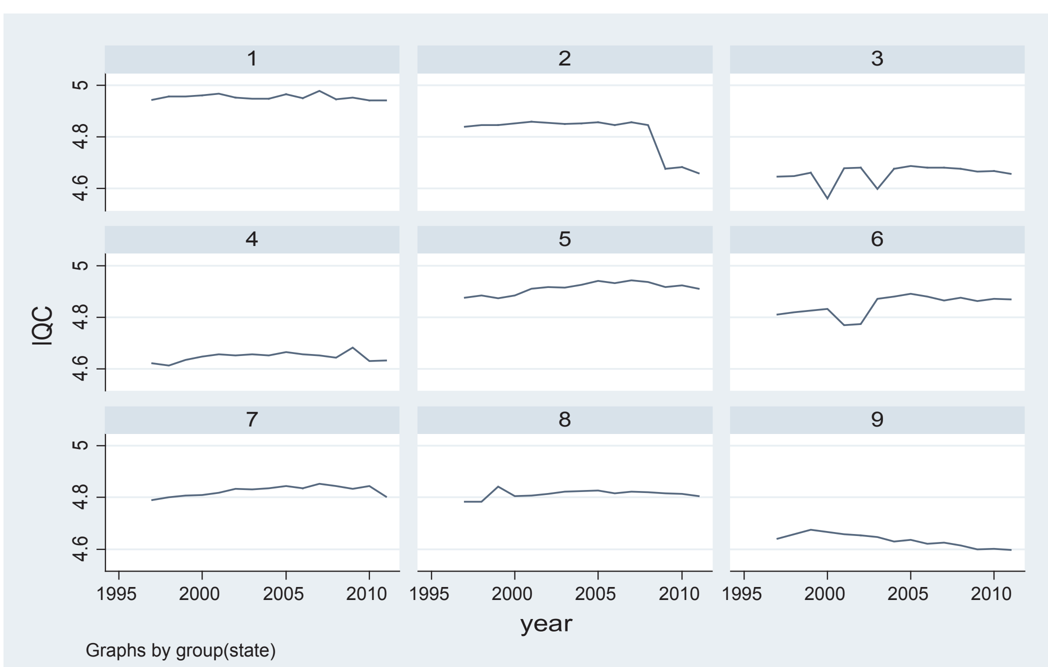

Fig. 3. Per capita electricity consumption (log value) in the commercial sector of the study area (1997-2011). Here, the state number are as follows: CT = 1, ME = 2, MA = 3, NH = 4, NJ = 5, NY = 6, PA = 7, RI = 8, VT = 9.

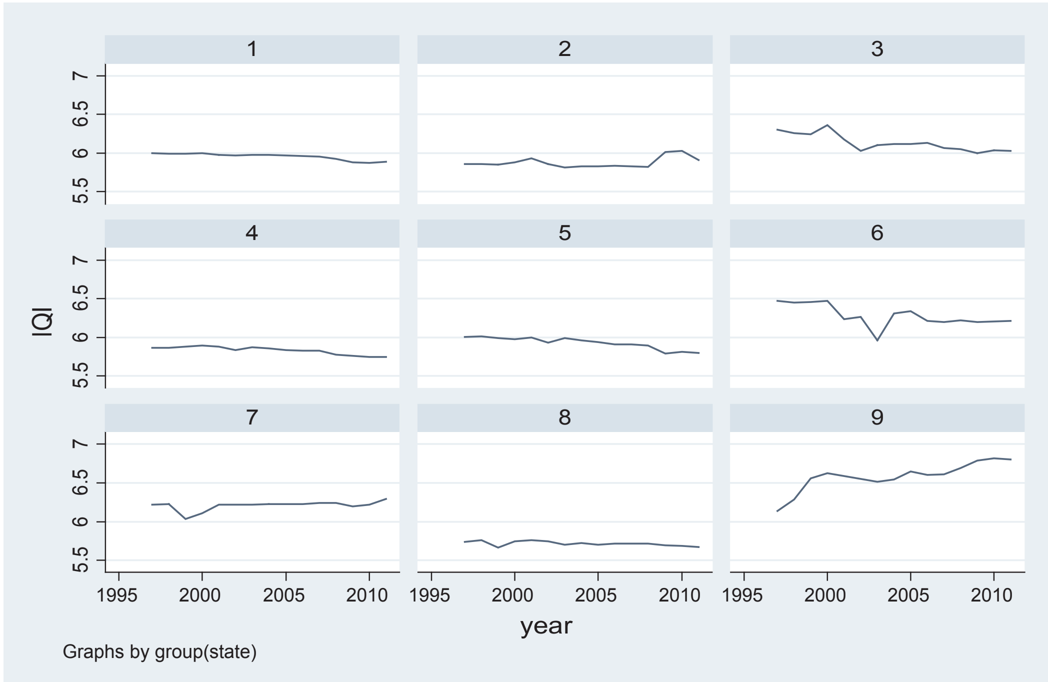

Fig. 4. Per capita electricity consumption (log value) in the industrial sector of the study area (1997-2011). Here, the state number are as follows: CT = 1, ME = 2, MA = 3, NH = 4, NJ = 5, NY = 6, PA = 7, RI = 8, VT = 9.

