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Accounting for Nonlinearity, Asymmetry, Heterogeneity, and Cross-Sectional Dependence in Energy Modeling: US State-Level Panel Analysis

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Academic Editor: Lin Zhang
Received: 9 June 2017; Accepted: 10 August 2017; Published: 15 August 2017

Abstract: This paper provides an example of several modeling and econometric advances used in the panel estimation of energy demand elasticities. The paper models the demand of total, industrial, and transport energy consumption and residential and commercial electricity consumption by analyzing US state-based panel data. The paper employs recently developed dynamic panel methods that address heterogeneity, nonstationarity, and cross-sectional dependence. In addition, the paper (i) considers possible nonlinear relationships between energy consumption and income without employing polynomial transformations of integrated income; and (ii) allows for and calculates possible asymmetric relationships between energy consumption and price. Finally, the paper models energy efficiency improvements by a nonlinear time trend. To our knowledge no other paper has combined all of the econometric and modeling advances that are applied here. Most of the results conformed to expectations; however, limited to no evidence of nonlinearities and asymmetries were uncovered.

Keywords: disaggregated energy demand; dynamic common factor panel models; nonstationary; heterogeneous panels; nonlinear; asymmetric relationships; US states

JEL Classification: C23; Q41

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1. Introduction

This short paper models the demand of energy consumption at several different levels of aggregation by analyzing US state-based panel data and by using methods that address heterogeneity, nonstationarity, and cross-sectional dependence. The paper models the demand of total, industrial, and transport energy consumption and residential and commercial electricity consumption. US state data is rich since (i) there is diversity among the states; and (ii) the states are (mostly) geographically connected, share institutions, and exhibit free movement of people, capital, and goods. In addition, the paper (i) considers possible nonlinear relationships between energy consumption and income, and (ii) allows for and calculates possible asymmetric relationships between energy consumption and price. Finally, the paper models energy efficiency improvements by a nonlinear time trend.

Estimating income and price elasticities for energy consumption is a popular subject in applied economics (e.g., see Graham and Glaister 2002 for a review of transport-focused studies). More recently, several single-country studies (Holtedahl and Joutz 2004; Halicioglu 2007; Dergiades and Tsoulfidis 2008; Liddle 2009) have focused on either residential energy/electricity or gasoline consumption and employed time-series based methods (i.e., methods that address nonstationarity/cointegration). In addition, other recent studies have used panel methods that address both nonstationarity and heterogeneity—but not cross-sectional dependence—e.g., Narayan et al. (2007), who considered residential electricity consumption demand, and Liddle (2012), who focused on gasoline demand. Yet, we believe that no paper has combined all of the econometric and modeling advances that are applied here, and so the present paper should be of interest to applied economic modelers.

2. Methodology and Data

2.1. Econometric Issues

The variables analyzed in energy demand studies (e.g., energy consumption, GDP) are highly trending, stock-based variables, and thus, may be nonstationary—in other words, their mean, variance, and/or covariance with other variables changes over time. When ordinary least squares (OLS) regressions are performed on time-series (or on time-series cross-sectional) variables that are not stationary, then measures like R-squared and t-statistics are unreliable, and there is a serious risk of the estimated relationships being spurious (Kao 1999; Beck 2008).

Also, for the macro-level variables typically considered in energy demand analyses, cross-sectional correlation/dependence is expected because of, for example, regional and macroeconomic linkages that manifest themselves through (i) common shocks; (ii) shared institutions; and/or (iii) local spillover effects between countries or regions. When the errors of panel regressions are cross-sectionally correlated, standard estimation methods can produce inconsistent parameter estimates and incorrect inferences (Kapetanios et al. 2011).

Yet, it is likely that the relationships (i.e., elasticities) will not be the same for each state—i.e., there should be a substantial degree of heterogeneity. And if one mistakenly assumes that the parameters are homogeneous (when the true coefficients of a dynamic panel in fact are heterogeneous), then all of the parameter estimates of the panel will be inconsistent (Pesaran and Smith 1995).

