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The relationship between disaggregate energy consumption and industrial production in the United States: An ARDL approach

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Abstract

We re-examine the relationship between disaggregate energy consumption and industrial output, as well as employment, in the United States using the autoregressive distributed lag (ARDL) approach developed by Pesaran and Pesaran [Pesaran, M.H., Pesaran, B., 1997. Working with Microfit 4.0. Camfit Data Ltd, Cambridge] and Pesaran, Shin and Smith [Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics 16; 289–326] In particular, we focus attention on the following energy consumption variables: coal, fossil fuels, conventional hydroelectric power, solar energy, wind energy, natural gas, wood, and waste. The sample period covers 2001:1–2005:6. Our results imply that real output and employment are long run forcing variables for nearly all measures of disaggregate energy consumption.
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1. Introduction

Energy plays a unique role in the supply chain as it is both a final good for end-users as well as an input into the production processes of many businesses. The decisions households and

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businesses must make regarding energy use are influenced by, and have implications for, short run changes in economic activity as well as longer term trends. For this reason, considerable attention has been placed on estimating the relationship between energy consumption and output. In the United States total energy expenditures account for more than 7% of Gross Domestic Product (Economic Report of the President, 2006). In fact, while petroleum comprises the largest imported energy source for the US, diversification of energy is generally considered important since it would lessen the dependence on foreign energy and thus dampen the effects of oil disruptions. Key strategies for smoothing price fluctuations often include more efficient energy production and improvements in demand management practices. Consequently, potential suppliers in the renewable sector, as well as in deregulated markets, may play a significant role in meeting the future energy requirements of the United States. Of course, newer technologies are developed and adopted as market signals dictate (Economic Report of the President, 2006). Given these recent trends and concerns, we examine the dynamic relationship between disaggregate energy sectors and real output in the US. In particular, our primary focus is on the consumption of renewable energy and the role that these greener energy sources may play in determining real economic activity.

We re-examine the link between disaggregate energy use, employment, and income in the US employing the ARDL method. We use the autoregressive distributed lag (ARDL) approach of Pesaran and Pesaran (1997) and Pesaran et al. (2001) to test for the existence of a relationship between the disaggregate energy data and industrial production (i.e., real output) in level form. Additionally, based on prior energy-related research which found the labor market to play a significant role in the determination of output, our study also incorporates total non-farm employment in the analysis. The ARDL approach may be applied to time series variables irrespective of whether they are I(0), I(1), or mutually cointegrated.

The paper proceeds as follows. First, we provide a brief review of related research followed by a description of the data and the ARDL approach. We then discuss the results and offer some concluding comments regarding the implication for energy-related policy.

2. A brief literature review

A number of studies have focused on the relationship between energy and output or income and the outcomes have varied considerably. Several factors may have led to this lack of consensus. For instance, the varied results may be due to the different economic structures of the particular countries studied, especially those that are at different stages of development. It is also possible that the use of aggregate energy data has led to differences in outcomes. The use of aggregate energy data does not capture the degree or extent to which different countries depend on different energy resources (Yang, 2000). Studies that focus solely on aggregate data may not be able to identify the impact of a specific type of energy on output. The use of disaggregate energy consumption in a study of the energy–output relationship allows us to identify the impact of different energy sources on income in the US.

Early work on the relationship between income and energy provided evidence of Granger causality running from income to energy in the US (Kraft and Kraft, 1978). Building on this, researchers have examined different countries over various time periods, using a number of different methodologies. Some of the studies that found evidence of Granger causality running from income to energy consumption include: Abosedra and Baghestani (1989) for the US, Yu and Choi (1985) and Soytas and Sari (2003) for South Korea, Erol and Yu (1987) for West Germany, Masih and Masih (1996) for Indonesia, Soytas and Sari (2003) for Italy, Wolde-Rufael (2005) for five African countries, Narayan and Smyth (2005) for Australia, and Lee (2006) for France, Italy and Japan. Additionally, Stern and Cleveland (2003) provide an excellent review of the literature on the topic.

