Revisiting the Income Elasticity of Energy Consumption: A Heterogeneous, Common Factor, Dynamic OECD & non-OECD Country Panel Analysis

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ABSTRACT

The current paper contributes to the literature on the relationship between economic development and energy demand by assembling a wide panel dataset of energy consumption and prices for 37 OECD and 41 non-OECD countries. The unbalanced data spans 1960–2016, with the full 56 years of data for 17 countries and all countries having at least 18 years. In addition, our dynamic panel estimates address nonstationarity, heterogeneity, and cross-sectional dependence. Most results suggest that the GDP elasticity is less than unity (e.g., 0.7)—i.e., energy intensity will fall with economic growth. Most evidence suggests that the GDP elasticity is similar for OECD and non-OECD countries, and for non-OECD countries, similar across income-bands. Also, there is no evidence that individual country elasticity estimates (for GDP or prices) vary systematically according to income. The price elasticity is larger (in absolute terms) for OECD than for non-OECD countries—indeed, it is typically insignificant for non-OECD countries.

Keywords: Economic development, Economic growth, Energy use, Energy intensity, Energy prices, Common factor panel models, Elasticity estimates, Dynamic models

https://doi.org/10.5547/01956574.41.3.blid

1. INTRODUCTION

Since the OPEC oil embargo in 1973, studies have emphasized the role of energy prices in shaping energy use and factor allocation. Similarly, in the applied energy economic literature, there has long been interest in estimating/understanding the macro-energy-GDP elasticity—the percentage change in energy consumption associated with a 1% change in GDP. Previous work on the income elasticity of energy consumption has found a lack of leapfrogging (i.e., economic growth has not become less energy intensive in developing/industrializing countries), despite obvious technology transfer (current developing countries employ technology more advanced than that used in OECD countries circa 1960–1970). Also, estimating the relationship between economic development and energy demand and determining whether that relationship changes as levels of development change have been popular questions in energy economics (e.g., Judson et al. 1999; Medlock and Soligo 2001; and van Benthem and Romani 2009). Understanding more about the energy demand-GDP relationship and its dynamics are important for several reasons. Knowing the income elasticity of energy consumption can help in assessing the feasibility/stringency of intensity-based targets (e.g., energy or carbon emissions over GDP); and the elasticity is utilized in energy

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forecasting and as an input to larger energy systems or integrated assessment models (IAM) that are used to examine climate change options.

Indeed, the macro energy elasticity of GDP is useful in projecting energy consumption for a given economic growth rate, and several countries, as part of the Paris Agreement on climate change, have committed to reduce their emissions intensity (i.e., the ratio of carbon emissions to GDP). But if the macro energy (or carbon) elasticity of GDP is less than unity, then energy/emissions intensity will fall in a business-as-usual economic growth scenario. Among the countries to set intensity-based targets are China, India, Malaysia, and U.S. Several other countries have set goals to reduce emissions off a business-as-usual (growth) scenario, including Indonesia, Thailand, and Republic of Korea. (Indonesia has a goal to lower its macro energy elasticity of GDP, too.) In addition, the APEC economies have an aspirational goal of lowering APEC aggregate energy intensity by 45% from 2005 levels by 2035; and the ASEAN countries have a goal of lowering energy intensity by 20% from 2005 levels by 2020 and 30% by 2025. These national actions demonstrate that energy intensity and energy demand responses are a critical element in climate change strategies, even though a host of other issues must also be addressed in mitigating greenhouse gas emissions.

The current paper contributes to the literature on aggregate energy demand estimation by assembling an unusually wide panel dataset that covers not only energy consumption and economic growth but also end-use energy prices for 37 OECD and 41 non-OECD countries. Moreover, the approach also employs estimation methods that address nonstationarity, heterogeneity, and cross-sectional dependence. (A detailed description of the data and methods follows in Section 3.) We seek to determine (i) whether (and if so, by how much) energy intensity will fall in business-as-usual economic growth scenarios, and (ii) whether energy forecasts/IAMs need to allow for energy elasticities that change with economic growth.

A major weakness in many previous empirical studies of international energy demand is the lack of energy price data that reflects local domestic conditions. Global oil prices are available for an extended period, but they exclude the prices of other important fuels as well as electric power. In addition, price controls and subsidies for domestic fuel production may distort world price conditions for any specific fuel. Occasionally, there may exist published domestic energy price data for select countries over limited horizons, but reliance upon this information alone may severely restrict the scope of the analysis. These problems may potentially introduce serious biases in the estimates of income elasticities and other responses because energy prices are not represented well.

A substantial reason for revisiting the income elasticity was our effort to splice various energy price series together to form a more complete set of energy prices for 78 countries covering an extended number of years. This important data development effort—a contribution in its own right—[1]provides a useful perspective on the potential advantages of including energy price information for a full range of countries.

2. LITERATURE REVIEW

There is now an extensive literature on energy demand studies that include evaluations of specific fuels and their substitution with other energy forms. Dahl and Roman (2004) survey the literature on many fuels through the early 2000s and conclude that most energy forms are both price and income inelastic in the long run. Although income responses are higher, similar responses apply for gasoline consumption (Dahl, 2014). Similar conclusions are also reached by Labandeira et al. (2017), who provide a meta-analysis combining estimated responses from many studies. Studies

1. Data available from authors.

included in these analyses are primarily from the richer OECD members. Preliminary conclusions offered by Huntington et al. (2019) suggest that price and income responses within the major industrializing economies outside the OECD do not appear to be dramatically different from those of OECD economies, although the studies for these rapidly growing economies are much sparser.

One of the major challenges in reaching conclusions from the previous literature is that researchers apply different methodologies to different countries and time periods as well as use different data sources. With some important exceptions like the early estimates by Pindyck (1979a, 1979b), few researchers have applied the same analytical framework to evaluate global energy demand in as many economies as possible.

The current paper is most like Galli (1998), Medlock and Soligo (2001), Gately and Huntington (2002)[2], van Benthem and Romani (2009), and van Benthem (2015), in that we analyze data that have both time series and cross-sectional dimensions, consider both GDP and energy prices, and employ a dynamic model. Galli analyzed 10 developing Asian economies over 1973–1990 that included Korea and Taiwan. Medlock and Soligo compiled data from 28 countries, of which seven were non-OECD (Brazil and six Asian countries), over 1978–1995. The dataset van Benthem and Romani analyzed contained 17 developing countries (including Israel and Korea)—for which individual country, end-use prices were available—and spanned 1978–2003. The individual country, end-use price data that van Benthem (2015) used ran from 1978–2006 and included observations from 58 countries. It appears only the Galli dataset was balanced. Also, only Galli's data—which was sourced from Pesaran et al. 1997—is publically available.

In addition to using a standard demand-type model in which energy consumption per capita is a function of GDP per capita and real energy price (all in natural logs), Medlock and Soligo (2001), van Benthem and Romani (2009), and van Benthem (2015) employed the partial adjustment mechanism of Koyck (1954); whereas, Galli (1998) estimated an error correction model. All papers used a homogeneous, fixed effects estimator; van Benthem and Romani (2009) and van Benthem (2015) included time effects, too; Galli also considered the weighted mean group procedure of Swamy (1971), and Medlock and Soligo (2001) employed the two-stage least squares approach of Balestra and Nerlove (1966) to address dynamic panel bias. To capture potential nonlinearities, all four papers added a GDP per capita squared term (van Benthem and Romani 2009 included price squared as well). In addition, van Benthem (2015) estimated a linear model across several income bands.

