NATIONAL ENERGY TECHNOLOGY LABORATORY

The Relationship between the Economy and Electricity Consumption

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Disclaimer

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I. Introduction

The observed relationship between growth in energy demand and the economy has been studied in the U.S. as well as other parts of the world. The literature to date provides mixed results as to whether energy consumption has a significant long term and short term relationship with the economy. Since there has never been a period in recent US economic history in which electricity consumption did not grow concomitantly with the economy, it may appear to be a truism that economic growth causes electricity consumption growth. However, some authorities assert that, though end-use efficiency measures, economic growth can develop with little, or much reduced, electricity growth.[1] The Energy Information Administration (EIA), for instance, has repeatedly lowered its projected electricity intensity even as it has lowered projected GDP growth. Between the Annual Energy Outlook 2006 (AEO 2006) and that of 2010 (AEO 2010), while GDP annual average growth estimates falls 20% (3.0% to 2.4% per annum), the electricity generation growth rate falls 44% (1.6% to 0.9% per annum) and industrial rate, 87% (from 0.8% to 0.1% per annum) More broadly, actual -lack of power generating capacity severely affected the South African economy in 2008, Pakistan in 2010, and currently raises concern in the United Kingdom.[2] To begin a statistical look at these issues, this paper looks specifically at electricity consumption's relationship with the U.S. economy, as measured by GDP or personal income.

For example, AEO 2010 forecasts electricity demand growth to average around 1.0 percent from 2008 to 2035 and to slow to about 0.9 percent from 2030 to 2035. AE0 2010 forecasts GDP to grow around 2.44 percent per year from 2008 to 2035. This implies electricity consumption growth rate would be about 41 percent as fast as real GDP. As Table 1 shows, such a slowdown in the growth rate of electricity consumption with continued economic growth would be similar to the trend seen from 1999-2009, but would be significantly lower than the other time periods examined. Other time comparisons are exampled as well, including 2010 using forecast data from the September 2010 release of the EIA Short Term Energy Outlook; these other cases serve to see implied impact of including recessions as start and end points (i.e., not including 1991 and 2008/09). Notice that electricity consumption growth as a percentage of real GDP growth is much lower in cases that end in 2009 and cases that begin in 1991, implying recessions may have a temporary change in the relationship between electricity consumption and GDP growth—signifying possible asymmetries in the relationship during periods of economic growth and periods of economic contraction. Also evident from the table is the ratios in cases beginning in 1991 and 1992 are higher than cases beginning in 1999, indicating a *possible* decline in the relationship in recent years.

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[1] North American Electric Reliability Corporation (NERC), *2009 Long-Term Reliability Assessment*, p. 1: "In Canada, Ontario in particular has set aggressive energy efficiency targets, *resulting in an expected 2.3 percent reduction in projected demand* over the ten-year period." (italics added)

[2] See (for instance) *Christian Science Monitor*, January 25, 2008,"Power Cuts Cripple South Africa"; *McClatchydc.com* (McClatchy newspapers), April 21, 2010, "As Power Shortages Spread, Pakistan Switches off the Lights," and *The Daily Telegraph*, March 6, 2010, "How Will David Cameron Keep the Lights On."

Table 1 Relationship between Electricity Consumption and Real GDP

Time Period	Electricity Consumption Growth Rate	Real GDP	Electricity consumption growth as a percentage of Real GDP growth
1991-2010	1.6%	2.7%	60.4%
1992-2010	1.7%	2.6%	64.5%
1999-2010	1.1%	1.9%	57.0%
1991-2009	1.5%	2.7%	54.3%
1992-2009	1.5%	2.6%	58.2%
1999-2009	0.7%	1.8%	40.1%
1991-2007	1.9%	3.2%	60.8%
1992-2007	2.1%	3.2%	65.0%
1999-2007	1.5%	2.6%	58.0%
2008-2035	**1.0%**	**2.4%**	**41.0%**