In contrast, evidence of causality running from energy consumption to income has also been found. For example, Stern (1993, 2000) for the US, Erol and Yu (1987) for Japan, Yu and Choi (1985) for Philippines, Masih and Masih (1996) for India and Indonesia, Soytas and Sari (2003) for Turkey, France, Germany and Japan, Wolde-Rufael (2004) for Shangai, and Lee (2005) for eighteen developing countries.

It is well known that economic systems may exhibit feedback effects or bi-directional causality. In fact, a number of researchers have reported that the energy-income relationship may be characterized by bi-directional causality. Erol and Yu (1987) report bi-directional causality for Japan and Italy. Similar results have been reported for Taiwan (Hwang and Gum, 1992), while additional evidence of bi-directional causality was found by Masih and Masih (1996) for Pakistan, Soytas and Sari (2003) for Argentina, Ghali and El-Sakka (2004) for Canada, Wolde-Rufael (2005) for Gabon and Zambia, and Lee (2006) for the US.

In stark contrast to the findings of causality, regardless of direction or the existence of feedback, is the neutrality of energy hypothesis. Under this hypothesis, energy consumption and income/output are unrelated and evolve independently from one another. Those finding evidence in favor of the neutrality hypothesis include Akarca and Long (1980), Yu and Hwang (1984), Yu and Choi (1985), Erol and Yu (1987) for the case of the US, Masih and Masih (1996) for Malaysia, Singapore and Philippines, Soytas and Sari (2003) for nine countries including the US, Asafu-Adjaye (2000) for Indonesia and India, Altinay and Karagol (2004) for Turkey, Wolde-Rufael (2005) for eleven African countries, Lee (2006) for the UK, Germany and Sweden, and Soytas and Sari (2006) for China.

Although there are studies that employ the ARDL technique to cointegration in the energy sector (e.g De Vita et al., 2006), few studies have explicitly examined the relationship between energy consumption and income using disaggregate data for the US (and to the extent of our knowledge none did so using ARDL) which may provide information as to the source, if any, of an energy-income relationship. Additionally, the disaggregate data allow for comparisons of the relative strengths of the relationship by energy source. The few studies that did utilize disaggregate data include Yang (2000), Wolde-Rufael (2004), Sari and Soytas (2004), and Ewing, Sari and Soytas (2007) who highlight the importance of this new avenue of research. Thus, our approach is to utilize the disaggregate data in conjunction with a methodology that does not impose the additional restriction that the underlying series be integrated of the same order. Our focus is on investigating the inter-temporal link between the consumption of energy from coal, fossil fuel, natural gas, hydroelectric power, solar, wind, wood, waste, and industrial production incorporating total non-farm employment in the US. The results shed light on at least one market signal, that is, the relative role that different energy sources may play in explaining movements in output. The findings have particular relevance for establishing research and development related policy in the US.

3. Data and methods

We examine monthly data for the United Sates over the period of 2001:1–2005:6.[1] We use industrial production, base year 2002, employment in thousands, coal, fossil fuels, conventional hydroelectric power, solar energy, wind energy, natural gas, wood, and waste consumption. Energy use data are in trillion British thermal units (Btu). Total renewable energy accounts for

[1] Data are from Economagic.com. The sample period is constrained by data availability across all series.

about 6% of total energy in the U.S. Fossil fuels make up about 86% of total energy with coal and natural gas each being around 23%. In terms of renewables, solar is the least utilized and comprises less than one-tenth of 1% and hydroelectric power, the most utilized, nearly 3% of total energy. All data are in natural logarithms and are seasonally adjusted.