The Pesaran (2006) common correlated effects mean group (CCE) estimator accounts for the presence of unobserved common factors by including in the regression cross-sectional averages of the dependent and independent variables. Also, as a mean group estimator, CCE first estimates cross-section specific regressions and then averages those estimated cross-sectional coefficients to arrive at panel coefficients (standard errors are constructed nonparametrically as described in Pesaran and Smith 1995). However, while the CEE estimator is robust to nonstationarity, cointegration, breaks,[1] and serial correlation, the CCE estimator is not consistent in dynamic panels since the lagged dependent variable is no longer strictly exogenous. Chudik and Pesaran (2015) demonstrated that the estimator becomes consistent again when additional $\sqrt[3]{T}$ lags (in our case, 2)[2] of the cross-sectional means are included. Hence, we employ the Dynamic Common Correlated Effects Estimator (DCCE) of Chudik and Pesaran (2015).[3]

2.2. Modeling Issues

Improvements in energy efficiency have important implications for energy demand but are notoriously difficult to model. One approach—recently suggested by Hunt and Ryan (2015)—is to include in the model a time trend and time trend-squared. We include a lag of the dependent variable to capture possible autocorrelation properties. So, the dynamic, heterogeneous model that we estimate is:

$$E_{sit} = \beta_i^1 E_{sit-1} + \beta_i^2 y_{it} + \beta_i^3 P_{sit} + \beta_i^4 Z_{sit} + \beta^5 t + \beta^6 t^2 + \alpha_i + \epsilon_{it} \quad (1)$$

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1 As an anonymous reviewer suggested, breaks could be explicitly considered. However, only 26 time observations is likely insufficient for a robust consideration of endogenous breaks. Furthermore, since the data begins in 1987, the two most important energy-related events in the US—the two oil crises, dated 1973–1974 and 1979–1981—would lie outside the sample range.

2 As outlined in the table notes, some regressions included only a single lag because allowing for two lags produced highly insignificant results.

3 The Dynamic Common Correlated Effects Estimator of Chudik and Pesaran (2015) is implemented by STATA command xtdcce2, which was developed by Jan Ditzen.

where subscripts *sit* denote a particular end-use energy demand sector, *s* (i.e., total, industrial, or transport energy or residential or commercial electricity), *i*th cross-section, and *t*th time period, respectively. *E* is per capita energy/electricity consumption, *P* is the corresponding sector price (in real terms), and *y* is real GDP per capita. A set of additional sector-specific variables is represented by Z—specifically heating and cooling degree days for total energy and residential and commercial electricity.[4] Since the time trend, *t*, and the time trend-squared are included to capture energy efficiency improvements, and because we believe such improvements should diffuse quickly throughout the US states, the coefficients for those two terms are constrained to be the same for all cross-sections. Lastly, α represents a state-specific intercept, and ϵ represents the error term.

For clarity, the cross-sectional average terms and their lags (of 1–2 periods) are not shown in Equation (1). All variables are in natural logs; thus, the estimated coefficients can be interpreted as elasticities. Since there is a lagged dependent variable term, those estimated elasticities are considered short-run. The long-run elasticities are calculated from:

$$\frac{\overline{\beta^n}}{1-\overline{\beta^1}} \tag{2}$$

where *n* varies from 2 to 4, the beta-bar terms are the panel coefficients, i.e., the average of the individual cross-sectional coefficients, and the corresponding standard errors are determined via the delta method.