*Source: Short-term Energy Outlook

Since this analysis relies on time-series econometric techniques, it is important to provide a few definitions and clarifications. Short-run causality, as used in this paper, refers to Granger causality. In a regression setting, a variable (X) is said to Granger cause another variable (Y) if lagged values of X (while controlling for lagged values of Y) are jointly significant predictors of variable Y—significance is determined via an F-test. As far as its role in this study, Granger causality is limited in that does not refer to a structural, theoretical relationship (i.e., cause and effect), but rather to a reduced form relationship. Similarly, the term long-run causality, as it is called in the literature, occurs in the context of Vector Error Correction (VEC) models, which allow the break out of testing between short-run and long-run relationships as well as the adjustment parameter, which implies a return to equilibrium after a shock that causes disequilibrium. The cointegration test, which is conducted prior to the VEC, also implies whether there is a long-run relationship.

With these caveats in mind, this analysis estimates whether electricity demand and the economy have historically strong short-term and long-term relationships. The two main analyses in the paper include:

1. Time-series econometrics approach to estimate the short-run Granger causality and long-run relationship between electricity consumption and GDP.
2. State-level panel econometric models to test whether electricity consumption has a significant short-run and long-run relationship with personal income.

II. Literature Review

While the direction of Granger-causality has been studied in various countries, the first part of this literature review focuses on studies that include the United States in order to see the variation in results. Additionally, this literature review looks at other studies in order to examine modeling issues, in particular the use of a panel model in some non-U.S. studies. The research into the causation characteristics of energy consumption and GDP is a well-studied topic globally, and the United States is no exception.

An important point of clarification: in the models discussed in the literature, there are basically four possible conclusions concerning Granger-causality between GDP and electricity consumption[3]:

1. GDP Granger-causes electricity consumption, but the reverse is not true; in this case causality is said to run from GDP to electricity consumption.
2. Electricity consumption Granger-causes GDP, but the reverse is not true; in this case, causality is said to run from electricity consumption to GDP
3. GDP Granger-causes electricity consumption and electricity consumption causes GDP; in this case, causality is said to be bidirectional
4. There is no Granger-causality in either direction

Throughout the literature review, the use of the term causality signifies Granger Causality in the case of a VAR and short-run Granger causality in the case of a VEC. In the case of a VEC, the cointegration tests imply a long-run relationship and there is a long-term coefficient in the VEC which can be thought of as expressing a long-term relationship between the variables. Granger causality is determined by a joint F test for significance. The results of the VARs typically use a Granger Causality test, which is a joint F-test. For the VEC models, a Granger test is used to test for short-run causality.

Kraft and Kraft (1978) is commonly cited in the literature as the first study examining the causal relationship between income and energy. Using the Sims (1972) technique they find unidirectional causality going from Gross National Product (GNP) to energy consumption in the United States. *(The idea of the Sims test is to regress Y on prior values of X; if causality runs from X to Y only, future values of X in the regression should have coefficients that are not statistically significant.)* However, Akarca and Long (1980) also use the Sims method, but find that the Kraft results are not robust by changing the time period by two years, which results in the finding of no causal relationship. Similarly, Yu and Choi (1985) find no causal relationship between GNP and total energy consumption. Absoreda and Baghestani (1989) use a VAR-type model and find unidirectional causality running from GNP to energy consumption.

For the time period 1947-90, Stern (1993) uses a Vector Autoregressive (VAR) model comprised of GDP, energy use, capital stock and employment and finds that a measure of

[3] In Vector Error Correction (VEC) models Granger causality can also be divided into short-run and long-run.

final energy use, adjusted for changing fuel composition, causes GDP, but GDP does not cause this measure of final energy use.
The adjusted energy use measure is constructed via a Divisia index, which takes into account various prices of fuels, and their quantities of Btu in final energy use. (However, using energy consumption that is not quality adjusted, causality is found to only run from GDP to energy consumption.) This is the first instance in which a study found any evidence of causality running from energy consumption to GDP in the United States.
Using data from 1947-1990 and including the variables GNP, energy consumption, and capital, Cheng (1995) finds that there is no causal relationship between GNP and energy consumption in the U.S. Lee (2006) uses a VAR[4] type of model[5] to estimate the causality between energy consumption and income in 11 countries (including the U.S.). For the U.S., Lee finds significant bi-directional causality. Stern (2000) reexamines the issue using a Vector Error Correction (VEC) model and once again finds that energy Granger-causes GDP and finds some evidence that GDP causes energy consumption. Finally, Mahadevan and Asafu-Adjaye (2007) find two-way short-run and long-run causality between energy and GDP in the U.S.