cointegrated, which in turn allows us to proceed with estimating the parameters of the dynamic error-correction models using PMG, DFE, MG, and CCMG methods. Finally, we use the Hausman test for model selection.

4.2. Parameter estimation results

General characteristics of the four estimators indicate that PMG is a mediator estimator in the sense that it imposes some restriction and allows some flexibility and hence performs better than DFE, MG, and CCEMG. Table 3 displays the parameter estimation results using the PMG method for electricity demand in residential, commercial, and industrial sector.

From Table 3, the long run own price elasticity of electricity demand in the residential sector is −0.11, which is significant at 1% significance level. It implies that a one percent increase in electricity price is associated with a 0.11% decrease in expected electricity demand in the residential sector. This value is almost similar to that found by Beierlein et al. [10]. An empirical analysis conducted by Gautam and Paudel [52] using the augmented mean group method for natural gas in the U.S. finds a significant long run impact of own price, fuel price, and HDD on natural gas demand. In the long run, residential consumers are more sensitive to price change compared to commercial and industrial consumers. In the industrial sector, own price elasticity is insignificant but properly signed. Price elasticity of −0.63 in the industrial sector indicates that the price change has some influence on electricity demand. The short run demand for electricity in the residential sector is inelastic, which indicates that residential consumers have little flexibility in electricity use, since its major use is lighting, operating appliances, cooling houses, and refrigerating. However; commercial consumers are responsive to price in the short run. The short run own price elasticity in the industrial sector is insignificant but correctly signed. It

Table 2
Cointegration Test using the Pedroni and Kao tests (H0: no cointegration).

Sector	Pedroni test: Weighted stat		Group stat		Kao test *t*-test
	Panel v-stat	−1.23(0.89)	Rho stat	2.78(0.99)	
Residential	Panel rho stat	1.78(0.96)	PP stat	−16.8(00)***	−4.74(00)***
	Panel PP stat	−7.34(00)***	ADF stat	0.52(0.74)	
	Panel ADF stat	0.65(0.74)			
	Panel v-stat	−2.81(0.99)	Rho stat	2.68(0.99)	
Commercial	Panel rho stat	1.47(0.93)	PP stat	−25.8(00)***	−4.89(00)***
	Panel PP stat	−11.61(00)***	ADF stat	−0.37(0.35)	
	Panel ADF	−0.70(0.24)			
	Panel v-stat	−1.57(0.94)	Rho stat	2.92(0.99)	
Industrial	Panel rho stat	1.83(0.96)	PP stat	−23.29(00)***	−4.38(00)***
	Panel PP stat	−11.92(00)***	ADF stat	−1.20(0.11)	
	Panel ADF stat	−1.40(0.07)			

Note: p-values in the parentheses.
*$p < 0.1$.
**$p < 0.05$.
*** $p < 0.01$.

Table 3
Parameter Estimates using a Pooled Mean Group (PMG) Method.

Variables	Residential	Commercial	Industrial
Short run			
ΔEC	−0.611***	−0.595***	−0.0460
	(0.0907)	(0.1531)	(0.0402)
ΔLPN	−0.0523***	0.0171	0.0620
	(0.0194)	(0.0450)	(0.0800)
ΔLPE	0.0223	−0.220***	−0.217
	(0.0423)	(0.0482)	(0.214)
ΔLPO	0.0842***	0.0504*	−0.0237
	(0.0147)	(0.0261)	(0.0841)
ΔLYI	−0.452***	0.137	0.613***
	(0.1670)	(0.100)	(0.2090)
ΔLCDD	0.0332***	0.0304**	0.0296
	(0.0085)	(0.0124)	(0.0272)
Long run			
LPN	0.0952***	0.105***	−1.198**
	(0.0171)	(0.0163)	(0.5140)
LPE	−0.110***	0.103***	−0.632
	(0.0224)	(0.0362)	(0.7580)
LPO	−0.0778***	0.0052	1.093**
	(0.0120)	(0.0108)	(0.5380)
LYI	0.938***	0.531***	1.957***
	(0.0513)	(0.0794)	(0.6700)
Constant	−0.524***	1.325***	−0.248
	(0.0805)	(0.3420)	(0.2180)
Observations	126	126	126

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 4
Parameter Estimates using a Dynamic Fixed Effect (DFE) Method.