Several papers have decomposed price movements in order to test for asymmetric price responses, and thus, potentially capture induced technical change in energy demand (e.g., Gately and Huntington 2002). Price is decomposed into the historic high price and the cumulative price increases and cumulative price decreases in such a way that these three new price variables sum to the original price series as shown in Equations (3)–(6):

$$p_{max,\,t} = max(p_1,\,\ldots,\,p_t) \tag{3}$$

$$p_{up,t} = \sum_{t=1}^{t} \max\{0, (p_t - p_{t-1}) - (p_{max,t} - p_{max,\,t-1})\} \tag{4}$$

$$p_{down,t} = \sum_{t=1}^{t} \min\{0, (p_t - p_{t-1}) - (p_{max,t} - p_{max,\,t-1})\} \tag{5}$$

$$p_t = p_{max,\,t} + p_{up,\,t} + p_{down,\,t} \tag{6}$$

Hence, Equation (1) is re-estimated with the respective prices decomposed (and the time trend terms not included). Post estimation, one can test whether asymmetries exist by coefficient pairs' difference of means tests. If the null hypothesis that the individual price elasticities are the same is rejected, one expects that in absolute terms elasticity for the maximum price would be greater than the elasticity for price increases, which would be greater than the elasticity for price declines (Gately and Huntington 2002). In other words, demand is expected to decrease more when prices rise than demand increases when prices fall, and high prices are expected to affect demand through induced technical change. So, decomposing price can be interpreted as a way to model technical change's impact on demand, and thus, replace the time trend terms in Equation (1).

Whether there is an inverted-U relationship between GDP per capita and some environmental impact measure per capita has become one of the most popular question in environmental economics/social science. The so-called Environmental Kuznets Curve/Carbon Kuznets Curve

[4] While several papers have found a negative relationship between *urban* density and transport energy consumption (e.g., Newman and Kenworthy 1989; Kenworthy and Laube 1999; Liddle 2013a), in earlier work on the present dataset, (state-level) population density was not statistically significant for transport energy consumption (Liddle 2017).

literature posits that environmental impact first rises with income and then falls after some threshold level of income/development is reached. Of course, one might expect not to find such an inverted-U relationship for energy consumption—a normal consumption good; indeed, we might expect a leveling of the income elasticity (as determined for carbon dioxide emissions in Liddle 2015). (Although, some studies have determined such an inverted-U relationship for energy consumption or the highly related carbon dioxide emissions, e.g., Agras and Chapman 1999) Yet, it is possible that higher income states may have less industry/manufacturing (and thus, less energy consumption in that sector); so, we test whether the individual state income elasticity estimates vary according to the level of income for total energy and industrial energy consumption.

Inverted-U studies typically model energy/emissions as a quadratic function of GDP per capita. (An inverted-U relationship between emissions per capita and income is said to exist if the coefficient for GDP per capita is statistically significant and positive, while the coefficient for its square is statistically significant and negative.) However, it is incorrect to make a nonlinear transformation of a nonstationary variable—GDP per capita was determined here to be nonstationary, as it often is—in ordinary least squares (Muller-Furstenberger and Wagner 2007). Furthermore, this polynomial model has been criticized for lacking flexibility (e.g., Lindmark 2004). Hence, we employ a method used in Liddle (2013b) that takes advantage of the heterogeneous nature of the estimations (i.e., elasticities are estimated for each state) by plotting those state-specific income elasticity estimates against the individual state average income for the whole sample period.

2.3. Data

The US Energy Information Agency (EIA), as part of the State Energy Data System (SEDS), collects state-level data of disaggregated energy consumption and the corresponding prices at those levels of disaggregation. The Bureau of Economic Analysis (BEA) collects data on real GDP per capita and economic structure, also at the state-level. These two data sets are combined to create a panel of the 50 US states over 1987–2013. The following five dependent variables are analyzed: total energy consumption per capita, industrial sector's energy consumption per capita, transport sector's energy consumption per capita, and the electricity consumed per capita in the residential and commercial sectors. Also, because electricity consumption in buildings is impacted by weather, the residential and commercial electricity regressions include the average heating degree days and the average cooling degree days (data from the National Oceanic and Atmospheric Administration).[5] Table 1 displays summary statistics.