Four of the nine aforementioned studies find at least some evidence of causality from energy consumption to GDP in the United States. This provides evidence that the literature has not established a definitive answer to the relationship between energy consumption and GDP in the United States. *(Note: Six of the nine above studies find at least some evidence of causality running from GDP to electricity consumption.)*

An examination of the literature reveals that VAR and VEC models are the norm for testing direction of causality. However, some of the more recent literature has been able to take advantage of richer panel data sets and have used panel error correction (PEC) models.

Chen et al. (2007) use a PEC to test for the short-run and long-run causality tests for electricity consumption and GDP in 10 Asian countries. A joint significance test indicates that in the short-run, there is causality running from economic growth to electricity consumption, but there is bi-directional long-run causality between electricity consumption and economic growth. Chen also uses a VEC model and finds mixed results in terms of whether energy consumption causes GDP. Lee (2005) uses a PEC for 18 developing countries and finds that long-run and short-run causalities flow from energy consumption to GDP, but not vice-versa. Sinha (2009) uses a panel of 88 countries (including the U.S.) and finds both short-run and long-run causality between GDP and energy consumption.

Mahadevan and Asafu-Adjaye (2007) examine 20 countries and find bidirectional causality between economic growth and energy consumption for developed countries; conversely, in the case of developing countries, they find energy consumption causes

[4] Lee (2006) indicates that a VEC model could be used, but cite Toda and Yamamoto (1995), who show that a VAR can still be used in the case of cointegration by adding one additional lag for each cointegrating equation.
[5] Cheng (1995) uses Specific Gravity Criterion (SGC) and Final Prediction Error (FPE) tests for causality.

growth only in the short-run. A comparison is made between the panel results and the individual results. *(As noted earlier in the paper, individual result from Mahadevan and Asafu-Adjaye (2007) indicate for the U.S., there is two-way short-run and long-run causality between energy and GDP.)* Ciarreta and Zarraga (2008) employ a panel generalized method of moments procedure and find no short-run causality between electricity consumption and GDP for twelve European countries. They indicate since the series are cointegrated, there is a long-run causality between energy consumption and GDP.

Several reasons for the differences in findings concerning causality between energy consumption and GDP include:

- Model used (VAR, VEC, PEC)
- Time periods studies (most studies use different time periods)
- Type of data (monthly, quarterly, annual)
- Number of lags
- The choice of variables used as proxies for energy and income

VAR, VEC, and PEC models all have their own advantages. VAR is the simplest of the models; under its specification, the dependent variable (Y) is a function of past values (lags) of Y and lags of other variables (X). VEC has the advantage that it separates the model into what can be interpreted as short-run and long-run causality. Some advantages of the PEC are that it includes more observations (i.e. more degrees of freedom), more variation in the data, as well as allow differing assumptions such as whether slope coefficients are constant or unique across groups.

III. Unit Root and Cointegration Tests

The two most common methods used to test Granger causality in a time-series setting are the Vector Autoregressive (VAR) model and the Vector Error Correction (VEC) model. The VAR model uses two or more time series where each variable is modeled as a linear function of the past values of all variables. The VEC is a special case of a VAR, which is used when two non-stationary variables are found to have a long-term relationship (cointegrated).[6]

The first step in determining whether a VAR or VEC model should be used is to conduct unit root tests to test if time series are stationary. A unit root takes place in a time series process when the current value is equal to the previous period's value, plus a weakly dependent disturbance. (A weakly dependent time series process is where some measure of dependence between variables at two points in time decreases as the interval between the two points in time increases.) A series that does not have a unit root is said to be integrated of order 0 or I(0) and a VAR model may be used. If the level of a series contains a unit root, but the first difference of the series does not, then it is said to be integrated of order 1 or I(1) and further tests need to be run to see what type of model is appropriate.

