MODELING DISAGGREGATED ENERGY CONSUMPTION: CONSIDERING NONLINEARITY, ASYMMETRY, AND HETEROGENEITY BY ANALYZING US 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 US 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 with respect to both income and price are allowed and calculated. 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., Doda 2013).

Data & Methods

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.

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, non-metallic 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 density has be demonstrated to be negatively correlated with transport (e.g.., Liddle 2013), the transportation energy regression includes population density.

Given the stock-based nature of the data and the fact that the US states are not independent, we know/suspect the data 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-section averages of the dependent and independent variables. The CGM estimator is robust to nonstationarity, cointegration, breaks, and serial correlation.

Results & Discussion

The results of the initial five regressions are shown in the table below. 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 building electricity consumption regressions. While, air condition may be more energy intensive than heating, the elasticity for heating is higher than that for cooling. This relationship suggests that for the geography/climate of the US, heating buildings is more important than cooling in determining electricity consumption. Whereas population density was significant and negative for the total energy consumption regression, it was insignificant for the transportation energy regression—a topic explored further below. Lastly, the industry GDP share of the most energy intensive sectors was highly insignificant—perhaps, not surprising since this share was only substantially above 10% for states with large mining sectors (e.g., Alaska, West Virginia, and Wyoming).

Dependent Variable	Total Energy	Transport Energy	Industrial Energy	Residential Electricity	Commercial Electricity
GDP p.c.	0.19****	0.31****	0.40***	0.12***	0.18**
Price	-0.39****	-0.43****	-0.30****	-0.14****	-0.08*
Heating degree days	0.11****			0.23****	0.08****
Cooling degree days	0.03****			0.10****	0.07****
Population density	-0.66***	-0.13			
Share of energy intensive industries	0.00		0.04		

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

It is possible that the GDP per capita/income elasticity could be different at different levels of income. Thus, we consider whether the individual state income elasticity estimates vary according to the level of income for total energy and industrial energy consumption by plotting those elasticity estimates against the individual state average income for the whole sample period. 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.

To further consider the possibility of income saturation, the sample was split in two, where the 15 wealthiest states in 1987 (those that had GDP per capita's that were greater than the US as a whole) formed one panel, and the transport energy and residential electricity models were rerun. For the high income panel the income elasticity for both transport energy and residential electricity were insignificant (the income elasticities remained significant for the other panel). Hence, for the wealthiest US states, increases in income have little impact on transport and residential energy consumption.

Since population density's impact on transport may be more important cross-sectionally than over time and heterogeneous estimators first calculate cross-sectional regressions, we split the panel into three based on the states' average population density for the sample period and rerun the transportation energy regressions (and exclude population density). The resulting GDP per capita elasticity became significantly smaller as the panel's average population density was greater (i.e., the panel with the lowest population densities had the largest GDP per capita elasticity and the panel with the highest densities had the smallest elasticity). Thus, population density does indeed appear to impact transport energy consumption in the US states.

To test for possible price response asymmetries, each price series was decomposed into three series: the historical high price, cumulative price drops, and cumulative price increases (as in Gately and Huntington 2002). The three decomposed price elasticities were never statistically significantly different. Lastly, it was tested whether energy consumption growth reacted symmetrically to positive vs. negative GDP growth. As with the price asymmetry analysis, while the estimated coefficients for positive and negative GDP growth were different, that difference was never statistically significant.

References

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