Again, given the stock-based nature of the data and the fact that the US states are not independent, we expect the data to exhibit both cross-sectional correlation and nonstationarity. Table 2, which reports the results of the Pesaran (2004) cross-sectional dependence (CD) test and the Pesaran (2007) panel unit root test, confirms those suspicions. The Pesaran (2004) CD test employs the correlation coefficients between the time-series for each panel member. The null hypothesis of cross-sectional independence was rejected for each variable considered (at the 0.1% level); furthermore, several of the absolute value mean correlation coefficients ranged from 0.8–1.0 (first two columns of Table 2). The Pesaran (2007) cross-sectionally augmented panel unit root test (CIPS) allows for cross-sectional dependence to be caused by a single (unobserved) common factor; the results of that test suggest that most of the variables are nonstationary in levels (last two columns of Table 2). These two tests—the Pesaran CD and Pesaran CIPS test—are used as diagnostics, too, in order to assess whether the regression residuals are independent and stationary.

[5] Heating and cooling degree days' data were not available for Alaska and Hawaii.

Table 1. Summary Statistics.

Variables	Observations	Mean	Std. Dev.	Min	Max
Total energy pc	1350	374.1	171.3	171	1196
Transport energy pc	1350	100.7	39.7	48	403
Industrial energy pc	1350	140.4	125.0	18	706
Residential electricity pc	1350	4.4	1.2	1.9	7.4
Commercial electricity pc	1350	3.9	0.9	1.2	8.1
GDP pc	1350	41,059	9,600	20,511	75,694
Cooling degree days	1296	1,068	798	42	3,827
Heating degree days	1296	5,270	2,083	430	10,810
Total energy price	1350	12.7	5.8	5.1	40.3
Transport energy price	1350	13.8	7.3	5.3	31.0
Industry energy price	1350	8.8	5.3	2.1	56.3
Commercial electricity price	1350	27.2	9.5	12.2	109.4
Residential electricity price	1350	23.6	8.4	10.9	102.2

pc: per capita; Std. Dev.: standard deviation.

Table 2. Cross-sectional and time-series properties of the data.

	Pesaran (2004) CD Test		Pesaran (2007) CIPS Test	
Variables	**Statistic**	**Abs. Corr. Coeff.**	**Specification W/O Trend**	**Specification W/Trend**
Log total energy pc	59.3 *	0.52	I(1)	I(1)
Log transport energy pc	56.2 *	0.44	I(1)	I(1)
Log industrial energy pc	58.6 *	0.61	I(1)	I(1)
Log residential electricity pc	119.7 *	0.77	I(0)	I(1)
Log commercial electricity pc	124.5 *	0.77	I(0)	I(1)
Log GDP pc	163.2 *	0.94	I(1)	I(1)
Log cooling degree days	78.2 *	0.51	I(0)	I(0)
Log heating degree days	89.9 *	0.57	I(0)	I(0)
Log total energy price	180.5 *	0.99	I(0)	I(1)
Log transport energy price	181.4 *	0.997	I(0)	I(1)
Log industry energy price	174.5 *	0.96	I(0)	I(1)
Log commercial electricity price	147.4 *	0.81	I(1)	I(1)
Log residential electricity price	156.2 *	0.86	I(1)	I(1)

pc: per capita; Abs. corr. coeff.: Absolute value mean correlation coefficient; I(0): stationary; I(1): integrated order one, nonstationary; Statistical significance level of 0.1% denoted by *.

3. Results and Discussion

3.1. Initial Results

The results of the initial five regressions are shown in Table 3. For all but commercial electricity, GDP per capita is statistically significant and well below unity—a saturation effect is expected for energy consumption in highly developed states. Prices are significant and negative for all five dependent variables—suggesting taxes could be used to reduce energy consumption (although none of the price elasticities are particularly large). Both heating and cooling degree days are positive and significant for the building electricity consumption regressions. For total energy and industry energy the time-squared term is significant and negative—as would be expected for energy efficiency improvements. However, both time terms are insignificant for transport energy and commercial electricity. Surprisingly, the linear time trend is significant and positive for residential electricity (more below).