All papers uncovered evidence of a nonlinear relationship between energy consumption and GDP, i.e., significant coefficients for both GDP and GDP squared (although, for Galli, those coefficients were insignificant when the mean group procedure was used). Hence, their results suggested that the income elasticity of energy changed with GDP. However, the shapes of the GDP-energy relationship were not always the same. Galli (1998) and Medlock and Soligo (2001) estimated inverted U-shaped relationships (i.e., the GDP term was positive while the GDP squared term was negative), as did van Benthem (2015) for income in the \$10,000–\$40,000 range. In contrast, van Benthem and Romani (2009) estimated U-shaped relationships (i.e., a negative GDP coefficient but a positive GDP squared one), as did van Benthem (2015) for GDP per capita less than \$10,000 (where the linear GDP term was insignificant). The van Benthem and Romani result of an increasing income elasticity appears to have been caused by observations from income levels less than \$5,000 since a subsequent regression based on income levels between \$5,000–\$10,000 produced an inverted-U shaped relationship.

2. The Gately-Huntington (2002) analysis is not explained in detail below because it allowed differences between country types but did not explore the non-linear response to income.

For a linear model, Galli estimated long run income and price elasticities of 1.18 and –0.32, respectively. Also, country-specific income elasticities were typically above unity for the developing Asian economies that Galli analyzed; yet, the forecasts implied that nearly all the countries considered would have an elasticity below unity today (given the higher income levels used in the forecasts and the negative GDP squared coefficient in Galli's model). In their linear model, van Benthem and Romani (2009), also considering developing countries, found substantially different GDP and price elasticities of 0.64 and –0.55, respectively (although, that regression did not include time effects, which are demonstrated to be significant). Another regression that was based on a \$5,000–\$10,000 income band and that included GDP squared (but not price squared) produced a much lower price elasticity of –0.11. While interested in other questions, van Benthem (2015) often estimated a GDP elasticity that was near unity for less developed countries and sometimes found that the elasticity varied across income bands (in such cases it was higher at lower incomes).

Two additional recent papers, Czereklyei et al. (2016) and Burke and Czereklyei (2016), applying static (and linear) models to a cross-sectional approach and considering more countries, provided some contrast to several of the earlier discussed papers. Czereklyei et al. uncovered a stable relationship between energy use and income over 1971–2010 and an energy elasticity of income less than unity (i.e., around 0.7) by comparing cross-sectional regressions (of 99 countries) taken at ten-year intervals. However, Czereklyei et al. estimated a bivariate model (but did not account for energy prices), and considering whether cross-sectional estimations vary over time assumes independence both over time and across units (Smith and Fuertes, 2016)—two assumptions that are unlikely to hold, as we demonstrate below. Burke and Czereklyei primarily relied on a single cross-section (2010) of 132 countries and used gasoline price as a proxy for economy-wide energy price (and other sectoral prices).[3] In contrast to Czereklyei et al., Burke and Czereklyei estimated a long-run energy-GDP elasticity of essentially unity (0.95) when primary solid biofuel consumption was excluded. More in line with Czereklyei et al., Burke and Czereklyei found virtually no difference in the energy-GDP elasticity when it was evaluated at different quartiles of GDP per capita.

So, the earlier studies—Galli (1998), Medlock and Soligo (2001), van Benthem and Romani (2009), and van Benthem (2015)—applied dynamic models that included energy prices and found that the GDP elasticity varied with income and was (typically) near one. The more recent work—Czereklyei et al. (2016) and Burke and Czereklyei (2016)—found no differences in the GDP elasticity over time or across income levels, respectively, and, in the case of Czereklyei et al., estimated an elasticity substantially below unity. However, that more recent work applied static models that either excluded energy prices or included a poor proxy for them. Moreover, neither sets of papers fully addressed heterogeneity or addressed cross-sectional dependence at all. As described in Section 5 below, our results adjust for these data and methodological issues and suggest a general rule that the income elasticity is likely (significantly) below unity and approximately equal to 0.7.

3. MODEL AND DATA

It is common when estimating demand models to incorporate lags of the variables to allow for a dynamic adjustment of the system and for short-run elasticities to differ from long-run elasticities. Cuddington and Dagher (2015) recommend using the flexible autoregressive distributed lag (ADL) model, which does not impose a priori restrictions of the relative relationship between short-

3. Our data suggests that while gasoline price is highly correlated with other transport fuel prices, it is not a particularly good proxy for the energy prices in other sectors. Indeed, for our data the correlation coefficients between gasoline price and industrial electricity price, residential electricity price, and economy-wide energy price are 0.30, 0.44, and 0.10, respectively.

run and long-run elasticities. Hence, we consider a dynamic, adjustment model whereby the lag of the dependent variable (energy consumption) is included on the right-hand-side along with income/GDP, energy price, and their one period lags:

$$lnTFC_{it} = \alpha_i + \gamma_t + \beta_i^1 lnTFC_{it-1} + \beta_i^2 ln\,GDP_{it} + \beta_i^3 ln\,price_{it} + \beta_i^4 ln\,GDP_{it-1} + \beta_i^5 ln\,price_{it-1} + \varepsilon_{it} \tag{1}$$

where subscripts *it* denote the *i*th cross-section and *t*th time period, *TFC* is total final energy consumption per capita, *GDP* is GDP per capita, and *price* is a measure of energy price, α is a cross-sectional specific constant, γ are common time effects, the βs are (potentially) cross-sectional specific coefficients to be estimated, and ε is the error term. So, the long-run GDP and price elasticities, respectively, are:

$$\frac{\beta^2 + \beta^4}{\left(1-\beta^1\right)} \text{ and } \frac{\beta^3 + \beta^5}{\left(1-\beta^1\right)} \tag{2}$$

The short-hand notation for this model is ADL (1,1,1). For robustness we also consider the partial adjustment model, which includes a lag of only the dependent variable, i.e., the ADL (1,0,0) model in short-hand.[4] We consider the partial adjustment model because (1) it has appeared frequently in the (previously cited) literature, and (2) the statistical routines we use do not allow for lag structure to vary across countries; but the ADL (1,0,0) model may fit (some) individual countries better than the ADL (1,1,1) model.[5] While it meant losing countries from our dataset, we considered an ADL (1,2,2) model; however, the joint insignificance of the two second lag terms could not be rejected. Both because of that result and since we do not want to lose additional countries, we did not consider further lag structures.[6] Similarly, we did not consider additional variables since (1) we wanted the availability of energy prices to be the limiting factor for the dataset, and (2) none of the papers discussed above included other variables. (We discuss in Appendix A this issue of potential variables not considered further.)

Real GDP (in 2010 U.S.$ using PPPs), population (to convert GDP to per capita), and total final energy consumption[7] (TFC) /population (in toe per capita) are from IEA's World Indicators dataset (extracted from OECD iLibrary in March 2018). This data cover 1960–2016 for OECD countries and 1971–2015 for non-OECD countries (the TFC/population data end in 2015 for all countries). Real GDP per capita was extended to 2016 for non-OECD countries by using World Bank World Development Indicators (i.e., assuming the same growth over 2015–2016 as in the series GDP per capita, PPP), except for Taiwan/Chinese Taipei, for which Enerdata[8] real GDP per capita data were used. For all countries final energy consumption per capita was extended to 2016 with Enerdata's final consumption per capita series (again, by assuming the same final period growth rate).