Variables	Residential	Commercial	Industrial
Short run			
ΔEC	−0.431***	−0.247***	−0.154**
	(0.0738)	(0.0804)	(0.0673)
ΔLPN	−0.0627**	−0.0121	0.0653
	(0.0260)	(0.0409)	(0.0584)
ΔLPE	0.0698*	−0.0154	−0.181
	(0.0414)	(0.0699)	(0.1140)
ΔLPO	0.0604***	0.0469*	−0.0077
	(0.0165)	(0.0283)	(0.0534)
ΔLYI	−0.0221	0.526***	0.775***
	(0.0952)	(0.1160)	(0.0892)
ΔLCDD	0.0356***	0.0113	−0.0011
	(0.0064)	(0.0133)	(0.0240)
Long run			
LPN	0.0012	0.215	−0.308
	(0.0561)	(0.1880)	(0.3550)
LPE	−0.294***	0.141	−0.329
	(0.0735)	(0.2571)	(0.6440)
LPO	−0.0674	−0.0968	0.148
	(0.0427)	(0.1012)	(0.3731)
LYI	1.058***	0.789*	0.692*
	(0.1980)	(0.4250)	(0.3610)
Constant	−0.582	0.194	0.214
	(0.3621)	(0.4210)	(0.4041)
Observations	126	126.	126.

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

indicates that the industrial consumers show some response to a price change in the short run similar to the long run impact. The significant but small magnitude of the own price elasticity of electricity demand in the residential sector, and the insignificant own price elasticity in the commercial and industrial sectors, implies that the pricing mechanism may not be an effective policy tool for energy conservation. However, if environmental quality is a concern then tax on heating fuel oil use can reduce its demand given the substitutability between electricity and heating fuel oil.

The cross price elasticity between electricity and natural gas is not important in the short run because substitutability is very limited as electricity is mainly used for lighting and natural gas for a heating purpose. However, the long run cross price elasticities of natural gas in residential and commercial sectors are significant at a 1% significance level, showing a higher impact in the commercial sector. This finding is consistent with the result obtained by Silva et al. [35] in the residential sector in Portugal. The substitutability between natural gas and electricity implies that commercial and residential sectors adjust electricity demand when the price of natural gas changes in the long run. It means that the increase in natural gas price tends to increase residential and commercial customers to demand more electricity. In the short run, the effect of the heating oil price on electricity demand is significant at 1% and 10% significance levels in the residential and commercial sectors, respectively. The result is consistent with observed behavior that the residential consumers tend to substitute electricity for heating oil in the short run for home heating purposes when the price of heating oil increases. The residential consumers are more sensitive to heating oil price change compared to commercial consumers. But, in the long run, the industrial consumers are sensitive to a heating oil price change. The substitutability between electricity and heating fuel oil in the short run and long run has some policy implications from an environmental perspective. Heating fuel oil is not as clean as electricity and natural gas. The Northeastern U.S. region uses heating oil for primarily space heating, use of which is not environmentally friendly. Formulation of a tax equivalent to the environmental loss could be an appropriate policy tool in order to discourage its excessive use. Additionally, awareness campaigns and education could be effective in promoting environmental sustainability. The long run cross price elasticity of heating oil in the industrial sector is 1.09, which is significant at a 10 percent significance level. The positive effect is the indication of the substitution effect. However, it is also worthwhile to note that the increase in heating oil price is the consequence of an increase in all other petroleum products which consequently leads to decrease in income level, and this negative income effect outweighs the positive substitution effect for a negative net effect [10].

The long run income[5] elasticities of electricity demand in the residential, commercial and industrial sectors are 0.93, 0.53, and 1.95, respectively. All are significant at one percent significance level. In the industrial sector, electricity demand is highly responsive to the level of value added by manufacturing in the long run. The magnitude of income elasticity at 1.96 makes electricity a luxury good in the the long run, but it seems like a normal good in the short run, as income elasticity lies between zero and one. In the residential and commercial sectors, electricity is a normal good in the long run. But, in the short run, residential consumers are irresponsive to income, and the commercial retail sales effect is unimportant for electricity demand. We reject the hypothesized long run unitary income elasticity of electricity demand in all three sectors. It indicates that the increase in income is not accompanied by the same proportionate increase in electricity demand. Higher income elasticity in the long run implies that energy efficient appliances and housing structures might be effective policy tools for energy conservation. The long run and short run income elasticities for all three sectors are graphed in Fig. 5. In Figs. 6 and 7, we show own and cross price elasticities, respectively, for all three sectors.