We employ the autoregressive distributed lag (ARDL) approach of Pesaran and Pesaran (1997) and Pesaran et al. (2001) to test for existence of a relationship between the energy data, employment, and industrial production in levels. As noted, this approach can be applied to series irrespective of whether they are I(0), I(1), or mutually cointegrated. The methods adopted in the literature in previous years mainly concentrate on cases in which the underlying variables are integrated of order one (Pesaran et al., 2001).

One of the most frequently adopted methods that requires variables to be integrated of order one was developed by Engle and Granger (1987). This approach consists of a procedure with two steps. In the first step, a test of the cointegration is tested in which a regression of one non-stationary series on another is run and the residuals are examined for stationarity. If the two non-stationary series form a stable linear relationship, then they are said to be cointegrated. According to the *Representation Theorem*, if the variables are cointegrated, then there is an error correction representation. The next step is to estimate the error correction model which identifies the short run dynamics of the system as well as the long run linkage. This approach is inefficient in multivariate cases. Another commonly used approach was developed by Johansen (1988, 1991) and Johansen and Juselius (1990) and is more efficient in multivariate systems. The ARDL approach has some advantages over these other approaches. First, the series used do not have to be I(1) (Pesaran and Pesaran, 1997). Second, even with small samples, more efficient cointegration relationships can be determined (Ghatak and Siddiki, 2001). Finally, Laurenceson and Chai (2003) state that the ARDL approach overcomes the problems resulting from non-stationary time series data. For instance, non-stationary time series data leads to spurious regression coefficients that are biased towards zero (Stock and Watson, 2003).

4. ARDL testing procedure and results

The ARDL method involves three steps (see Pesaran and Pesaran (1997) for more details and an application using MICROFIT econometric software.). The *first* step is to test for the presence of cointegration among the variables by employing the bounds testing procedure (Pesaran and Pesaran, 1997; Pesaran, Shin and Smith, 2001). This test can identify the long run relationship with a dependent variable followed by its *forcing variables*. Without having any prior information about the direction of the long run relationship between industrial production and disaggregate energy consumption, we construct the following regressions. Thus,

$$\begin{aligned}\Delta \ln \mathrm{INDPR}_t = a_{0\mathrm{indpr}} + \sum_{i=1}^{n} b_{\mathrm{iindpr}} \Delta \ln \mathrm{INDPR}_{t-i} + \sum_{i=0}^{n} c_{\mathrm{iindpr}} \Delta \ln \mathrm{EMP}_{t-i} + \sum_{i=0}^{n} d_{\mathrm{iindpr}} \Delta \ln \mathrm{EN}_{t-i} \\ + \lambda_{1\mathrm{indpr}} \ln \mathrm{INDPR}_{t-1} + \lambda_{2\mathrm{indpr}} \ln \mathrm{EMP}_{t-1} + \lambda_{3\mathrm{indpr}} \ln \mathrm{EN}_{t-1} + \varepsilon_{1t} \qquad (1)\end{aligned}$$

$$\begin{aligned}\Delta \ln \mathrm{EN}_t = a_{0\mathrm{ien}} + \sum_{i=0}^{n} b_{\mathrm{ien}} \Delta \ln \mathrm{INDPR}_{t-i} + \sum_{i=0}^{n} c_{\mathrm{ien}} \Delta \ln \mathrm{EMP}_{t-i} + \sum_{i=1}^{n} d_{\mathrm{ien}} \Delta \ln \mathrm{EN}_{t-i} \\ + \lambda_{1\mathrm{en}} \ln \mathrm{INDPR}_{t-1} + \lambda_{2\mathrm{en}} \ln \mathrm{EMP}_{t-1} + \lambda_{3en} \ln \mathrm{EN}_{t-1} + \varepsilon_{2t} \qquad (2)\end{aligned}$$

where EN represents the particular disaggregate energy variable under investigation, INDPR denotes industrial production, and EMP denotes employment. The parameters b, c and d are the short run coefficients and λs are the corresponding long run multipliers of the underlying ARDL model. The null hypothesis of "no cointegration" in Eqs. (1) and (2) is $\lambda_1=\lambda_2=\lambda_3=0$. The hypotheses are tested by computing the general F-statistics and comparing them with critical values in Pesaran and Pesaran (1997) and Pesaran et al. (2001).