4. We (primarily) do not consider the error-correction model, which was used by Galli (1998), because that model requires an additional four time observations per cross-section compared to the ADL (1,1,1) model when employing our preferred estimator (more on methods below). It is important to note that the error-correction model is nested within the ADL (1,1,1) model anyway.

5. For OECD countries, the ADL (1,0,0) model was rejected, in favor of the ADL (1,1,1) model, at the *panel-level*.

6. As will be discussed below, our preferred estimation method requires 18 time observations for the ADL (1,1,1) model. Each additional lag of the *independent* variables (only) would require an additional two time observations.

7. Total final energy consumption excludes losses associated with extraction, refining or transporting energy that are included in total primary energy supply.

8. Enerdata Global Energy & CO_2 database. https://www.enerdata.net/research/energy-market-data-co2-emissions-database.html.

For 31 IEA countries, energy price data is sourced from IEA's real index for industry and households (2010 base year) from Indices of Energy Prices by Sector. For Iceland, the IEA index, consumer prices-energy was used (also 2010 base year). The IEA price data typically spans 1978–2016. Data from Baade (1981) is used to extend IEA's price series from 1978 to 1960 for 17 OECD countries. Following the standard procedure for splicing time series, the 1978 IEA price level was extrapolated backward in time by the growth rate in energy prices reported in the Baade analysis.

It is particularly challenging to assemble energy price data for non-IEA/OECD countries. Along these lines, we develop a new real price index for aggregate end-use energy from Enerdata's Global Energy and CO_2 database, which begins in 1978. The initial price data are in constant 2015 U.S. dollars. Three real indices are calculated (base year set to 2005) from the data available for three sectors: residential, industry, and transport. The final, aggregate index is a weighted average (by their share of total final energy consumption measured in tons of oil equivalent) of the three end-use indices (following standard practice). Each aggregate real index observation was estimated from a year in which each of the three end-use indices had an observation (i.e., there is no aggregate energy price observation for a year in which only one or two of the end-use prices is available).

The residential index is based on a weighted average of real price indices for households using PPP (and including taxes) for bituminous coal, light fuel oil, electricity, and natural gas. The industry index is based on a weighted average of real price indices for industry (that includes taxes) for bituminous coal, light fuel oil, heavy fuel oil, electricity, and natural gas. To create both the residential and industry real price indices, those individual sector price indices are weighted by their share in final energy consumption of the residential and industry sectors, respectively. In several instances (country observations) the final sector index is based on a subset of the respective energy prices discussed above. The transport real index is based on a weighted average (again by consumption shares) of real price indices, based on PPP and including taxes, of premium gasoline and diesel. Premium gasoline prices are highly correlated with unleaded gasoline prices, as are diesel prices with commercial diesel prices. The prices for premium gasoline and diesel had by far the greatest degree of coverage.

Pesaran et al. (1998) contains energy price data for 10 Asian economies from 1973–1992 (this is the data Galli employed in her analysis); so, the previously explained index can be extended back to 1973. For five countries (Bangladesh, Malaysia, Pakistan, Philippines, and Sri Lanka), there is a gap between the end of the Enerdata series and the beginning of the Pesaran et al. data; so, because the two real indices have different base years, a consumer prices deflator (sourced from Enerdata) was used as a bridge. (Typically, a series was extended by applying the growth rates from the secondary series to the last entry of the primary series.)

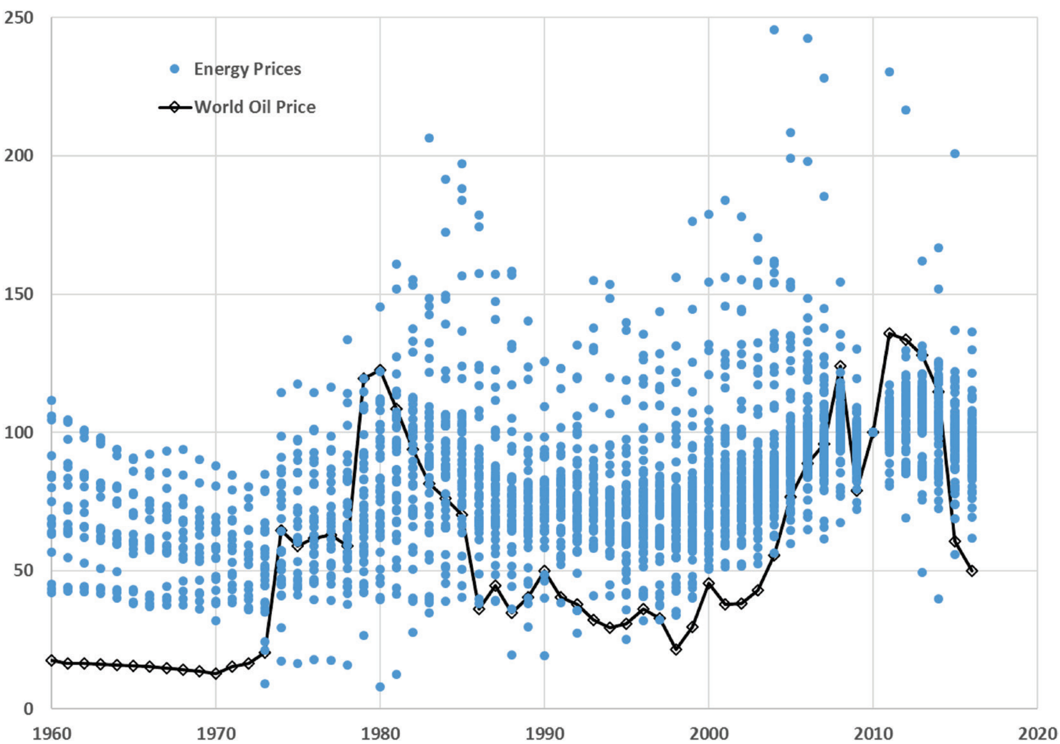
Every country for which at least 18 years of price data could be assembled is included. Ultimately, the dataset has 78 countries (of which 37 are OECD/high income) and spans 1960–2016. The data is unbalanced: all 170 observations from the 1960s are from OECD countries; over two-thirds of the observations from the 1970s and 1980s are from OECD countries (482 out of 707 observations; but, from 1990–2016, the observations are roughly evenly split between OECD and non-OECD countries (948 vs. 924). Appendix Table A1 describes the dataset.

Reliable quantitative estimates depend upon not only appropriate corrections for bias and consistency, but also whether the underlying data series display sufficient variation across countries and over time. Table 1 reports the means, standard deviations, and coefficients of variation (standard deviations divided by the corresponding mean) for all 78 countries, OECD countries, and non-OECD countries for 1960–2016. Considerable variation exists in the dependent variable (the natural logarithm of per-capita final energy consumption) within the OECD but particularly among the other industrializing economies. The (natural logarithm) energy price and per-capita real GDP counterparts demonstrate less variation than final energy consumption, but still confirm substantial differences in energy market and economic conditions. Figure 1 tracks the individual country real energy prices (indexed to 2010) and compares them with the real world crude oil price (also indexed to 2010). Although energy and oil prices move upward and downward in tandem throughout the period, the cross-country variation in energy prices in any one year is substantial.