The short run impact of cooling degree days to electricity demand is positive in all sectors as expected. The estimated values for residential and

[5] Income is represented by household per capita income for the residential sector, retail sales for the commercial sector, and value added by manufacturing for the industrial sector.

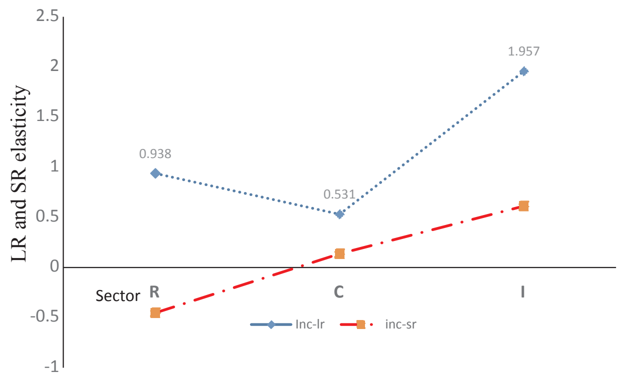

Fig. 5. SR and LR income elasticity of electricity demand in all three sectors (R = Residential, C = Commercial, I = Industrial) in short run (SR) and long run (LR).

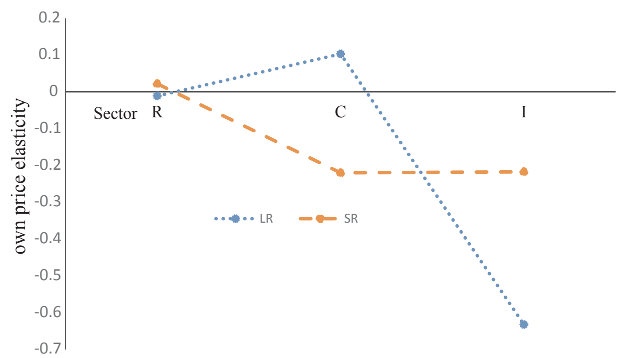

Fig. 6. Own price elasticity of electricity demand in all three sectors (R = Residential, C = Commercial, I = Industrial) in short run (SR) and long run (LR).

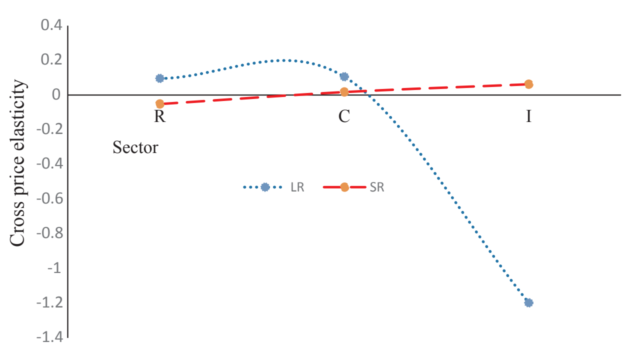

Fig. 7. Cross price (NG price) elasticity of electricity demand in all three sectors (R = Residential, C = Commercial, I = Industrial) in short run (SR) and long run (LR).

commercial sectors are significant at one percent and 10 percent significance level respectively. The elasticities of the cooling degree days to electricity demand are almost the same in these two sectors. The CDD elasticity implies that a one percent increase in CDD is associated with a 0.033% and 0.030% increase in expected electricity demand in the residential and commercial sectors respectively in the short run. The magnitude of CDD impact on electricity demand for the Northeastern U.S. is much lower than that found in Shanghai and Singapore. The short run effect of CDD on industrial electricity demand is not significant but is positively signed. The CDD elasticity of electricity demand varies from region to region due to the differences in temperature variation, as noted by many authors [11–13,23]. So, the energy policy should address the regional climatic impact in energy demand-supply stabilization.

The estimated results using DFE[6] indicate a significant income effect in all three sectors although the degree of magnitude is maximum in the residential sector followed by the commercial sector. The long run own price elasticity in the residential sector is highly significant and the magnitude is more than twice the value that has been found using PMG method. The long run coefficients in MG[7] method are insignificant except for natural gas price in the commercial sector. The short run impact of cooling degree days is similar to the results obtained from the PMG method. The CCEMG[8] estimates are properly signed except for own price and natural gas price for the commercial sector. The own price elasticity for residential and industrial sectors are significant at 10 percent and one percent significance level respectively. Similarly, the retail sales price in the commercial sector is highly responsive to the electricity demand. Overall, own price, cross price, substitute fuel oil, income elasticities, and heating degree days have better estimates with the PMG method compared to the other three methods. However, the Hausman test indicates DFE is preferred over PMG and MG (Appendix Tables A6–A11).