In addition, the regression diagnostics are good—all of the residuals were stationary (according to the Pesaran CIPS test, results not shown), and cross-sectional independence in residuals cannot be rejected for all but the transport energy and residential electricity regressions. The coefficient on the lagged dependent variable is always significant and rather small—indicating a limited amount of persistence in energy consumption. The lagged dependent variable is negative for residential electricity (but only marginally significant)—suggesting that residential consumption is falling over time, which is not the case. However, as mentioned above, the time trend is significant and positive—the opposite of what one would expect for efficiency improvements. Hence for residential electricity, the lagged dependent variable and time trend seem to be compensating for one another in a manner that is not consistent with the proposed model.

Table 3. Disaggregated energy demand equations with dynamic common correlated effects estimator (DCCE) by Chudik and Pesaran (2015). Panel 48/50 US states, 1987–2013.

Dependent Variable	Total Energy	Industrial Energy	Transport Energy	Residential Electricity	Commercial Electricity
Short-Run Elasticities					
LDV	0.204 ****	0.205 ****	0.141 ****	−0.152 *	0.280 ****
GDP pc	0.177 ***	0.560 ***	0.255 ***	0.290 ***	0.178
Price	−0.156 ****	−0.118 ****	−0.241 ****	−0.129 ****	−0.162 **
HDD	0.173 ****			0.180 ****	0.137 ***
CDD	0.040 ****			0.118 ****	0.054 ***
Long-Run Elasticities					
GDP pc	0.222 ***	0.705 ***	0.297 ***	0.252 ***	0.247
Price	−0.196 ****	−0.148 ****	−0.280 ****	−0.112 ****	−0.224 **
HDD	0.217 ****			0.156 ****	0.190 ***
CDD	0.050 ****			0.103 ****	0.075 ***
Pooled Coefficients					
Time	−0.000	0.005	0.001	0.006 ****	0.001
Time-squared	−0.0001 **	−0.0002 *	0.000	−0.000	0.000
Observations	1202	1150	1250	1108	1202
x-sections	48	50	50	48	48
CD (p)	−0.8 (0.43)	−0.6 (0.55)	−2.1 (0.04)	2.8 (0.00)	1.5 (0.14)

LDV: lagged dependent variable; pc: per capita; HDD: heating degree days; CDD: cooling degree days. All variables logged. All dependent variables in per capita. Statistical significance level of 10%, 5%, 1% and 0.1% denoted by *, **, ***, and ****, respectively. CD: test statistic from Pesaran (2004) CD test, corresponding *p*-value in parentheses. The null hypothesis is cross-sectional independence. Industry energy and residential electricity regressions include two lags of the cross-sectional average terms; all other regressions include one such lag.

Comparing the estimations across dependent variables, residential electricity has the lowest (long-run) price elasticity. Low price elasticities for electricity use in buildings is not surprising given how electricity is typically billed—high fixed costs and rather underutilized marginal/peak pricing. It is somewhat surprising for residential and commercial electricity that the heating degree days' elasticity is greater than the cooling degree days' elasticity. This difference is surprising since air conditioning may be more energy intensive than heating, and air conditioning is very likely more electricity intensive than heating since not all heating uses electricity. However, the difference between the heating and cooling degree days' elasticities was only statistically significant for commercial electricity, and only then at the 10% level of significance.

Perhaps, this surprising relationship suggests that for the geography/climate of the US, heating buildings is more important than cooling them in determining electricity consumption; alternatively, it may reflect differences in occupancy intensity, i.e., people may be at home more during the winter. To examine this issue further, we re-run the residential and commercial electricity regressions using only southern states. The results for commercial electricity are the same (i.e., the heating degree day elasticity is greater than the cooling degree day one); however, for residential electricity, the cooling degree day elasticity is statistically significantly larger than the heating degree day elasticity for southern states (results not shown).