Table 1: Summary Statistics for 78 Countries, 1960–2016.

Variable	Mean	Std. Dev.	Coeffs. of Variation
All Countries			
Ln(TFC)	0.327	0.919	2.806
Ln(GDP)	9.617	0.851	0.088
Ln(Price)	4.413	0.355	0.081
OECD Countries (37)			
Ln(TFC)	0.882	0.559	0.634
Ln(GDP)	10.125	0.485	0.048
Ln(Price)	4.387	0.273	0.062
Non-OECD Countries (41)			
Ln(TFC)	–0.445	0.748	–1.681
Ln(GDP)	8.911	0.739	0.083
Ln(Price)	4.449	0.443	0.100

Figure 1: Real Energy Prices Indexed to 2010 for 78-Country Sample, 1960–2016.



Notes: Excludes a few extreme outlier values (>250) for Ecuador (1996–99), Indonesia (2008), Iran (1980–82) and Venezuela (1981–2003). Source for the world crude oil price is the 2018 BP Statistical Review of World Energy.

4. METHODS

Most of the previous panel analyses have used the fixed effects (FE) estimator (with country and/or time dummies). A fixed effects regression involves subtracting out cross-sectional means so that the regressions exploit variation over-time, and the estimated coefficients/slopes are assumed to be the same for all cross-sections (i.e., FE is a homogeneous estimator).

We think it is likely, however, that the relationships (i.e., elasticities) will not be the same for each country—i.e., there should be a substantial degree of heterogeneity. And if one mistakenly assumes that parameters are homogeneous (when the true coefficients of a dynamic panel in fact are heterogeneous), then all parameter estimates of the panel will be inconsistent (Pesaran and Smith, 1995). Hence, we use a mean group-type estimator (MG) that first estimates cross-section specific regressions and then averages those estimated individual-country coefficients to arrive at panel coefficients (standard errors are constructed nonparametrically as described in Pesaran and Smith, 1995).

For the macro-level variables we consider, cross-sectional correlation/dependence is expected because of, for example, regional and macroeconomic linkages that manifest themselves through (i) common global shocks; (ii) institutional memberships like OECD; or (iii) local spillover effects between countries or regions. Indeed, the Pesaran (2004) cross-sectional dependence (CD) test,[9] 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. Furthermore, the absolute value mean correlation coefficients ranged from 0.6–0.8 (see Appendix Table A2). When the errors of panel regressions are cross-sectionally correlated, standard estimation methods can produce both inconsistent parameter estimates and incorrect inferences (Kapetanios et al., 2011). Thus, because cross-sectional dependence can impart bias problems as well as inefficiency, only making adjustments to the standard errors (e.g., via Driscoll and Kraay, 1998) may not be sufficient.

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. The CCE estimator is not consistent in dynamic panels, however, since the lagged dependent variable is no longer strictly exogenous. Chudik and Pesaran (2015) demonstrated that the estimator becomes consistent again when an additional $\sqrt[3]{T}$ lags (in our case, 2, for series with at least 18 years) of the cross-sectional means are included. Hence, we employ, as our preferred estimator, the Dynamic Common Correlated Effects (DCCE) estimator of Chudik and Pesaran (2015).[10] The combination of independent variables, their lags, cross-sectional average terms, and two additional lags of those cross-sectional average terms, means each cross-section must have at least 18 observations. (For robustness, we also run a homogenous version of CCE—CCEP—whereby cross-sectional average terms are added to a fixed effects regression.)[11] The DCCE estimator applied to the ADL (1,1,1) model, i.e., Equation 1, looks like:

$$
\begin{aligned}
ln\,TFC_{it} = {} & \alpha_i + \beta_i^1 ln\,TFC_{it-1} + \beta_i^2 ln\,GDP_{it} + \beta_i^3 ln\; price_{it} + \beta_i^4 ln\,GDP_{it-1} + \beta_i^5 ln\; price_{it-1} \\
& + Z_{it} + \varepsilon_{it}
\end{aligned}
\qquad (3)
$$

where Z represents the cross-sectional average terms.

The cross-sectional average terms from Equation 3 are displayed in Equation 4 below:

9. This test is implemented via the STATA command xtcd, which was developed by Markus Eberhardt.

10. The Dynamic Common Correlated Effects estimator of Chudik and Pesaran (2015) is implemented by STATA command xtmg—which was developed by Markus Eberhardt—and by augmenting code from Eberhardt and Presbitero (2015).

11. CCEP is performed in STATA by adopting code from Eberhardt and Presbitero (2015).

$$Z_{i,t} = \sum\nolimits_{l=0}^{2} \rho_i^l \overline{TFC_{t-l}} + \sum\nolimits_{l=0}^{2} \rho_i^l \overline{price_{t-l}} + \sum\nolimits_{l=0}^{2} \rho_i^l \overline{GDP_{t-l}} \qquad (4)$$

where the bar represents an average over the cross-sections (countries). The cross-sectional average terms are intended to capture more than omitted variables or be more than nuisance terms, and can be considered a set of latent drivers of the macro economy (Eberhardt and Presbitero, 2015); however, their estimated coefficients do not have a meaningful interpretation, and thus, are not reported in practice. Like time dummies, the cross-sectional average terms can account for so-called strong-form cross-sectional dependence, i.e., temporary, global shocks. For example, the cross-sectional average time series of GDP will dip/level, corresponding to events like the Great Recession. But cross-sectional dependence also is caused by so-called spillover effects or weak-form dependence (e.g., shared culture/institutions, economic and social interactions) that are much more accurately modeled by cross-sectional averages than merely time dummies/trends. Moreover, these spillover effects are not simply a proximity/geographical phenomenon that could be modeled by a spatial lag. As a diagnostic test, we run on the regression residuals and report the Pesaran CD test to determine the extent of cross-sectional dependence.

When using MG methods, there are two ways to calculate panel long-run parameters from a dynamic model.[12] First, one can apply the panel short-run estimates (which themselves are the average of the individual country short-run coefficients) to Equation 2. Such an approach is referred to as the long-run average (LRA) and is the most common approach in the literature (standard errors are then computed via the Delta method). For the second approach, one computes the long-run coefficient for each country first (again applying Equation 2) and then computes the average to arrive at the panel coefficient. This average long-run (ALR) method—less used, perhaps because of the extra steps involved—is closer to the spirt of MG estimations since the panel long-run is directly based on the average of the individual country long-run coefficients.

The variables analyzed are also 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. The Pesaran (2007) panel unit root test (CIPS) for heterogeneous panels, which allows for cross-sectional dependence to be caused by a single (unobserved) common factor,[13] suggests that the variables are likely nonstationary in levels (see Appendix Table A3). 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). Unlike (static) FE, MG-style estimators are typically robust to nonstationarity and cointegration (as well as to breaks and serial correlation). As an additional diagnostic test, we run on the regression residuals and report the Pesaran CIPS test to confirm stationarity.