The robustness of the estimated parameters is very important in empirical analyses. The reliability of empirical results is associated with the robustness of the empirical results. Generally, in demand estimation, endogeneity is considered to be a common problem, and without addressing this issue, estimated results could be questionable in terms of reliability. In the case of a fixed effects type of model, simultaneous equation bias may arise from the endogeneity between the error term and lagged dependent variables, as explained by Baltagi [53]. The Hausman test can be used to detect the presence of endogeneity caused by simultaneous equation bias. The Hausman test statistics show that the simultaneous equation bias is minimal for these data, implying that our results do not suffer from an endogeneity problem. Additionally, cluster (id) option in the DFE estimation provides us with a robust standard error.

5. Concluding remarks and discussion

The demand for electricity in the residential, commercial, and industrial sectors of the Northeastern United States has been estimated using the most recently available annual panel data over the period 1997-2011. We employed a pooled mean group method to estimate the parameters in the electricity demand equation. We used CIPS and the Maddala and Wu procedures of panel unit root tests to examine whether the series are nonstationary. The majority of the test statistics indicate that the series are integrated of order one [I (1)] and cointegrated. Additionally, Pedroni and Kao approaches to cointegration test results confirm the existence of cointegration.

The estimated results show that own price for the residential sector and income for all three sectors are highly elastic in electricity demand in the long run. Short run, commercial electricity demand is own price elastic, and industrial sector electricity demand is income elastic. Residential electricity demand is not responsive to its own price in the short run. The cooling degree days have significant positive effects on electricity demand in the short run except for in the industrial sector. The heating oil price has a significant positive effect in the residential and commercial sectors in the short run, implying that the residential and commercial customers are likely to adjust electricity consumption when there is a significant change in fuel oil price. Short run electricity demand is irresponsive to natural gas price in all sectors. The long run cross price effect of the natural gas price is significantly positive except in the industrial sector. Regarding the robustness of the estimator, the pooled mean group method seems to be robust compared with alternative estimators, such as the mean group, dynamic fixed effect, and common correlated effect mean group.

The findings of this study have some policy implications that can be

[6] See parameter estimation results in Table 4.
[7] See parameter estimation results in Appendix Table A4.
[8] See parameter estimation results in Appendix Table A5.

summarized in three major points. First, higher income elasticity in the long run implies that energy efficient appliances and housing structures might be effective policy tools for energy conservation. Second, the small magnitude of the own price elasticity of electricity demand indicate that the pricing mechanism could be an ineffective policy tool for energy conservation. However, the substitutability between electricity and heating fuel oil points out a need to formulate a tax equivalent to the environmental loss so as to reduce heating oil use. Third, the significant impact of cooling degree days in electricity demand requires that the energy policy should address the regional climatic impact in energy demand-supply stabilization.

We noted that the electricity demand is sensitive to cooling degree days and income factors. However, we are unable to capture a monthly variation in energy demand pattern as our analysis is based on annual data. In our estimation results with state annual data, income effect is highly significant. But the sensitivity of income could be differentiated based on income level and rural and urban areas, as noted by Silva et al. [36], Silva et al. [35]; and Schulte and Heindl [34]. In order to suggest an appropriate policy tool, welfare implications for the poor households need to be considered. For this reason, household level electricity demand analysis incorporating various household characteristics would be more effective. In this study with annual panel data, we are able to address the unit specific fixed effect in the error correction model and the unobserved heterogeneity in the common correlated effect mean group method. But at the same time we failed to capture unit specific variation in cooling degree days, income, and price. For more effective results, we should consider monthly data in household level and alternative estimators such as the instrumental variable approach. For future research, the inclusion of a longer time series and finer scale would help to establish the relationship between income, price, temperature, and housing characteristics to electricity demand more authoritatively.

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Appendix A

See Tables A1–A11.

Table A1
Panel Unit Root Tests (Residential Sector), H0: series is I (1).