Appendix A Table A1 displays the results of the regressions shown in Table 3 when a cross-sectional fixed effects estimator is used instead of the DCCE estimator. This fixed effects estimator uses the dynamic panel bias correction proposed by Kiviet (1995).[6] We include and discuss this estimator because fixed effects is a commonly used—but flawed—estimator in time-series, panel

[6] This estimator is implemented by STATA command xtlsdvc, which was developed by Giovanni Bruno.

analysis. While the table results demonstrate that some estimates are similar to and others are different from those in Table 3, we focus the discussion on the diagnostics. Including a lagged dependent variable does result in stationary residuals for all of the regressions in Appendix A Table A1; however, the coefficient on that lagged dependent variable is very large (although, likely, less than unity). That large coefficient for the lagged dependent variable implies that despite stationary residuals, time series issues remain (by contrast, Kapetanios et al. 2011 argued that cross-sectional average terms account for nonstationarity). Moreover, the CD test statistics are particularly large, and cross-sectional independence is very strongly rejected for each regression. Still, the fixed effects estimator does not fully account for heterogeneity since the elasticities are constrained to be equal for all cross-sections. Hence, we argue that the results in Appendix A Table A1 are likely biased, and the DCCE estimator is preferred for the nonstationary, cross-sectionally correlated, and heterogeneous data we consider here.

3.2. Price Asymmetry

Table 4 displays the results for the price asymmetry regressions. For total energy and transport energy all three price terms have significant and negative elasticities. However, the elasticities are never significantly different, i.e., no price asymmetries—high prices, upward movements in prices, and downward movements in prices all impact demand similarly. For industrial energy and residential and commercial electricity only one price has a significant (negative) elasticity—downward price movements for both industrial energy and commercial electricity and high price for residential electricity. (As before, the regression residuals are always stationary).

Table 4. Disaggregated energy demand equations and price asymmetry with dynamic common correlated effects estimator (DCCE) by Chudik and Pesaran (2015). Panel 48/50 US states, 1987–2013.

Dependent Variable	**Total Energy**	**Industrial Energy**	**Transport Energy**	**Residential Electricity**	**Commercial Electricity**
LDV	-0.018	0.172	0.009	−0.026	0.150 *
GDP pc	0.097	0.581	0.414 ****	0.112	0.020
Price up	−0.437 ****	−0.310	−0.385 **	-0.013	0.214
Price down	−0.304 *	−0.544 ***	−0.699 ****	7608	−0.900 **
Price high	−0.478 ****	0.106	−0.447 ****	−0.191 ***	0.060
HDD	0.220 ****			0.227 ****	0.010
CDD	0.032 *			0.113 ****	0.062 **
Observations	1202	1150	1250	1202	1202
x-sections	48	50	50	48	48
CD (p)	−1.1 (0.28)	−1.8 (0.07)	0.9 (0.89)	5.1 (0.00)	2.1 (0.04)

LDV: lagged dependent variable; pc: per capita; HDD: heating degree days; CDD: cooling degree days. All variables logged. All dependent variables in per capita. Statistical significance level of 10%, 5%, 1% and 0.1% denoted by *, **, ***, and ****, respectively. CD: test statistic from Pesaran (2004) CD test, corresponding *p*-value in parentheses. The null hypothesis is cross-sectional independence. Industry energy and residential electricity regressions include two lags of the cross-sectional average terms; all other regressions include one such lag.

So, the price decomposition results for industry and commercial electricity particularly fail to correspond with expectations. However, when price is decomposed as in Equations (3)–(6), the series have much less time variance (e.g., the high price series would change continuously only during periods of sustained price increases); and thus, the series are possibly less appropriate for heterogeneous estimation. Hence, we re-run the price decomposition regressions to constrain all of the price elasticities to be equal across states, i.e., similar to the time trend terms in Equation (1).[7] (The other variable elasticities are still allowed to vary by cross-section.) These new results are displayed in Table 5. All of the price elasticities for transport are now insignificant—so those results are not shown. However, for the other demand equations, some price asymmetry emerges.