Nonlinearities are often investigated by considering a quadratic (or higher) function of GDP per capita (e.g., Galli, 1998; Medlock and Soligo, 2001; van Benthem and Romani, 2009). However, it is incorrect to make a nonlinear transformation of a nonstationary (and potentially cointegrated) variable, like GDP per capita, in ordinary least squares (Muller-Furstenberger and Wagner, 2007). Furthermore, this polynomial model has been criticized for lacking flexibility (e.g., Lindmark, 2004), and is clearly wrong/cartoonish at the limits. (Indeed, both Galli and Medlock and Soligo recognized that a quadratic relationship between energy demand and income was unrealistic at the limits of high income, but employed the model as an approximation.)

12. In both cases, we follow the standard practice of robust regressions (see Hamilton, 1992), where outliers are weighted down in the calculation of averages.

13. This test is implemented via the STATA command pescadf, which was developed by Piotr Lewandowski.

Hence, instead of the GDP polynomial, we take advantage of the heterogeneous nature of MG estimations (i.e., elasticities are estimated for each cross-section) and plot individual country-specific elasticity estimates against the individual country average GDP per capita for the whole sample period (as in Liddle, 2015). Also, we consider income/development-based partitions of the data (as in van Bentham, 2015).

Dynamic models estimated with panel data (using either fixed effects- or MG-style estimators) are subject to a downward bias, called the dynamic panel or Nickell bias. Since this bias is on the order of 1/T (Nickell, 1981), it can be mitigated by having several time observations. In addition, there are methods to adjust for the bias (e.g., Kiviet, 1995). Beck and Katz (2009) claim that with at least 20 time observations, bias correction is counter-productive; whereas, Judson and Owen (1999) are more conservative recommending bias correction unless there are 30 time observations. However, since the long-run coefficient is a non-linear function of the short-run coefficient (e.g., Equation 2), Pesaran et al. (1999) caution that bias correction to the short-run coefficients can exacerbate the bias of the long-run coefficient. Bruno (2005) determined that in unbalanced panels (like ours), the bias declines with average group (cross-section) size (i.e., the bias is not determined entirely by the shortest series). It is important to note that our shortest cross-sections have 18 years of data; our average cross-section size is 35. (Still, we run some static models for robustness.)

5. RESULTS AND DISCUSSION

Table 2 shows the results for a static model. Since we prefer the dynamic model, the main points to take away from Table 2 are that the residuals for the fixed effects estimator are nonstationary. Nonstationarity could only be uniformly rejected for a lags (zero to three) for CCE. Also, while cross-sectional independence was rejected for all estimators, adding cross-sectional average terms appears to mitigate cross-sectional correlation in the residuals (the resulting mean absolute correlation coefficient is much higher for fixed effects).

Table 2: Static Model, 78 Countries 1960–2016, Unbalanced.

	2–FE	CCEP	MG	CCE
GDP	0.70****	0.80****	0.55****	0.72****
	[0.64 0.77]	[0.73 0.86]	[0.44 0.66]	[0.62 0.82]
Price	–0.18****	–0.071****	–0.17****	–0.08****
	[–0.21 –0.14]	[–0.099 –0.043]	[–0.202 –0.12]	[–0.13 –.038]
Observations	2749	2749	2749	2749
RMSE	0.16	0.082	0.080	0.048
CD ρ	–2.5** 0.52	3.5**** 0.26	22.7**** 0.27	5.6**** 0.20
CIPS	I(1)	I(1)/I(0)	I(0)/I(1)	I(0)

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. 95% confidence intervals shown in brackets.
2-FE=fixed effects with country and time dummies. CCEP=2-FE with cross-sectional average terms. MG=mean group. CCE=MG with cross-sectional average terms.
Diagnostics: RMSE = root mean squared error. CD ρ = Pesaran (2004) CD test statistic and mean absolute correlation coefficient of the residuals. The null hypothesis is cross-sectional independence. CIPS= Pesaran (2007) CIPS test on residuals; I(0)=stationary.

Table 3 displays the results for the dynamic, ADL (1,1,1) model for both FE-type (2-FE, CCEP) and MG-type (MG, CCE, DCCE) estimators. For the MG estimators, the long-run coefficient for GDP is significantly less than unity, and the panel long-run average (LRA) is similar to the panel average long-run (ALR). The price elasticity for all estimators is significant and negative, but relatively small. That the lagged GDP coefficient is negative suggests a correction/adjustment process is at work. While all estimators produced stationary residuals, only for the MG methods that were augmented with cross-sectional average terms (CCE, DCCE) could cross-sectional independence not be rejected in the residuals. Also, both homogeneous/FE methods—excluding and including cross-sectional average terms (2-FE, CCEP, respectively)—had relatively high coefficients (i.e., near one) for the lagged dependent variable. (The near-one coefficient on the lagged dependent variable suggests that the estimators may not have sufficiently addressed the nonstationary data despite producing stationary residuals.)

Table 3: Dynamic Model (ADL (1,1,1)), 78 Countries 1960–2016, Unbalanced.

	2–FE	CCEP	MG	CCE	DCCE
TFC t–1	0.94****	0.84****	0.68****	0.51****	0.49****
	(0.0072)	(0.014)	(0.035)	(0.043)	(0.050)
GDP	0.49****	0.45****	0.58****	0.45****	0.46****
	(0.04)	(0.043)	(0.041)	(0.049)	(0.053)
Price	–0.039****	–0.048****	–0.060****	–0.064****	–0.032
	(0.010)	(0.010)	(0.013)	(0.014)	(0.021)
GDP t–1	–0.43****	–0.30****	–0.41****	–0.18***	–0.14***
	(0.040)	(0.041)	(0.047)	(0.052)	(0.053)
Price t–1	0.022**	0.019**	–0.0002	–0.0076	–0.0064
	(0.0010)	(0.0093)	(0.012)	(0.016)	(0.021)
			Long run		
GDP	0.98****	0.91****	0.52***	0.56****	0.62****
LRA	[0.80 1.15]	[0.77 1.05]	[0.13 0.92]	[0.26 0.86]	[0.31 0.94]
ALR			0.56****	0.70****	0.72****
			[0.46 0.66]	[0.56 0.84]	[0.57 0.88]
Price	–0.20****	–0.18****	–0.19***	–0.15***	–0.075
LRA	[–0.41 –0.13]	[–0.27 –0.098]	[–0.30 –0.074]	[–0.23 –0.059}	[–0.19 0.038]
ALR			–0.30****	–0.15***	–0.16***
			[–0.38 –0.21]	[–0.24 –0.063]	[–0.26 –0.055]
Observations	2654	2654	2654	2654	2566
RMSE	0.040	0.037	0.032	0.023	0.020
CD ρ	–4.2**** 0.20	–4.1**** 0.20	13.5**** 0.19	–1.1 0.19	–0.8 0.22
CIPS	I(0)	I(0)	I(0)	I(0)	I(0)

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets for the long-run coefficients.
2-FE=fixed effects with country and time dummies. CCEP=2-FE with cross-sectional average terms. MG=mean group. CCE=MG with cross-sectional average terms. DCCE=CCE with additional two lags of all cross-sectional average terms.
LRA=long-run average, calculated directly from pooled/mean group panel results (standard errors computed via the Delta method).
ARL=average long-run, individual country long-run coefficients are computed from mean group results; panel mean and standard errors are drawn from robust regression (on that series of country results).
Diagnostics: RMSE = root mean squared error. CD (p) ρ = Pesaran (2004) CD test statistic and mean absolute correlation coefficient of the residuals. The null hypothesis is cross-sectional independence. CIPS= Pesaran (2007) CIPS test on residuals; I(0)=stationary.

