Modeling Disaggregated Energy Consumption: Considering Nonlinearity, Asymmetry, and Heterogeneity by Analyzing U.S. State-level Panel Data

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OVERVIEW

This project models the demand of energy consumption at several different levels of aggregation by analyzing U.S. state-based panel data and by using methods that address both nonstationarity and cross-sectional dependence. In addition to considering possible nonlinear relationships between energy consumption and income, possible asymmetric relationships between energy consumption and both income and price are allowed and calculated. U.S. state data is rich since the (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. Previous work has argued that price changes may be asymmetric (eg., Gately and Huntington 2002). More recent work has considered that the impact of income on carbon emissions may be asymmetric as well (e.g., York 2012; Burke et al., 2015).

DATA & METHODS

The U.S. 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 U.S. 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.

Since not all manufacturing is energy intensive, the industry energy consumption regression includes the share of industry GDP that is derived from the most energy intensive sectors (e.g., mining, nonmetallic minerals, primary metals, paper products, and chemicals, petro-chemicals, and rubber). 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). Lastly, since population density has been demonstrated to be negatively correlated with transport (e.g., Liddle 2013a), the transportation energy regression includes population density.

Given the stock-based nature of the data and the fact that the U.S. states are not independent, we expect the data to exhibit both cross-sectional correlation and nonstationarity, in addition to heterogeneity. Thus, we employ a heterogeneous panel estimator that addresses both nonstationarity and cross-sectional dependence, i.e., the Pesaran (2006) common correlated effects mean group estimator (CMG). The CMG estimator accounts for the presence of unobserved common factors by including in the regression cross-sectional averages of the dependent and independent variables. The CGM estimator is robust to nonstationarity, cointegration, breaks, and serial correlation.

The Pesaran (2004) CD test, which employs the correlation coefficients between the time-series for each panel member, rejected the null hypothesis of cross-sectional independence for each variable considered (at the 0.1% level). Furthermore, several of the absolute value mean correlation coefficients ranged from 0.8-1.00 (results not shown, but are available upon request). The Pesaran (2007) panel unit root test 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 (results not shown, but are available upon request).

MAIN RESULTS AND DISCUSSION

The results of the initial five regressions are shown in Table 1. For all five dependent variables, GDP per capita is statistically significant and well below unity—a saturation effect is expected for energy consumption in highly developed states. Prices are also significant and negative—suggesting taxes could be used to reduce energy consumption. Both heating and cooling degree days are positive and significant for the

Dependent Variable	Total Energy	Industrial Energy	Transport Energy	Residential Electricity	Commercial Electricity
GDP pc	0.19**** [0.07 0.31]	0.40*** [0.10 0.69]	0.31**** [0.18 0.45]	0.12*** [0.03 0.20]	0.18** [0.03 0.34]
Price	-0.39**** [-0.48 -0.30]	-0.30**** [-0.44 -0.16]	-0.43**** [-0.61 -0.26]	-0.14**** [-0.18 -0.09]	-0.08* [-0.17 0.01]
Heating degree days	0.11**** [0.08 0.14]			0.23**** [0.19 0.26]	0.08*** [0.02 0.14]
Cooling degree days	0.03**** [0.02 0.05]			0.10**** [0.07 0.12]	0.07**** [0.05 0.09]
Population density	-0.66*** [-1.12 -0.19]		-0.13 [-0.66 0.40]		
Share of energy intensive industries	0.001 [-0.02 0.02]	0.04 [-0.03 0.11]			
Observations	1296	1350	1350	1296	1296
x-sections	48	50	50	48	48
RMSE	0.012	0.04	0.026	0.012	0.043
Order of integration	I(0)	I(0)	I(0)	I(0)	I(0)
CD (p)	-1.5 (0.14)	0.1 (0.94)	-1.3 (0.19)	5.9 (0.00)	4.2 (0.00)
Mean rho	0.20	0.19	0.18	0.23	0.22

Notes: All variables logged. All dependent variables in per capita. Statistical significance level of 10%, 5%, 1% and 0.1% denoted by *, **, *, and ****, respectively. 95% confidence intervals in brackets. Diagnostics: Order of integration of the residuals is determined from the Pesaran (2007) CIPS test: I(0)=stationary. Mean rho is the mean absolute correlation coefficient of the residuals from the Pesaran (2004) CD test. CD is the test statistic from that test along with the corresponding p-value in parentheses. The null hypothesis is cross-sectional independence.**

Table 1 Disaggregated energy demand equations. Pesaran (2006) CMG estimator. Panel 48/50 U.S. states, 1987-2013.

building electricity consumption regressions. Whereas population density was significant and negative for the total energy consumption regression, it was insignificant for the transportation energy regression—a result that went against expectations. The industry GDP share of the most energy intensive sectors was highly insignificant—perhaps, not surprising since this share was substantially above 10% only for states with large mining sectors (e.g., Alaska, West Virginia, and Wyoming). In addition, the regression diagnostics were good—all of the residuals were stationary, and cross-sectional independence in residuals could not be rejected for all but the electricity regressions. However, in the two building electricity regressions, the resulting mean correlation coefficient was small suggesting that, at least, dependence was mitigated.