The unit root test used is the Augmented Dickey-Fuller Test (ADF), which has the following formula:

$$\Delta Y_t = \alpha + \beta t + \pi y_{t-1} + \phi \Delta Y_{t-1} + ... + \phi \Delta Y_{t-n} + \varepsilon_t$$

ΔY_t is the change in the dependent variable
α is a constant
β is the coefficient on a time trend (t)
π is the coefficient on the lag of the level of Y
n is the lag order

Additionally, Dickey Fuller Generalized Least Squares (DFGLS) tests were run. DFGLS is similar to ADF, but a GLS transformation is made to the time-series. Some researchers have found this test has more power than the ADF (See Stata Time Series Manual 10).

The null hypothesis of both unit root tests is there is a unit root, which is tested by the significance of π. As is common in the literature, for the unit root test, the natural logarithms of electricity consumption and real GDP are used, rather than the levels. The results of the various unit root tests are reported in Table 2. The majority of tests fail to reject the null hypothesis of a unit root at the 99% level; therefore, they suggest that both variables are non-stationary in their level forms. Next, unit root tests were conducted using the first difference of both variables, in which the null was rejected at the 99% level of confidence in most cases. These tests indicate the variables are I(1).

[6] See Hamilton (1994) or Lutkepohol (2006) for a detailed treatment.

Table 2 Unit Root Tests

			P-values (significance level in DFGLS cases)	
Variable	**Test assumption**	**# lags**	**Level**	**First difference**
Ln elec. cons	No trend	1	0.3800	0.0000**
Ln elec. cons	No trend	2	0.4472	0.0000**
Ln elec. cons	No trend	3	0.0052**	0.0000**
Ln elec. cons	No trend	4	0.0236	0.0000**
Ln elec. cons	Trend	1	0.0005**	0.0000**
Ln elec. cons	Trend	2	0.0013**	0.0000**
Ln elec. cons	Trend	3	1.0000	0.0000**
Ln elec. cons	Trend	4	0.9288	0.0000**
Ln elec. cons	DFGLS	1	**	**
Ln elec. cons	DFGLS	2	**	**
Ln elec. cons	DFGLS	3	NS	NS
Ln elec. cons	DFGLS	4	NS	NS
Ln GDP	No trend	1	0.2209	0.0005**
Ln GDP	No trend	2	0.1685	0.0000**
Ln GDP	No trend	3	0.0537	0.0016**
Ln GDP	No trend	4	0.1774	0.0030**
Ln GDP	Trend	1	0.8465	0.0005**
Ln GDP	Trend	2	0.2300	0.0000**
Ln GDP	Trend	3	0.5981	0.0013**
Ln GDP	Trend	4	0.6292	0.0048**
Ln GDP	DFGLS	1	NS	**
Ln GDP	DFGLS	2	NS	**
Ln GDP	DFGLS	3	NS	**
Ln GDP	DFGLS	4	NS	*

Null hypothesis is unit root; variables are in natural logarithm
**Reject null at 99% level   *Reject at 95% level   NS= Not significant (DFGLS cases)
p-values are not given in the case of DFGLS, but significance levels are given

Next, to determine whether a VEC model should be used, cointegration tests were run. Cointegration is when a linear combination of two series, each of which is I(1), is I(0). Cointegration implies that two variables have a long-term relationship. In this case, a regression using the two first-differenced variables is misspecified, and a VEC model should be used in place of the standard VAR.