Test	Trend	Lags	LPN	LQE	LPE	LPO	LYI	LCDD
MW Chi-sq	No Trend	0	11.39(0.87)	23.60(0.16)	20.26(0.31)	2.87(1.00)	47.24(00)	172.60(00)
		1	13.13(0.78)	19.06(0.38)	29.87(0.03)	4.50(0.99)	46.21(00)	159.30(00)
		2	22.06(0.22)	9.00(0.96)	30.27(0.03)	6.90(0.99)	36.17(00)	54.00(00)
		3	21.74(0.24)	10.40(0.50)	31.31(0.02)	2.25(1.00)	55.23(00)	32.60(0.01)
	With Trend	0	1.86(1.00)	30.60(0.03)	13.30(0.77)	40.40(00)	33.40(0.01)	132.00(00)
		1	3.02(1.00)	61.70(00)	16.70(0.54)	21.80(0.24)	12.70(0.84)	133.00(00)
		2	1.93(1.00)	23.60(0.16)	19.70(0.35)	2.76(1.00)	47.10(00)	45.30(00)
		3	1.78(1.00)	25.80(0.10)	14.40(0.69)	22.30(0.21)	25.30(0.11)	28.10(0.06)
CIPS Pesaran Zt-bar	No Trend	0	−3.70(00)	−0.11(0.45)	−3.88(00)	−1.10(0.13)	−0.29(0.38)	−4.70(00)
		1	−1.20(0.11)	−1.07(0.14)	−2.06(0.01)	0.53(0.70)	0.07(0.53)	−0.02(0.40)
		2	−1.99(0.02)	2.56(0.99)	0.48(0.68)	−1.30(0.08)	−0.53(0.29)	−0.039(0.30)
		3	−6.50(00)	4.59(1.00)	−3.23(00)	0.46(0.68)	−6.01(00)	1.48(0.93)
	With trend	0	−2.80(00)	−1.00(0.15)	−3.27(00)	−1.00(0.15)	0.61(0.73)	−3.50(00)
		1	−1.60(0.05)	−0.67(0.25)	−0.34(0.36)	0.66(0.74)	1.32(0.90)	0.91(0.81)
		2	−1.70(0.03)	3.60(1.00)	1.35(0.91)	−0.92(0.17)	−0.10(0.46)	0.62(0.73)
		3	10.60(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)

(P-values within the parentheses), all variables are in natural logarithm.

Table A2
Panel Unit Root Tests (Commercial Sector), H0: Series is I (1).

Test	Trend	Lags	LPN	LQE	LPE	LPO	LYI	LCDD
MW Chi-sq.	No Trend	0	11.50(0.87)	18.40(0.43)	18.20(0.44)	3.40(1.00)	16.80(0.53)	172.00(00)
		1	17.30(0.50)	20.20(0.31)	23.20(0.18)	6.30(0.99)	13.90(0.72)	159.00(00)
		2	24.70(0.13)	18.70(0.41)	46.90(00)	9.10(0.95)	10.10(0.92)	54.00(00)
		3	36.50(0.06)	28.10(0.06)	27.60(0.06)	3.60(1.00)	16.90(0.52)	32.60(0.01)
	With Trend	0	1.74(1.00)	11.40(0.87)	24.08(0.15)	27.40(0.07)	12.70(0.80)	132.00(00)
		1	202(1.00)	3.34(1.00)	34.50(0.01)	10.00(0.93)	12.00(0.84)	133.00(00)
		2	0.59(1.00)	4.09(1.00)	23.40(0.17)	1.40(1.00)	8.70(0.96)	45.30(00)
		3	1.33(1.00)	10.70(0.90)	25.10(0.12)	14.20(0.71)	6.50(0.99)	28.10(0.06)
CIPS Pesaran Zt-bar	No Trend	0	−4.80(00)	−1.90(0.02)	−3.30(00)	−4.30(00)	−1.10(0.12)	−4.76(00)
		1	−2.40(00)	0.18(0.57)	−3.10(00)	−1.60(0.05)	0.24(0.59)	−0.02(0.49)
		2	−1.50(0.05)	−2.50(00)	−2.07(0.01)	−0.91(0.18)	−1.50(0.05)	−0.30(0.34)
		3	1.28(0.90)	−0.31(0.37)	−2.90(00)	−0.98(0.16)	−1.40(0.07)	1.40(0.93)
	With trend	0	−3.20(00)	−2.00(0.01)	−2.90(00)	−2.30(00)	−1.20(0.10)	−3.50(00)
		1	−1.90(0.02)	0.57(0.71)	−2.70(00)	0.73(0.76)	0.40(0.65)	0.91(0.81)
		2	0.13(0.55)	0.51(0.30)	−0.25(0.40)	0.99(0.84)	−1.70(0.03)	0.62(0.73)
		3	10.60(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)

(P-values within the parentheses), all variables are in natural logarithm.