Table 4 shows the results of two dynamic models—ADL (1,1,1) and ADL (1,0,0)—for OECD and non-OECD country panels using our preferred DCCE estimator. While the partial adjustment model was rejected in favor of the ADL (1,1,1) model at the *panel-level* for OECD countries (the same was not true for non-OECD countries), we show both model results for robustness/completeness. For both models, the long-run GDP elasticities are similar for both the OECD and non-OECD panels and for both the LRA and ALR calculations. The GDP elasticity is usually significantly below unity for the OECD panel, but for the non-OECD panel it is only significantly below unity for the partial adjustment model (ADL (1,0,0)). By comparison, the long-run price elasticity is statistically significantly negative for the OECD panel (for all regressions/long-run coefficients), but is insignificant for the non-OECD panel. Lastly, the CD test suggests that even in the presence of cross-sectional average terms, cross-sectional correlation cannot be removed entirely from an OECD country panel.

Table 4: Dynamic Models—ADL (1,1,1) & ADL (1,0,0), OECD vs Non-OECD. DCCE Estimator.

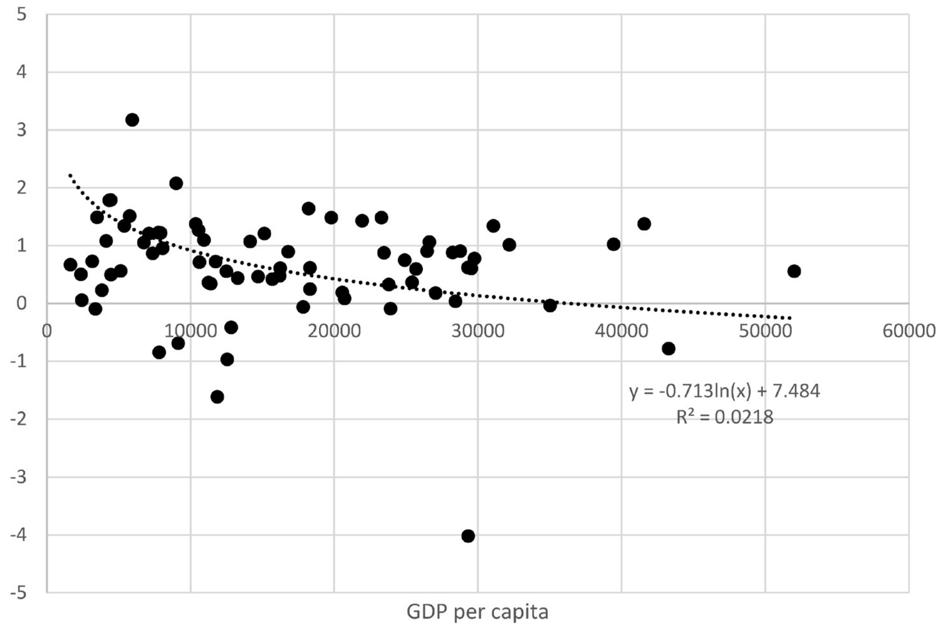
	OECD		Non-OECD	
	ADL (1,1,1)	ADL (1,0,0)	ADL (1,1,1)	ADL (1,0,0)
TFC t–1	0.63****	0.57****	0.38****	0.39****
	(0.050)	(0.051)	(0.072)	(0.053)
GDP	0.40****	0.21****	0.51****	0.39****
	(0.041)	(0.028)	(0.12)	(0.082)
Price	–0.094****	–0.076***	0.031	–0.0067
	(0.024)	(0.023)	(0.030)	(0.019)
GDP t–1	–0.17**		–0.10	
	(0.068)		(0.87)	
Price t–1	0.013		–0.024	
	(0.031)		(0.029)	
		Long run		
GDP	0.64***	0.50****	0.66***	0.63****
LRA	[0.18 1.10]	[0.33 0.68]	[0.16 1.16]	[0.35 0.92]
ALR	0.70****	0.75****	0.73****	0.72****
	[0.53 0.88]	[0.59 0.92]	[0.45 1.01]	[0.49 0.94]
Price	–0.22**	–0.18***	0.011	–0.011
LRA	[–0.44 –0.0056]	[–0.29 –0.066]	[–0.12 0.14]	[–0.071 0.049]
ALR	–0.27***	–0.25****	–0.083	–0.042
	[–0.45 –0.098]	[–0.39 –0.12]	[–0.19 0.021]	[–0.11 0.026]
Obs (N)	1526 (37)	1526 (37)	1040 (41)	1040 (41)
RMSE	0.20	0.022	0.20	0.023
CD ρ	6.6**** 0.19	8.3**** 0.21	0.9 0.24	1.3 0.24
CIPS	I(0)	I(0)	I(0)	I(0)

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets for the long-run coefficients.
LRA=long-run average, calculated directly from mean group panel results (standard errors computed via the Delta method).
ARL=average long-run, individual country long-run coefficients are computed from mean group results; panel mean and standard errors are drawn from robust regression (on that series of country results).
Obs (N)= observations (cross-sections).
Diagnostics: RMSE = root mean squared error. CD ρ= Pesaran (2004) CD test statistic and corresponding mean absolute correlation coefficient of the residuals. The null hypothesis is cross-sectional independence. CIPS= Pesaran (2007) CIPS test on residuals; I(0)=stationary.

Figures 2 and 3 display the individual country elasticity coefficients from the DCCE estimator for both GDP and price according to the sample average GDP per capita. The figures indicate a high degree of heterogeneity in the elasticity estimates, including several non-economic results of either negative GDP elasticities or positive price elasticities, as well as coefficients that are substantial outliers. This displayed heterogeneity implies the importance of both allowing individual coefficients to vary and unweighting outlying coefficients in order to produce a more accurate understanding of panel-level relationships.

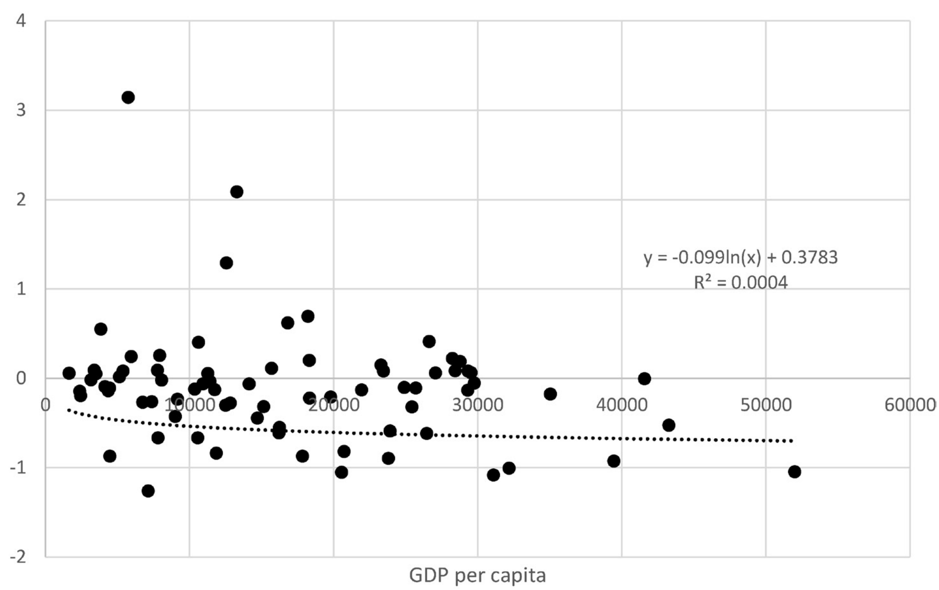
On the other hand, the figures display little evidence that either the GDP or price elasticity varies systematically according to income/development level. The finding of an income/develop-

Figure 2: Individual cross-sectional GDP elasticity estimates plotted against the cross-sectional average GDP per capita for the sample period.