Cointegration tests estimate the rank of the matrix, Π , as seen in the error correction equation:

$$\Delta Y_t = \Pi \ln Y_{t-1} + \Gamma_1 \Delta \ln Y_{t-1} + ... + \Gamma_k \Delta \ln Y_{t-k+1} + \varepsilon_t$$

$$\Pi = \Pi_1 + ... + \Pi_k - I$$

The rank is equal to the number of cointegrating vectors. In the two variable case, there can either be 0 or 1 cointegrating vectors. *(Π equals the product αβ′ where β′ is the vector of parameters defining the long run relationships and α is the vector of adjustment parameters.)*

The Johansen method was used to test for cointegration via the vecrank Stata command, which implements three types of methods for determining the number of cointegrating equations. These include the Johansen trace statistic method, the maximum eigenvalue statistic method, and a minimization of the information criterion[7]. Table 3 displays the results of the Johansen tests, in which various numbers of lags and test assumptions were used to allow for comparison. The majority of Johansen tests for cointegration indicate the two variables are cointegrated and the VEC is preferred over the VAR model.

Table 3 Cointegration Tests

Test assumption	# lags	Logarithm	Level
Constant	1	Yes	Yes
Constant	2	Yes	Yes
Constant	3	Yes	Yes
Constant	4	No	No
Constant	5	No	No
Constant	6	No	No
No constant or trend	1	Yes	Yes
No constant or trend	2	Yes	Yes
No constant or trend	3	Yes	Yes
No constant or trend	4	Yes	Yes
No constant or trend	5	Yes	Yes
No constant or trend	6	Yes	Yes

"Yes" means the null hypothesis of no cointegration is rejected at 95% level

[7] See Stata 10 Time Series manual for a more complete description.

IV. VEC Model (Electricity Consumption/GDP)

For the VEC analysis, quarterly data from 1982 to 2010 for electricity consumption and real GDP were used from the Bureau of Economic Analysis (BEA) and the Energy Information Administration (EIA).

The results of the above unit root and cointegration tests indicate a VEC model should be run, rather than a VAR. The VEC equation is:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + V + \delta t + \varepsilon_t$$

Where:
Y is a Kx1 vector of I(1) endogenous variables (electricity consumption and GDP)
ΔY_t is the vector of the first difference of electricity consumption and GDP
ΔY_{t-i} is the vector of first differences in electricity consumption and GDP, lagged i periods
α is a matrix of parameters; its coefficients represent the speed of adjustment parameters
β is a cointegrating vector, representing the long-run equilibrium relationship between electricity consumption and GDP.
Γ_i is a matrix of parameters, representing the short-run responses of changes to electricity consumption and GDP
ε_t is a vector of normally distributed errors.
V is a vector (the constant)
δ is a vector of trend coefficients

The results of VEC model are summarized in Table 4. The results are broken out into three major categories: Short-run Granger causality (joint F-test); Adjustment parameter (α coefficient); and Long-run relationship (β coefficient)

In the electricity consumption equation (ln electricity consumption is the dependent variable), the majority of tests find that GDP Granger causes electricity consumption in the short-run. Also, seven of the ten tests find the adjustment parameter to be significant, indicating a readjustment to equilibrium in the case of disequilibrium. All of the long run results are significant, implying a significant long-run relationship between the two variables.

In the GDP equation (ln GDP is the dependent variable), half of the tests find electricity consumption Granger causes GDP in the short-run and half of the tests find the adjustment parameter to be significant. Seven of the ten tests find a significant long-run relationship.

Overall, the tests show significant short-run and long-run relationships between GDP and electricity consumption.