To determine the order of the series, we conducted six different unit root tests. We used the augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), Elliot et al. (1996) Dickey-Fuller GLS detrended (DF–GLS) and Point Optimal (ERS–SPO), Kwiatkowski et al. (1992) (KPSS), and Ng and Perron's (2001) MZ_α (NP) tests. To conserve space, we do not discuss the details of the unit root tests here (see Maddala and Kim (1998) for a review of ADF, PP, KPSS, and DF–GLS; and Ng and Perron (2001) for more on NP). The results of these unit root tests are available from the authors upon request.

The unit root test results indicate that for models including conventional hydroelectric power, waste and wind energy consumption, we should use upper bounds for determination of cointegration, while for the rest of the models, we should use both lower and upper bound critical values reported in Pesaran, Shin and Smith (2001), and Pesaran and Pesaran (1997). The calculated F-statistics are reported in Table 1.

The comparisons indicate that there are unique cointegrating relationships between the variables in the models and that the *long run forcing variables* are employment and industrial production in all relationships with the exception being when coal is the disaggregated energy consumption variable. $F(\text{Industrial Production}_t|\text{Employment}_t, \text{Coal}_t)=4.15$ indicates that there is a cointegrating relationship when the dependent variable is industrial production. In this case, the forcing variables are employment and coal consumption. These results indicate that in all relationships, except for coal, employment and industrial production are the forcing variables that move first when a common stochastic shock hits the system. Then, energy consumption follows

Table 1
Bounds-testing procedure results

Cointegration hypotheses	F-statistics
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Coal}_t)$	4.15***
$F(\text{Coal}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	2.79
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Fossil Fuel}_t)$	2.30
$F(\text{Fossil Fuel}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	30.19*
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Hydroelectric}_t)$	2.40
$F(\text{Hydroelectric}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	9.10*
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Natural Gas}_t)$	2.40
$F(\text{Natural Gas}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	9.10*
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Solar}_t)$	2.05
$F(\text{Solar}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	40.16*
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Waste}_t)$	3.06
$F(\text{Waste}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	11.72*
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Wind}_t)$	2.65
$F(\text{Wind}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	25.99*
$F(\text{Industrial Production}_t\|\text{Employment}_t, \text{Wood}_t)$	2.93
$F(\text{Wood}_t\|\text{Employment}_t, \text{Industrial Production}_t)$	32.34*

*represents significance at 1%, ** at 5%, and *** at 10%. The critical values from Pesaran and Pesaran (1997) are 3.182–4.126, 3.793–4.855, 4.404–5.524, 5.288–6.309 for 10%, 5%, 2.5%, and 1% significance level, respectively. Similarly, from Pesaran, Shin and Smith (2001) we have critical values 3.17–4.15, 3.79–4.85, 4.41–5.52, 5.15–6.36 for 10%, 5%, 2.5%, and 1% significance level, respectively.

Table 2
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Coal Consumption*, dependent variable: industrial production, ARDL(1,1,1))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Employment	−2.2153	11.2983	−0.1961[.845]
Coal	−1.6786	5.5031	−0.3050[.762]
Intercept	43.3908	171.8561	0.2525[.802]
Panel B. Error correction representation for the selected ARDL			
ΔEmployment	2.4292	0.8100	2.9993[.004]
ΔCoal	0.0524	0.0306	1.7134[.093]
Intercept	0.9131	1.3455	0.6786[.501]
ecm(−1)	−0.0210	0.0566	−0.3718[.712]

the changes in the employment and industrial production. In the case of coal, it is the industrial production that follows due to the unexpected shocks to the system.