Notes: DCCE estimator, ADL (1,1,1) model, 78 countries, 1960–2016 unbalanced data. Y-axis is cropped so that the largest and two smallest (most negative) estimations are not shown. Trend line, equation, and R-squared also displayed. The very low R-squared indicates that the trend line explains GDP elasticities poorly and with very wide confidence intervals (not shown for clarity reasons).

Figure 3: Individual cross-sectional price elasticity estimates plotted against the cross-sectional average GDP per capita for the sample period.



Notes: DCCE estimator, ADL (1,1,1) model, 78 countries, 1960–2016 unbalanced data. Y-axis is cropped so that the largest (most positive) and two smallest (most negative) estimations are not shown. Trend line, equation, and R-squared also displayed. The extremely low R-squared indicates that the trend line explains price elasticities very poorly and with very wide confidence intervals (not shown for clarity reasons).

ment invariant GDP elasticity accords with the results from Table 4. However, the implication from Figure 3—that the price elasticity does not vary by income—does not contradict the result (from Table 4) of an insignificant price elasticity for the non-OECD panel since Figure 3 does not indicate the statistical significance of the individual country estimates.

Since the non-OECD panel is comprised of a more diverse set of countries than the OECD panel, we further partition the non-OECD panel and present the results of DCCE estimations in Table 5. Again, we allow for both the ADL (1,1,1) and ADL (1,0,0) models. For the six countries whose economies are most dominated by fossil fuel exports (OIL), the model does not fit at all (see Appendix Table A1 for country classifications). Given, among other things, (i) the widespread use of administered prices below market levels and fuel allocation programs and (ii) the potential endogeneity between energy price and GDP, the poor fit for these countries is an unsurprising result.

In the other columns the six petrol-state countries are removed, and upper middle-income countries (UMI) as defined by the World Bank are separated from lower middle-income (LMI) countries. For the ADL (1,1,1) model the long-run GDP estimations for UMI provide an example in which the LRA and ALR calculations differ substantially. However, for the arguably preferred ALR measure, the long-run GDP elasticity is highly similar for all panels/models except OIL. So, again, the GDP elasticity does not vary according to income level. While that panel mean GDP elasticity is nearly always below unity, it is only occasionally statistically significantly below one. Lastly, the finding that the price elasticity is insignificant for non-OECD countries is reinforced.

A common criticism (e.g., Baltagi and Griffin, 1997) of MG-style estimations is that the individual coefficients often exhibit substantial dispersion, including some estimates that are economically implausible. Both of those phenomena are displayed in Figure 2 for example. Yet, when averages of those individual coefficients are taken, the panel results are sensible and not always that different from FE-style estimates (Smith and Fuertes, 2016). Furthermore, the problem of individual estimate outliers can be mitigated by (un)weighting (e.g., Swamy, 1970) and/or by increasing the number of cross-sections and/or time observations (Smith and Fuertes, 2016)—approaches that were all applied here. Moreover, as demonstrated here, weighted MG panel averages can be quite consistent/stable across various panels despite the underlying dispersion displayed in Figures 2 and 3. It should also be noted that the FE restriction that the coefficients are equal across individuals/countries is almost always rejected (Smith and Fuertes, 2016), as Figures 2 and 3 suggest is the case for the present dataset.

We could draw conclusions from the results shown in Table 4 that use our preferred estimator (DCCE) and long-run average calculation (ALR). For OECD countries, the preferred model is ADL (1,1,1); hence, the GDP elasticity is 0.7 and is statistically significantly below one, and the price elasticity is significant at –0.3. For non-OECD countries, we consider both models (ADL (1,1,1) and ADL (1,0,0)), and so the GDP elasticity is likewise 0.7, but we cannot say it is less than one quite at 95% confidence. The price elasticity is on average negative, but it is highly statistically insignificant.

Alternatively, we could take a "grand" average—the average of all the regressions we performed (regressions reported in Tables 2–5 as well regressions not discussed, but a sampling of which is displayed in Appendix Table A4). Those regressions varied across several lines: FE vs MG averaging, type of FE (time dummies, cross-sectional averages), type of MG (cross-sectional averages, lags of such averages), different MG long-run averages (ALR, LRA), composition of non-OECD panels (UMI, LMI), and the consideration of dynamics (static, partial adjustment, ADL (1,1,1)). As it turns out, the conclusions drawn from Table 4 and the grand averages are quite similar.

Table 5: Dynamic Models: ADL (1,1,1) vs ADL (1,0,0), DCCE Estimator, Non-OECD Countries.

	ADL (1,1,1)					ADL (1,0,0)				
	Oil	non-Oil	LMI	UMI	UMI, non-Oil	Oil	non-Oil	LMI	UMI	UMI, non-Oil
TFC t–1	0.33	0.41****	0.47****	0.38****	0.39****	0.57****	0.37****	0.40****	0.36****	0.34****
	(0.17)**	(0.083)	(0.11)	(0.099)	(0.11)	(0.052)	(0.060)	(0.092)	(0.071)	(0.080)
GDP	–0.045	0.58****	0.71****	0.47***	0.50***	0.17	0.42****	0.37****	0.46***	0.48***
	(0.44)	(0.12)	(0.17)	(0.17)	(0.19)	(0.12)	(0.087)	(0.098)	(0.15)	(0.15)
Price	0.094	0.016	0.0086	0.028	0.043	–0.020	–0.0069	–0.0057	–0.029	–0.017
	(0.073)	(0.032)	(0.042)	(0.043)	(0.049)	(0.020)	(0.025)	(0.014)	(0.041)	(0.045)
GDP t–1	–0.067	–0.13	–0.022	–0.20*	–0.34***					
	(0.052)	(0.099)	(0.12)	(0.10)	(0.12)					
Price t–1	–0.18	–0.012	–0.038	0.008	0.011					
	(0.16)	(0.031)	(0.058)	(0.028)	(0.030)					
					Long run					
GDP	–0.17	0.77***	1.29***	0.43	0.25	0.39	0.67****	0.62***	0.71***	0.73***
LRA	[–1.48 1.14]	[0.21 1.32]	[0.36 2.22]	[–0.20 1.06]	[–0.47 0.96]	[–0.16 0.95]	[0.37 0.96]	[0.25 0.99]	[0.24 1.19]	[0.25 1.21]
ALR	0.34	0.80****	0.86***	0.72***	0.76***	0.48	0.74****	0.80***	0.75****	0.73****
	[–0.71 1.38]	[0.50 1.09]	[0.36 1.37]	[0.35 1.09]	[0.34 1.17]	[–0.61 1.57]	[0.51 0.98]	[0.37 1.22]	[0.47 1.04]	[0.43 1.03]
Price	–0.13	0.0038	–0.054	0.058	0.090	–0.045	–0.011	–0.0095	–0.045	–0.025
LRA	(0.26)	(0.075)	(0.13)	(0.083)	(0.096)	(0.045)	(0.039)	(0.023)	(0.064)	(0.068)
ALR	–0.19	–0.057	–0.047	–0.092	–0.059	–0.093	–0.027	–0.0022	–0.070	–0.046
	(0.16)	(0.050)	(0.049)	(0.092)	(0.12)	(0.076)	(0.038)	(0.027)	(0.057)	(0.066)
Obs (N)	143 (6)	897 (35)	424 (16)	576 (23)	473 (19)	143 (6)	897 (35)	424 (16)	576 (23)	473 (19)
RMSE	0.024	0.020	0.02	0.021	0.020	0.027	0.023	0.022	0.024	0.023
CD ρ	–1.5 0.33	0.4 0.23	–0.2 0.24	1.4 0.25	0.4 0.24	0.2 0.19	0.3 0.24	0.5 0.22	0.7 0.23	0.1 0.23
CIPS	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)/I(1)	I(0)	I(0)	I(0)	I(0)