Table 4 VEC Results

Equation	Assumption	Lags	SR Granger causality test p-value	Adjustment parameter p-value	Long-run relationship p-value
ln elec cons	Constant included	2	0.01***	0.00***	0.00***
ln elec cons	Constant included	3	0.06*	0.00***	0.00***
ln elec cons	Constant included	4	0.00***	0.09*	0.00***
ln elec cons	Constant included	5	0.01***	0.07*	0.01***
ln elec cons	Constant included	6	0.02**	0.06*	0.00***
ln elec cons	Constant and trend	2	0.03**	0.00***	0.00***
ln elec cons	Constant and trend	3	0.12	0.00***	0.00***
ln elec cons	Constant and trend	4	0.00***	0.76	0.00***
ln elec cons	Constant and trend	5	0.02**	0.81	0.01***
ln elec cons	Constant and trend	6	0.04**	0.63	0.02**
lnGDP	Constant included	2	0.21	0.98	0.00***
lnGDP	Constant included	3	0.10*	0.47	0.00***
lnGDP	Constant included	4	0.14	0.00***	0.00***
lnGDP	Constant included	5	0.16	0.04**	0.97
lnGDP	Constant included	6	0.25	0.12	0.52
lnGDP	Constant and trend	2	0.29	0.86	0.00***
lnGDP	Constant and trend	3	0.07*	0.14	0.00***
lnGDP	Constant and trend	4	0.05**	0.01***	0.06*
lnGDP	Constant and trend	5	0.09*	0.02**	0.11
lnGDP	Constant and trend	6	0.08*	0.04**	0.07*

******Significant at 1% level   **Significant at 5% level   *Significant at 10% level***

V. Panel Error Correction Model Analysis

This section of the paper estimates the following panel error correction models:

1. Pooled mean group (PMG) estimator
2. Dynamic fixed effects (DFE) model
3. Mean group (MG) estimators

These estimators allow for error correction models to be run using panel data. PMG allows the intercept, long run coefficients, and error variances to differ across groups, but constrains the long run coefficients to be equal across groups. DFE models only allow the intercepts to differ between groups. MG allows intercepts, slope coefficients, and error variances to differ across groups. See Blackburne and Frank (2007) for a detailed description.

The data set is from 1969 to 2008 and uses state level annual panel data from BEA to measure personal income (PI), which is then converted to real 2000 dollars, and EIA (electricity consumption). The panel data is summarized in Table 5.

Table 5 State-Level Data from 1969-2008

	Electricity Consumption (Million kWh)	Personal Income (Thousand Real 2000$)
#Observations	2,040	2,040
Mean	50,976	117,000,000
Standard Deviation	51,990	153,000,000
Minimum	938	4,604,639
Maximum	347,059	1,310,000,000

As in the VEC analysis, tests for unit roots and cointegration are used to estimate if the variables are I(1) and if they are cointegrated.

First unit root tests are conducted via the Im-Pesaran-Shin (Im) panel unit root tests. To allow for serial correlation in the errors, lags of the dependent variable are used. The majority of the versions of the Im-Pesaran-Shin panel unit root tests[8] for the level of the variables fail to reject the null hypothesis of a unit root at the 1 percent level of significance. All unit root tests for the first differenced variables reject the null hypothesis at the 1 percent level (Table 6). Therefore, the variables are determined to be I(1) and thus cointegration tests are conducted.

[8] For more detail on panel unit root tests, see Im and Pesaran (2003).

Table 6 Im-Pesaran-Shin Unit Root tests

# Lags	Test	Variable (Level)	P-value	Reject null of unit root at 1% level?	First differenced variable	P-value	Reject null of unit root at 1% level?
1	IPS constant	Elec	1	No	Elec	0.000	Yes
1	IPS constant and trend	Elec	0.781	No	Elec	0.000	Yes
2	IPS constant	Elec	0.999	No	Elec	0.000	Yes
2	IPS constant and trend	Elec	0.324	No	Elec	0.000	Yes
3	IPS constant	Elec	1	No	Elec	0.000	Yes
3	IPS constant and trend	Elec	0.781	No	Elec	0.000	Yes
1	IPS constant	LnElec	0.366	No	LnElec	0.000	Yes
1	IPS constant and trend	LnElec	0.508	No	LnElec	0.000	Yes
2	IPS constant	LnElec	0.354	No	LnElec	0.000	Yes
2	IPS constant and trend	LnElec	0.242	No	LnElec	0.000	Yes
3	IPS constant	LnElec	0.384	No	LnElec	0.000	Yes
3	IPS constant and trend	LnElec	0.301	No	LnElec	0.000	Yes
1	IPS constant	LnPI	0.14	No	LnPI	0.000	Yes
1	IPS constant and trend	LnPI	0.234	No	LnPI	0.000	Yes
2	IPS constant	LnPI	0.043	No	LnPI	0.000	Yes
2	IPS constant and trend	LnPI	0.006	Yes	LnPI	0.000	Yes
3	IPS constant	LnPI	0.045	No	LnPI	0.000	Yes
3	IPS constant and trend	LnPI	0.006	Yes	LnPI	0.000	Yes
1	IPS constant	PI	1	No	PI	0.000	Yes
1	IPS constant and trend	PI	0.847	No	PI	0.000	Yes
2	IPS constant	PI	1	No	PI	0.000	Yes
2	IPS constant and trend	PI	0.833	No	PI	0.000	Yes
3	IPS constant	PI	1	No	PI	0.000	Yes
3	IPS constant and trend	PI	0.91	No	PI	0.000	Yes