The *second* step is to estimate the coefficient of the long run relationships identified in the first step.[2] Having found long run relationships (i.e. cointegration) among industrial production, employment, and the various disaggregate energy consumption variables, in the next step the long run relationship are estimated using the following selected ARDL(h, z, r) models (See Tables 2–9).

$$\mathrm{INDPR}_t = a_{0\mathrm{ien}} + \sum_{i=0}^{h} \alpha_i \ln\mathrm{COAL}_{t-i} + \sum_{i=1}^{z} \beta_i \ln\mathrm{INDPR}_{t-i} + \sum_{i=0}^{r} \gamma_i \ln\mathrm{EMP}_{t-i} + \varepsilon_{2t} \tag{3}$$

$$\mathrm{EV}_t = a_{0\mathrm{ien}} + \sum_{i=1}^{h} \alpha_i \ln\mathrm{EV}_{t-i} + \sum_{i=0}^{z} \beta_i \ln\mathrm{INDPR}_{t-i} + \sum_{i=0}^{r} \gamma_i \ln\mathrm{EMP}_{t-i} + \varepsilon_{2t} \tag{4}$$

where EV denotes the particular energy variable under investigation except for coal consumption which will not be a dependent variable based on results reported above. The lag lengths h, z and r are determined by Schwartz Bayesian Criteria (SBC) criterion following the suggestion of Pesaran and Pesaran (1997). Taking into consideration the limited number of observations, a maximum of 3 lags was used. Tests for models of fossil fuel, wind, and solar energy include minimum of 1 lag for dependent variable to ensure lagged explanatory variables are present in the error correction model (ECM).

The long run test results (Panel A in Tables 2–9) reveal that industrial production and employment are the key determinants of fossil fuel, conventional hydroelectric power, solar, waste and wind energy consumption. In contrast, neither employment nor industrial production is found to have a significant long run impact on consumption of natural gas and wood energy. The industrial production equation indicates that neither employment nor coal energy consumption has a significant long run impact on real output.

The long run impact of industrial production on energy consumption is generally positive as expected, with the sole exception being a negative impact on solar energy. Mixed results are obtained for the energy and employment relationship. Usually the relationship is negative and

[2] See Pesaran and Pesaran (1997) for more details and an application using MICROFIT econometric software.

Table 3
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Fossil Fuels Consumption*, dependent variable: Fossil Fuels, ARDL(1,0,1))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Industrial Production	1.1628	0.2491	4.6691[.000]
Employment	−1.7707	0.5814	−3.0455[.004]
Intercept	24.3477	5.9890	4.0654[.000]
Panel B. Error correction representation for the selected ARDL			
ΔIndustrial Production	1.0282	0.2513	4.0908[.000]
ΔEmployment	−8.2547	4.0875	−2.0195[.049]
Intercept	21.5288	6.0223	3.5748[.001]
ecm(−1)	−0.8842	0.1381	−6.4039[.000]

significant indicating that energy use and employment are substitutes in the production processes. However, in wood consumption the relationship is positive because labor intensive technologies tend to require the wood use.

The *third* step is to estimate the short run dynamic coefficients. The short run dynamics are provided in Panel B of Tables 2–9. In terms of signs and significances, the results are generally consistent with the long run findings. However, for the model including natural gas in which we found no significant long run relationship, we do find significance in the short run. Once again, the relationship between employment, industrial production and conventional hydroelectric power, solar, waste, and wind energy use are found to be statistically significant.