Table A3
Panel Unit Root Tests (Industrial Sector), H0: series is I (1).

Test	Trend	Lags	LPN	LQE	LPE	LPO	LYI	LCDD
MW Chi-sq	No Trend	0	10.40(0.91)	45.90(00)	8.95(0.96)	4.20(1.00)	25.40(0.11)	172.00(00)
		1	17.30(0.49)	49.70(00)	10.40(0.91)	6.10(0.99)	19.40(0.36)	159.00(00)
		2	33.60(0.01)	14.90(0.66)	13.90(0.73)	8.40(0.97)	60.60(00)	54.00(00)
		3	29.80(0.03)	31.40(0.02)	15.00(0.66)	3.90(1.00)	10.30(0.91)	32.60(0.01)
	With Trend	0	2.07(1.00)	46.00(00)	22.50(0.20)	23.40(0.17)	24.07(0.15)	132.00(00)
		1	0.75(1.00)	54.60(00)	87.00(00)	9.20(0.95)	38.90(00)	133.00(00)
		2	0.28(1.00)	11.10(0.88)	17.30(0.50)	3.90(1.00)	18.20(0.43)	45.00(00)
		3	0.14(1.00)	10.40(0.91)	12.70(0.80)	19.00(0.38)	9.70(0.93)	28.00(0.06)
CIPS Pesaran Zt-bar	No Trend	0	−3.40(00)	−1.90(0.02)	−3.30(00)	−4.80(00)	−1.80(0.03)	−4.76(00)
		1	−1.10(0.12)	−2.00(0.02)	−2.90(00)	−2.50(00)	−1.50(0.05)	−0.02(0.49)
		2	−1.20(0.10)	−1.40(0.07)	−1.90(0.02)	−1.08(0.13)	0.75(0.77)	−0.39(0.34)
		3	1.80(0.96)	−2.00(0.02)	−5.40(00)	−1.20(0.11)	2.10(0.98)	1.40(0.93)
	With trend	0	−3.60(00)	−2.80(00)	−2.08(0.01)	−3.60(00)	−0.29(0.38)	−3.50(00)
		1	−0.60(0.26)	−1.90(0.02)	−2.60(00)	−1.60(0.05)	−0.18(0.42)	0.91(0.81)
		2	0.93(0.82)	−0.050(0.47)	−2.80(00)	−0.10(0.45)	2.34(0.99)	0.62(0.73)
		3	10.60(1.00)	10.6(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)	10.60(1.00)

(P-values within the parentheses), all variables are in natural logarithm.

Table A4
Parameter Estimates using a Mean Group (MG) Method.

Variables	Residential	Commercial	Industrial
Short run			
ΔEC	−0.591***	−1.000***	−0.521***
	(0.2260)	(0.131)	(0.1530)
ΔLPN	−0.0146	−0.0551	0.0294
	(0.0362)	(0.0481)	(0.1230)
ΔLPE	−0.0150	−0.154	0.0668
	(0.0769)	(0.106)	(0.3031)
ΔLPO	0.0925***	0.0808**	−0.0262
	(0.0266)	(0.0398)	(0.1071)
ΔLYI	−0.672***	−0.187	0.223
	(0.1790)	(0.250)	(0.3272)
ΔLCDD	0.0380***	0.0275***	0.0320
	(0.0115)	(0.0074)	(0.0252)
Long run			
LPN	−0.449	0.416*	−0.164
	(0.4561)	(0.2210)	(0.2330)
LPE	−0.0906	0.0596	−0.383
	(0.3620)	(0.1742)	(0.4801)
LPO	−0.601	−0.191*	−0.0880
	(0.5680)	(0.1150)	(0.2881)
LYI	3.532	0.225	0.835
	(2.6221)	(0.3880)	(0.7151)
Constant	−1.658	1.997***	1.408
	(1.0861)	(0.6701)	(2.2860)
Observations	126	126	126

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A5
Parameter Estimates Using a Common Correlated Effect Mean Group (CCEMG) Method.