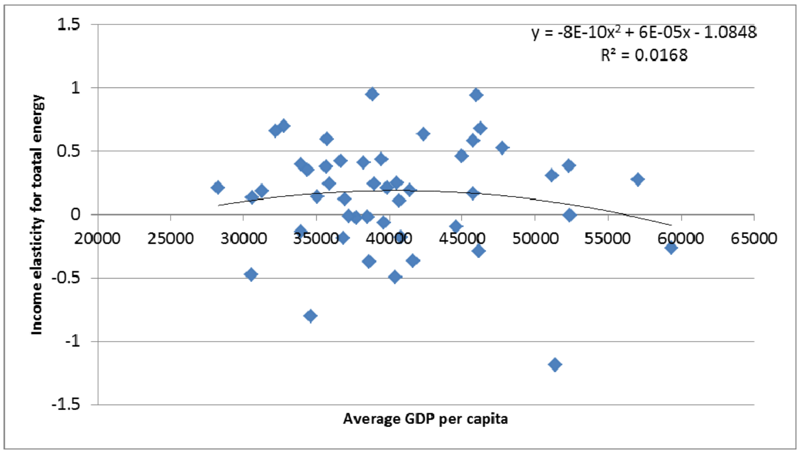
Comparing the estimations across dependent variables, the income elasticities were smaller for residential and commercial electricity; yet, the displayed confidence intervals suggest that those estimations were likely not significantly different at the 5% level. By contrast, the lower price elasticities for residential and commercial electricity likely are significantly different (as suggested by the confidence intervals). 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. The elasticity for heating degree days is significantly larger (in absolute terms) for residential electricity compared to commercial electricity. This result may be expected since commercial buildings are primarily occupied during daylight hours, and thus, would have lower heating demand. Yet, it is somewhat surprising for residential electricity that the heating degree days elasticity is significantly greater than the cooling degree days elasticity. This 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. Perhaps, this surprising relationship suggests that for the geography/climate of the U.S., heating buildings is more important than cooling in determining electricity consumption; alternatively, it may reflect differences in occupancy intensity, i.e., people may be at home more during the winter.

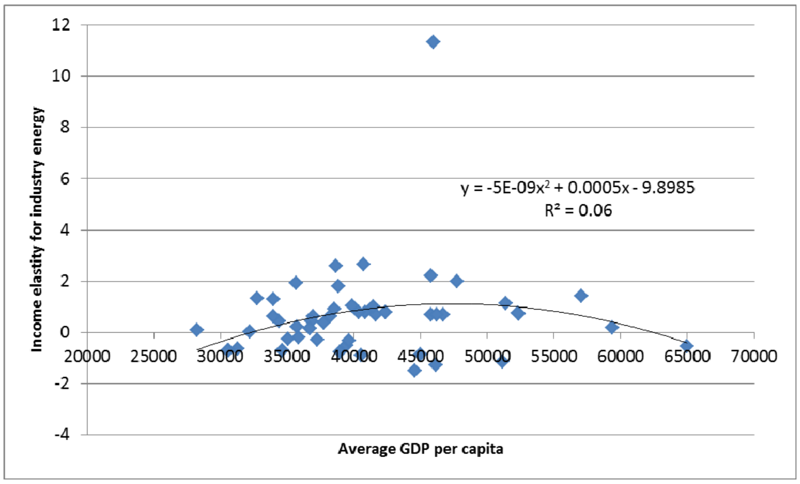
NONLINEARITIES

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 EKC/CKC 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 CO_2 emissions in Liddle 2015). (Although, some studies have determined such an inverted-U relationship for energy consumption or the highly related CO_2 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 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 in ordinary least squares (income was determined here to be nonstationary, as it often is). 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.

Those plots are displayed in Figures 1-a&b (Figure 1-a for total energy and Figure 1-b for industry energy). There is 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 trendlines were very small.





Figures 1-a&b. Individual state income elasticity estimates for total energy (Figure 1-a) and for industry energy (Figure 1-b) and the state average GDP per capita for the sample period. Trend line and R-squared also shown.