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[7] This specification is estimated by using the pooled option in STATA command xtdcce2.

Table 5. Disaggregated energy demand equations and pooled/homogeneous price asymmetry with dynamic common correlated effects estimator (DCCE) by Chudik and Pesaran (2015). Panel 48/50 US states, 1987–2013.

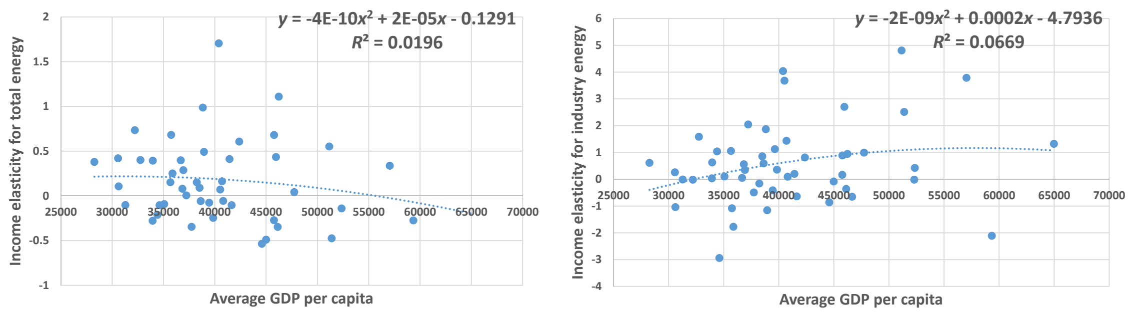
Dependent Variable	Total Energy	Industrial Energy	Residential Electricity	Commercial Electricity
		Heterogeneous Elasticities		
LDV	0.369 ****	0.367 ****	0.091 **	0.334 ****
GDP pc	0.178 ***	0.281	0.140 ***	0.101
HDD	0.163 ****		0.242 ****	0.098 *
CDD	0.030 ***		0.133 ****	0.052 **
		Pooled Elasticities		
Price up	−0.067 ***	−0.397 ****	−0.039	−0.002
Price down	0.039	−0.126 **	−0.130 ****	−0.292 ****
Price high	−0.031 ****	−0.164 ****	−0.037 ***	0.061 *
Observations	1202	1150	1108	1202
x-sections	48	50	48	48
CD (p)	−0.7(0.48)	14.5(0.00)	11.1(0.00)	6.3(0.00)

LDV: lagged dependent variable; pc: per capita; HDD: heating degree days; CDD: cooling degree days. All variables logged. All dependent variables in per capita. Statistical significance level of 10%, 5%, 1% and 0.1% denoted by *, **, ***, and ****, respectively. CD: test statistic from Pesaran (2004) CD test, corresponding p-value in parentheses. The null hypothesis is cross-sectional independence. Industry energy and residential electricity regressions include two lags of the cross-sectional average terms; all other regressions include one such lag.

For total energy, both upward price movements and high price are significantly larger (in absolute terms) than downward price movements (which are insignificant); however, upward prices and high price are not significantly different from each other. For industry, as expected—and as for total energy—the elasticity for upward price movements is significantly larger than that for downward price movements (which is statistically significant). But contrary to expectations for industry, the elasticity for upward movements is significantly greater than that of high price, too. Whereas, for buildings electricity there is evidence of price asymmetry—such asymmetry being opposite to expectations. For both residential and commercial electricity, upward price movements are insignificant, and the elasticity for downward price movements is statistically significantly the largest (in absolute terms) of the three price terms.