Next, Westerlund panel cointegration tests were run. The Stata command xtwest implements the four panel cointegration tests developed by Westerlund (2007). The basic idea is to test for the absence of cointegration by estimating if individual panel members are error correcting.

The Westerlund cointegration test results support the hypothesis of cointegration and are summarized in Table 7. The analysis proceeds assuming that both variables are I(1) and cointegrated, which implies a long-run relationship exists between the variables.

Table 7 Westerlund Cointegration Tests[9]

Test	Number of Lags	P-value	Reject null of no cointegration at 1% level?
Gt	1	0.000	Yes
Ga	1	0.000	Yes
Pt	1	0.001	Yes
Pa	1	0.000	Yes
Gt	2	0.000	Yes
Ga	2	0.000	Yes
Pt	2	0.000	Yes
Pa	2	0.000	Yes
Gt	3	0.000	Yes
Ga	3	0.000	Yes
Pt	3	0.029	No
Pa	3	0.001	Yes

The remainder of the paper uses three error-correction panel models to estimate whether electricity Granger causes personal income in the short-run and long-run. The models are basically a version of autoregressive distributed lag models (ARDL) in the first difference, which also includes a cointegration vector, to allow for a long-run relationship.

The equation of the panel error correction model is as follows for the ARDL(2,2) case:

$$\Delta PI_{it} = \phi_i (PI_{i,t-1} - \vartheta_{0i} - \vartheta_{1i} EL_{it}) + \delta_{11i}\Delta EL_{it} + \delta_{21i}\Delta EL_{it-1} + \delta_{31i}\Delta PI_{it-1}\varepsilon_{it}$$

PI = Personal Income

EL = Electricity Consumption

ϕ_i is the error-correction speed of adjustment parameter. The coefficient is negative if the variables demonstrate a return to long-run equilibrium. (*Thus, a shock to electricity consumption would be associated with personal income adjusting to bring the variables back into equilibrium.)*

ϑ_{1i} is the long run coefficient for electricity consumption. The expectation in this case would be a positive value, since electricity consumption is expected to have a positive long-run relationship with personal income.

[9] See Westerlund (2007) for a detailed treatment.

δ_{11i} is the short run coefficient for the first difference of electricity consumption in time t

δ_{21i} is the short run coefficient for the lagged first difference of electricity consumption

δ_{31i} is the short run coefficient for the lagged first difference of personal income

The results of both models (See Table 8) indicate that electricity has a significant short-run and long-run relationship with personal income. The long-run significance is demonstrated by the significant positive coefficient for electricity consumption in the EC equation and the cointegration between variables. The short run significance is shown by the joint significance of the difference and the lagged first difference of the electricity coefficients. The significant negative coefficient on the error correction coefficient demonstrates that electricity consumption and personal income return in the long-run to equilibrium[10]. (Note: Pooled MG and Dynamic FE models are both preferred to MG model.[11]) The small coefficients on the adjustment coefficient indicates a slow return to equilibrium.