Employment seems to negatively affect the consumption of energy from all sources, except for solar energy. The sign is reversed for the coefficient of industrial production, solar energy again being an exception. The reason may be due in part to technology as solar power does not require turning of turbines to produce electricity. The economic impact on jobs and output may thus differ as other sources (i.e., wind, hydro, wood, waste) require manufacturing of turbines and related equipment which is not required in the case of solar. Accordingly, it is possible that the economic multipliers associated with construction and ongoing operations may differ. In fact, the Natural Renewable Energy Laboratory (NREL) has developed an economic impact model (referred to as

Table 4
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Hydroelectric Power*, dependent variable: Hydroelectric, ARDL(1,0,0))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Industrial production	3.3266	1.0144	3.2795[.002]
Employment	−11.5452	3.5276	−3.2728[.002]
Intercept	126.0499	38.4305	3.2799[.002]
Panel B. Error correction representation for the selected ARDL			
ΔIndustrial production	1.2967	0.6111	2.1218[.039]
ΔEmployment	−4.5002	1.9527	−2.3045[.026]
Intercept	49.1326	21.0665	2.3323[.024]
ecm(−1)	−0.3898	0.1221	−3.1919[.003]

Table 5
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Natural Gas Consumption*, dependent variable: Natural Gas, ARDL(1,1,2))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Industrial production	−0.2946	1.2218	−0.2411[.811]
Employment	0.0438	2.4670	.017737[.986]
Intercept	8.3864	24.3973	0.3437[.733]
Panel B. Error correction representation for the selected ARDL			
ΔINDPR	2.2886	1.2127	1.8871[.065]
ΔEmployment	−15.5954	7.7633	−2.0088[.050]
ΔEmployment(−1)	16.7650	7.4350	2.2549[.029]
Intercept	4.1217	12.5619	0.3281[.744]
ecm(−1)	−0.4915	0.13924	−3.5298[.001]

JEDI) that is unique to the wind energy industry. Future research may examine differences in economic impacts based on energy source.

The findings in Table 2 reveal that coal consumption and employment are positively and significantly related in the short run but not in the long run. A similar relationship exists between coal consumption and output. These findings may be due to the many investment issues related to future expectations of energy markets in general and, in particular, the associated risks. The market may see alternative sources as the future for energy but recognizes the more immediate role that coal plays in the economy. Further, the current production technologies for alternatives, including oil-to-liquids, are not yet mature and production costs are high relative to conventional sources (Economic Report of the President, 2006).

In all energy equations, except coal consumption, the error correction term (denoted ecm(−1) in Tables 2–9) is found to be negative and statistically significant. This term indicates the speed of adjustment process to restore equilibrium following a disturbance in the long run equilibrium relationship. A negative and significant error correction term implies how quickly variables return to equilibrium. A relatively high ecm coefficient (in absolute magnitude) implies a faster adjustment process. For instance, the model with fossil fuels implies that almost 89% (ecm

Table 6
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Solar Energy Consumption*, dependent variable: Solar, ARDL(1,0,0))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Industrial production	−0.6441	0.1152	−5.5902[.000]
Employment	1.3181	0.4069	3.2397[.002]
Intercept	−10.8810	4.4311	−2.4556[.018]
Panel B. Error correction representation for the selected ARDL			
ΔIndustrial production	−0.5155	0.1315	−3.9199[.000]
ΔEmployment	1.0549	0.3679	2.8672[.006]
Intercept	−8.7080	3.7882	−2.2987[.026]
ecm(−1)	−0.8003	0.1468	−5.4530[.000]

Table 7
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Waste*, dependent variable: Waste, ARDL(1,0,0))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Industrial production	1.3971	0.4649	3.0048[.004]
Employment	−4.0774	1.6548	−2.4640[.017]
Intercept	45.4342	18.0099	2.5227[.015]
Panel B. Error correction representation for the selected ARDL			
ΔIndustrial produciton	0.5107	0.2477	2.0622[.045]
ΔEmployment	−1.4905	0.8284	−1.7993[.078]
Intercept	16.6084	9.0920	1.8267[.074]
ecm(−1)	−0.3656	0.1109	−3.2970[.002]

coefficient = −0.8842) of the disequilibrium of the previous month's shocks adjust back to the long run equilibrium in the current month. This value is approximately 39%, 49%, 80%, 37%, 79%, and 68% for equations including conventional hydroelectric power, natural gas, solar, waste, wind and wood energy use, respectively.