3.3. Nonlinear Income Elasticities

Figure 1a,b plot the state-specific income elasticity estimates for both total energy and industrial energy against the individual state average income for the whole sample period. Those plots suggest some evidence that the GDP per capita elasticity for both total energy and industrial energy consumption rises and then falls with average GDP per capita (thus forming an inverted-U); however, the R-squares for both simple trend lines were very small.



(a) Total energy (b) Industry energy

Figure 1. Individual state income elasticity estimates for total energy and industrial energy and the state average GDP per capita (in real US$) for the sample period. Trend line and *R*-squared also shown.

4. Summary

This paper modeled the demand of total, industrial, and transport energy consumption and residential and commercial electricity consumption by analyzing US state-based panel data and by using methods that address heterogeneity, nonstationarity, and cross-sectional dependence. Most of the results conformed to expectations. Residential electricity had the smallest price elasticity and among the smallest income elasticities. Both heating and cooling degree days were important for building electricity demand.

Lastly, limited to no evidence of nonlinearities and asymmetries were uncovered. The three decomposed price elasticities—the historical high price, cumulative price drops, and cumulative price increases—were rarely statistically significantly different. Again, price decomposition was proposed as a way to model technical change and has been demonstrated to produce significant differences among the decomposed prices (e.g., Gately and Huntington 2002). Unfortunately, the present dataset does not allow us to capture the price increases of the two oil crises. Indeed, by 1987 (the first year of data) the international oil price had fallen to a level that was lower, in real terms, than it was before the first oil crises in 1974 (and, capturing the effects of these crises was an important motivation for Gately and Huntington). Also, the nature of the price decomposition constrains/reduces time observations, and thus, places degrees of freedom restrictions on mean-group type estimations. Hence, perhaps, if more time observations were available, the price decomposition results might have produced stronger evidence of asymmetries.

Acknowledgments: An earlier version of this paper was presented at the 1st IAEE Eurasian Conference, Baku, Azerbaijan on 29 August 2016, and appeared in the IAEE Energy Forum, 1st Quarter 2017, pp. 35–39.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Disaggregated energy demand equations with fixed effects estimator (with the Kiviet 1995 dynamic panel bias correction). Panel 48/50 US states, 1987–2013.

Dependent Variable	Total Energy	Industrial Energy	Transport Energy	Residential Electricity	Commercial Electricity
			Short Run		
LDV	0.870 ****	0.863 ****	0.800 ****	0.721 ****	0.914 ****
GDP pc	0.126 ****	0.201 ***	0.139 ***	0.028	0.060
Price	−0.021 ****	−0.029 ***	−0.029 ****	−0.060 ****	−0.035 ***
HDD	0.127 ****			0.157 ****	0.049 **
CDD	0.023 ****			0.072 ****	0.051 ****
			Long Run		
GDP pc	0.971 ****	1.466 ***	0.699 ****	0.102	0.692 *
Price	-0.159 ***	−0.214 **	−0.148 ****	−0.215 ****	−0.410 ***
HDD	0.980 ****			0.564 ****	0.569 *
CDD	0.174 ***			0.259 ****	0.585 ***
			Time Trends		
Time	−0.002 ****	−0.005 ***	−0.001	0.002 ***	0.001
Time-squared	0.00005 ****	0.0001 ***	0.00004 *	0.000	−0.000
Observations	1248	1300	1300	1248	1248
x-sections	48	50	50	48	48
CD (p)	44.8 (0.00)	31.8 (0.00)	28.0 (0.00)	47.0 (0.00)	20.8 (0.00)

Notes: LDV: lagged dependent variable; HDD: heating degree days; CDD: cooling degree days. All variables logged. All dependent variables in per capita. Statistical significance level of 10%, 5%, 1% and 0.1% denoted by *, **, ***, and ****, respectively. CD: test statistic from Pesaran (2004) CD test, corresponding p-value in parentheses. The null hypothesis is cross-sectional independence. Pesaran (2007) CIPS test confirmed that all regression residuals are I(0).

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