[10] *For an explanation of the differences between the various estimators in the table, see Blackburne and Frank (2007))*

[11] Hausman tests were used to determine whether the *pooled* mean group estimator is preferred to the mean group (mg) estimator and whether the dynamic fixed effects estimator is preferred to the mg estimator. Both tests indicate that the mg estimate is the least preferred method. For more detail see Frank and Blackburne (2007).

Table 8 Dynamic Panel Error-Correction Estimates for Personal Income

Dependent variable = D.pi			
	Pooled MG	**Dynamic FE**	**MG**
Adjustment coefficient	-0.03** (0.006)	-0.02** (0.005)	-.099** (0.012)
Long-run coefficient (elec)	1.56** (0.044)	1.053* (0.104)	1.505** (0.139)
Short-run coefficients			
LD.pi	.179** (0.027)	0.146** (0.022)	0.193** (0.027)
D.elec	.224** (0.025)	0.201** (0.016)	0.179** (0.020)
LD.elec	0.145** (0.023)	0.125** (0.017)	0.125** (0.022)

**99% significance level *95% significance level
D=First Difference; L= Lag; pi = personal income; elec = electricity consumption
Note: Standard errors are in parentheses; variables are all in natural logarithm form; constant was estimated but is excluded from results

VI. Conclusion

This paper provides statistical evidence that electricity consumption and the economy (U.S. GDP or personal income) have significant long-run and short-run relationships. Previous papers offer mixed evidence whether energy consumption has a short-term and long-term relationship with the U.S. economy. Differences in types of models, time-periods used and other assumptions such as number of lags have led to a split in the literature as to whether energy consumption has a significant relationship with economic growth.

The Vector error correction models find:

- Significant long-run relationship between GDP and electricity consumption, also demonstrated by the cointegration tests;
- Short-run Granger causality runs from GDP to electricity consumption;.
- Mixed evidence as to whether short-run Granger causality also runs from electricity consumption to GDP;
- Results are generally sensitive to assumptions, such as number of lags and whether a time trend is included.

This is the first paper to use a panel of U.S. states to test the causal relationship between personal income and consumption.
The Panel error correction models find:

- Significant long-run relationship between personal income and electricity consumption, also demonstrated by the cointegration tests;
- Short-run Granger causality from electricity consumption to personal income, a result not found with VEC models..

A future area of research would be to examine the role of infrastructure in terms of electric generation *capacity* and economic growth. Examination would study whether enough capacity is present to accommodate economic growth. This is a very relevant area to study as other countries (e.g., South Africa and Pakistan) have had blackouts due to a shortage of capacity[12], which likely had significant adverse effects on their economies. Using its results along with the evidence on energy and electricity consumption's relationship with economic growth may provide a clearer picture concerning the dynamic relationships concerning energy and the economy.

Another area of future research would be to examine if household income is a better indicator of electricity consumption than GDP in more recent years. Table 9 provides a comparison across recent expansionary periods of GDP growth and household income growth. These rates are compiled for the following time periods: 1984-89; 1993-2000; 2002-07. An interesting finding from this comparison is that 2002-07 is the only time

[12]Dawn.com. "Power shortages to end by summer 2010: Raja."
http://www.dawn.com/wps/wcm/connect/dawn-content-library/dawn/news/pakistan/13+power+shortages+to+end+by+summer+2010+raja-za-05

period in which median household income grew at a slower rate than real GDP per household. This brings up the question as to whether the relative paucity of household income growth in the 2002-07 time period could support broad-based electricity end use.

Table 9 Growth Rates of Household income and household GDP

Annualized Growth Rates	1984-1989	1993-2000	2002-2007
Lowest Quintile HH Income	1.79%	2.34%	0.06%
Second Quintile HH Income	1.77%	2.12%	0.11%
Third Quintile HH Income	1.83%	2.03%	0.26%
Fourth Quintile HH Income	1.93%	2.03%	0.39%
Highest Quintile HH Income	3.18%	2.61%	0.28%
Real GDP per HH	1.71%	1.18%	1.20%
Median Household Income	1.84%	1.96%	0.55%

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