The last issue we address is related to the goodness of fit of the ARDL models. For this purpose we perform a series of diagnostic and stability tests. The diagnostic tests examine serial correlation using the Lagrange multiplier test of residual serial correlation, functional form by employing Ramsey's RESET test using the square of the fitted values, and heteroscedasticity based on the regression of squared residuals on squared fitted values. The diagnostic tests reveal no evidence of misspecification and, additionally, we find no evidence of autocorrelation. To test for structural stability we utilize the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ). The results of CUSUM and CUSUMSQ stability test indicate that the estimated coefficients of all models are stable.[3]

5. Conclusion and policy implications

In this paper we examined the relationship between disaggregate energy consumption and industrial output, as well as employment, in the United States using the autoregressive distributed lag (ARDL) approach developed by Pesaran and Pesaran (1997) and Pesaran et al. (2001). This research contributes to the field of energy economics in two important ways. First, following the recent trend, we utilize measures of disaggregate energy consumption thus providing a comprehensive analysis. Second, we employ a relatively new time series approach capable of uncovering relationships that might otherwise be missed using more conventional methods.

The results of the bounds testing procedure confirm the presence of cointegration between the energy measures, employment and industrial output. Over the long run output and labor are the key determinants of fossil fuel, conventional hydroelectric power, solar, waste and wind energy consumption. Employment and output are not found to have significant long run impacts on natural gas, and wood energy. Our results also reveal information on the short run

[3] Results of all diagnostic and stability tests are available upon request.

Table 8
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Wind Energy*, dependent variable: Wind, ARDL(1,0,0))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Industrial production	11.0669	0.9072	12.1984[.000]
Employment	−22.3938	3.1882	−7.0240[.000]
Intercept	214.9290	34.7046	6.1931[.000]
Panel B. Error correction representation for the selected ARDL			
ΔIndustrial production	8.7216	1.6647	5.2392[.000]
ΔEmployment	−17.6481	3.9285	−4.4923[.000]
Intercept	169.3808	39.8057	4.2552[.000]
ecm(−1)	−0.7881	0.1306	−6.0366[.000]

speed of adjustment process to restore long run equilibrium. The model with fossil fuels, conventional hydroelectric power, natural gas, solar, waste, wind and wood energy use implies that about 89%, 39%, 49%, 80%, 37%, 79%, and 68%, respectively, of the disequilibrium of the previous month's shocks adjust back to the long run equilibrium in the current month.

The results presented in this paper have important implications for public US energy policy and private sector investment in energy production. For example, the results for the renewable energy measures help identify the particular sectors in which economic growth is tied to energy consumption over long periods of time. Thus, developers of renewable energy, both public and private, can take this information into account when conducting benefit-cost analyses and economic impact studies. Furthermore, payback periods for investment in wind energy farms, etc. often take years, and knowledge about the long run relationships with output and employment should help to provide more accurate forecasts of future energy trends. Finally, for all the energy sectors (i.e., conventional and renewable), the speed of adjustment estimates provide direct information as to the behavior of short run fluctuations that can be incorporated into the demand management strategies of energy market producers and policy makers.

Table 9
Estimated autoregressive distributed lag models, long run coefficients, and short run error correction model (*Wood Energy*, dependent variable: Wood, ARDL(1,0,0))

Regressor	Coefficient	Standard error	T-ratio[prob]
Panel A. Estimated long run coefficients			
Industrial production	0.4045	0.2566	1.5764[.122]
Employment	0.6397	0.9094	.70341[.485]
Intercept	−4.3177	9.8922	−.43647[.664]
Panel B. Error correction representation for the selected ARDL			
ΔIndustrial production	0.2744	0.1727	1.5885[.119]
ΔEmployment	0.4340	0.6420	.67598[.502]
Intercept	−2.9290	6.8621	−.42684[.671]
ecm(−1)	−0.6784	0.1396	−4.8606[.000]

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