Variables	Residential	Commercial	Industrial
LPN	0.0776	−0.234	0.0392
	(0.0601)	(0.1440)	(0.2091)
LPE	−0.127**	0.125	−0.337***
	(0.0641)	(0.1120)	(0.1150)
LPO	0.101	0.129	−0.558
	(0.0726)	(0.6590)	(0.5230)
LYI	0.256	1.046***	0.367
	(0.4901)	(0.2541)	(0.4170)

(continued on next page)

Table A5 (*continued*)

Variables	Residential	Commercial	Industrial
LCDD	0.0658*	0.0783	0.193
	(0.0373)	(0.1560)	(0.2910)
LQE_avg	0.940***	0.897**	0.887***
	(0.0995)	(0.3670)	(0.3161)
LPN_avg	−0.105	0.284*	0.0329
	(0.1030)	(0.1472)	(0.2481)
LPE_avg	0.120	−0.367*	0.429
	(0.0861)	(0.2072)	(0.4461)
LPO_avg	−0.0966	−0.0888	0.453
	(0.0799)	(0.6090)	(0.5881)
LYI_avg	−0.205	−1.140***	−0.345
	(0.5461)	(0.3380)	(0.3861)
LCDD_avg	−0.0614*	−0.0280	−0.187
	(0.0347)	(0.1830)	(0.2630)
Constant	0.0283	0.325	0.480
	(0.6701)	(2.7851)	(3.0751)
Observations	135	135	135
Number of States	9	9	9

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A6
Hausman Test to Compare MG and PMG Estimators (Residential Sector).

	Coefficients			
VAR.	MG (b)	PMG (B)	Difference (b-B)	Sqrt (diag(v_b-v_B)) S.E.
LPN	−0.449	0.095	− 0.544	1.397
LPE	−0.091	−0.110	0.020	1.111
LPO	−0.601	−0.078	−0.523	1.742
LYI	3.532	0.938	2.594	8.042

Note: $\chi^2(4) = 0.97$ and Prob > $\chi^2 = 0.913$ indicates that PMG is efficient estimator.

Table A7
Hausman Test to Compare DFE and PMG Estimators (Residential Sector).

	Coefficients			
VAR.	PMG (b)	DFE (B)	Difference (b-B)	Sqrt (V_b-V_B)) S.E.
LPN	0.095	0.001	0.094	17.503
LPE	−0.110	−0.294	0.184	23.015
LPO	−0.078	−0.067	−0.010	12.255
LYI	0.938	1.058	−0.120	52.615

Note: $\chi^2(4) = 0.00$ and Prob > $\chi^2 = 1.00$ indicates that simultaneous equation bias is minimal for these data and we conclude that the DFE method is preferred over the PMG.

Table A8
Hausman Test to Compare MG and PMG Estimators (Commercial Sector).

	Coefficients			
VAR	MG (b)	PMG (B)	Difference (b-B)	sqrt(diag(V_b-V_B)) S.E.
LPN	0.416	0.105	0.311	0.768
LPE	0.060	0.103	−0.043	0.604
LPO	−0.191	0.005	−0.196	0.399
LYI	0.225	0.531	−0.306	1.349

Note: $\chi^2(4) = 0.69$ and Prob > $\chi^2 = 0.952$ indicates that PMG is efficient estimator.

Table A9
Hausman Test to Compare DFE and PMG Estimators (Commercial Sector).

	Coefficients			
VAR.	PMG (b)	DFE (B)	Difference (b-B)	sqrt(diag(V_b-_B)) S.E.
LPN	0.105	0.215	−0.110	3.107
LPE	0.103	0.141	−0.038	6.903
LPO	0.005	−0.097	0.102	2.051
LYI	0.531	0.789	−0.258	15.153

Note: χ^2 (4) = 0.01 and Prob > χ^2 = 1.00 indicates that simultaneous equation bias is minimal for these data, and we conclude that the DFE method is preferred over the PMG.

Table A10
Hausman Test to Compare MG and PMG Estimators (Industrial Sector).

	Coefficients			
VAR.	MG	PMG	Difference	sqrt(diag(V_b-V_B))
	(b)	(B)	(b-B)	S.E.
LPN	−0.164	−1.198	1.035	1.130
LPE	−0.383	−0.632	0.249	0.473
LPO	−0.088	1.093	−1.181	0.521
LYI	0.835	1.957	−1.122	1.150

Note: χ^2 (4) = −17.22 and Prob > χ^2 < 0 indicates that PMG is efficient estimator compared to MG.

Table A11
Hausman Test to Compare DFE and PMG Estimators (Industrial Sector).

	Coefficients			
VAR.	PMG (b)	DFE (B)	Difference (b-B)	sqrt(diag(V_b-V_B)) S.E.
LPN	−1.198	−0.308	−0.890	57.753
LPE	−0.632	−0.329	−0.304	85.138
LPO	1.093	0.148	0.946	60.469
LYI	1.957	0.692	1.265	75.275

Note: χ^2 (4) = 0.00 and Prob > χ^2 = 1.00 indicates that simultaneous equation bias is minimal for these data, and we conclude that the DFE method is preferred over the PMG.

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