PRICE ASYMMETRIES

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 1-4.

$$p_{max,t} = max(p_1, \dots, p_t) \quad (1)$$

$$p_{up,t} = \sum_{t=1}^{t} \max\{0, (p_t - p_{t-1}) - (p_{max,t} - p_{max,t-1})\} \quad (2)$$

$$p_{down,t} = \sum_{t=1}^{t} \min\{0, (p_t - p_{t-1}) - (p_{max,t} - p_{max,t-1})\} \quad (3)$$

$$p_t = p_{max,t} + p_{up,t} + p_{down,t} \quad (4)$$

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). Table 2 displays the results for the price asymmetry regressions.

For total energy, industry energy, and transport energy all three price terms had significant and

Dependent Variable	Total Energy Energy	Industrial Energy	Transport Energy	Residential Electricity	Commercial Electricity
GDP pc	0.20**** [0.09 0.31]	0.15 [-0.07 0.36]	0.31**** [0.19 0.47]	0.09** [0.003 0.18]	0.12* [-0.000 0.25]
Price up	-0.52**** [-0.65 -0.39]	-0.34*** [-0.54 -0.14]	-0.45*** [-0.71 -0.19]	0.01 [-0.15 0.17]	-0.02 [-0.24 0.20]
Price down	-0.47**** [-0.64 -0.28]	-0.31*** [-0.52 -0.10]	-0.65**** [-0.90 -0.41]	-0.15** [-0.28 -0.02]	-0.36*** [-0.60 -0.11]
Price high	-0.51**** [-0.64 -0.39]	-0.30**** [-0.44 -0.16]	-0.47**** [-0.68 -0.25]	-0.20**** [-0.25 -0.15]	-0.11** [-0.21 -0.003]
Heating degree days	0.13**** [0.09 0.17]			0.23**** [0.19 0.26]	0.08**** [0.03 0.12]
Cooling degree days	0.03**** [0.02 0.05]			0.09**** [0.07 0.11]	0.07**** [0.05 0.09]
Observations x-sections	1296 48	1350 50	1350 50	1296 48	1296 48

Notes: All variables logged. All dependent variables in per capita. Statistical significance level of 10%, 5%, 1% and 0.1% denoted by *, **, ***, and ****, respectively. 95% confidence intervals in brackets.

Table 2. Disaggregated energy demand equations and price asymmetry. Pesaran (2006) CMG estimator. Panel 48/50 U.S. states, 1987-2013.

negative elasticities. However, the elasticities were never significantly different, i.e., no price asymmetries—high prices, upward movement prices, and downward movement in prices all impacted demand similarly. For residential electricity, upward price movements had an insignificant elasticity. Again, all three price coefficients were not significantly different.

By contrast, for commercial electricity some of the price coefficients were significantly different, but contrary to the expected directions. The coefficient for high price was smaller (in absolute terms) than the coefficient for downward price movements at the 10% level of significance (test statistic was 1.84 and p-value 0.065). Also, the coefficient for downward price movements was larger (in absolute terms) than the corresponding coefficient for upward price movements (which was insignificant) at the 5% level of significance (test statistic was 1.98). Since residential and commercial electricity demand was the least sensitive to prices (from Table 1), perhaps it is not surprising that some of the decomposed price components would not be significant.

INCOME GROWTH ASYMMETRIES

Recently, there has developed a discussion on the effects of the business cycle on CO_2 emissions and whether the income elasticity of emissions differs at times of economic growth and contraction (e.g., York 2012; Burke et al., 2015). To see whether such an asymmetric relationship may hold for U.S. energy consumption, we take first differences of all series (thus, converting them to growth rates). Then we separate the years with positive income growth from the years with negative income growth. For most years, very few states experienced negative income growth; however, there were a few years in which the majority of states did (1991, 2007, 2008). Since the negative income growth variable will have few observations for most states, heterogeneous methods are no longer appropriate; hence, we employ a pooled fixed effects with state and time dummy variables model.

In general, there was very little evidence of asymmetric income growth effects. Indeed, the variables representing positive and negative income growth were never both statistically significant (results not shown, but are available upon request). Only for residential electricity were the coefficients statistically different—in that case, the coefficient for positive income growth was highly insignificant (p-value of 0.62).

SUMMARY

This paper modeled the demand of total, industrial, and transport energy consumption and residential and commercial electricity consumption by analyzing U.S. state-based panel data and by using methods that address both nonstationarity and cross-sectional dependence. Most of the results conformed to expectations. Buildings (residential and commercial) electricity had the smallest income and price elasticities. Both heating and cooling degree days were important for building electricity demand, but population density was insignificant for transport (perhaps, greater resolution than the state-level is necessary to capture the population density-mobility demand relationship). 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. Similarly, energy consumption growth reacted symmetrically to positive vs. negative GDP growth, i.e., the difference between the estimated coefficients for positive and negative GDP growth were rarely statistically significant.

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