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets for the long-run coefficients.

Oil=oil and natural gas dominate economy and exports. LMI=lower middle-income. UMI=upper middle-income.

LRA=long-run average, calculated directly from mean group panel results (standard errors computed via the Delta method).

ARL=average long-run, individual country long-run coefficients are computed from mean group results; panel mean and standard errors are drawn from robust regression (on that series of country results).

Obs (N)= observations (cross-sections).

Diagnostics: RMSE = root mean squared error. CD ρ= Pesaran (2004) CD test statistic and corresponding mean absolute correlation coefficient of the residuals. The null hypothesis is cross-sectional independence. CIPS= Pesaran (2007) CIPS test on residuals; I(0)=stationary.

For OECD countries the grand average GDP elasticity is between 0.6 and 0.7, and for non-OECD countries it is around 0.7. For OECD countries the panel average GDP elasticity was usually less than unity at the 95% confidence level; for non-OECD countries, the panel average was nearly always below one, but only sometimes below one at a high level of statistical significance (i.e., it is more than likely below unity).

The GDP elasticity of 0.7 is relatively consistent with the long-run income elasticity estimates by Gately and Huntington (2002), who controlled for asymmetric responses to oil price movements. The Gately and Huntington sample covered 96 nations over the 1971–97 period; they estimated a response for total energy use of about 0.6 for the mature OECD countries and between 0.5 and 0.7 for non-OECD countries, excluding those that were either oil exporters or those mainly Asian economies whose income grew rapidly and steadily. The 0.7 GDP elasticity is also close to Czereklyei et al. (2016), even though they relied on more cross-sectionally focused data/methods and did not control for energy prices or allow for dynamics.

The grand average price elasticity for OECD countries was between –0.2 and –0.3. The price elasticity for non-OECD countries typically was small and insignificant. A small or even insignificant price elasticity may not be that surprising given (i) the level of aggregation in an economy-wide price index, and (ii) the index itself is based on the temporal aggregation of averaged yearly prices.

6. CONCLUSIONS

While the GDP elasticity of energy varied substantially from country to country, we did not find evidence that the elasticity varied systematically according to GDP per capita/level of development, e.g., in considering country specific estimations by sample average GDP per capita or partitions of the dataset by OECD status or income level (UMI vs LMI). Our preferred estimate (as well as our grand average of all regressions) of the economy-wide GDP elasticity of energy is 0.7 (again, albeit this is a parameter that can vary substantially from country to country), and thus, the elasticity is likely (even if not at the 95% level of certainty) below unity. Hence, the answers to our initial two questions are: (1) that energy intensity will fall with economic growth—because the GDP elasticity of energy is less than one and not because the elasticity changes with economic growth; and (2) therefore, energy forecasts/IAMs do not need to allow energy elasticities to change with GDP per capita.[14]

We acknowledge the possibility that future responses to prices and income may differ from the past, but we also strongly believe that the 1960–2016 experience provides a valuable benchmark for understanding these relationships. So, various energy outlooks may however want to incorporate energy efficiency improvements that are less directly related to economic growth, such as the demands created by space heating and cooling requirements and urbanization and other social changes not directly tied to current economic growth. Our estimates incorporate these adjustments as exogenous country and time factors associated with the average cross-country terms.

We began by compiling a novel, large dataset of economy-wide real energy prices (not merely incorporating recent releases of publicly available GDP and energy consumption data) that is greater in coverage than previously analyzed data in both time and non-OECD observations. Our

14. To make the recommendation to modelers more explicit, if one is interested in an elasticity for, say, US or China, individually, it may be best to estimate one using that country's data. However, if the model or forecast is grouping/aggregating countries, like Latin America, Europe, Africa, or Asia less China/India, an elasticity of 0.7 seems to be a reasonable place to start.

approach was most similar to earlier work (e.g., Galli, 1998; Medlock and Soligo, 2001; Gately and Huntington, 2002; van Benthem and Romani, 2009), in that we analyze data that have both time series and cross-sectional dimensions, account for energy prices, and employ dynamic models. But unlike that earlier work, we fully address heterogeneity and cross-sectional dependence. Our conclusion that the GDP elasticity of energy is less than one differs from some of these earlier efforts but is highly similar to Czereklyei et al. (2016), despite the substantial differences in data, model, and methods. Relatedly, our conclusion that the GDP elasticity of energy does not change with GDP per capita differs from much of that earlier work, but is in concert with the findings of Burke and Czereklyei (2016) that were based on a single cross-section, again, despite those same substantial differences in data, model, and methods. However, our estimated GDP elasticity of energy is substantially lower than that of Burke and Czereklyei (2016). Hence, one might surmise that improving our understanding of the GDP elasticity of energy depends both on analyzing more recent data from as many countries as possible and on employing robust estimation methods/models.[15]

ACKNOWLEDGMENTS

Comments and suggestions from seminar participants at the Asian Institute for Technology, Thailand, the Energy Information Administration, Washington, DC, the School of Business and Economics, RMIT University, Australia, the Crawford School of Public Policy, ANU, Australia, the School of Accounting and Finance, Hong Kong Polytechnic University, and the World Bank Graduate Scholarship Program Public Policy and Taxation, Faculty of Economics, YNU, Japan; as well as, from three anonymous referees from this journal helped to improve the final version.

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15. We note that Czereklyei et al. (2016) considered several additional questions that we do not address and that Burke and Czereklyei (2016) estimated GDP elasticities of energy demand at several sectoral levels as well as for decade-by-decade growth rates.

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APPENDIX A: POTENTIAL ADDITIONAL EXPLANATORY VARIABLES NOT CONSIDERED.

Because energy price data—particularly for non-OECD countries—has proven difficult to compile, we wanted its availability to be the limiting factor for dataset inclusion. Moreover, most of the previous literature has not included variables beyond income and price. In this appendix we discuss why some possible additional variables are inappropriate/unnecessary for aggregate energy demand modeling.

Urbanization. Urbanization is highly correlated with GDP per capita. Yet, urbanization is most likely an indicator/a result of development/economic growth rather than a catalyst for it (Henderson, 2003). Moreover, the forces of modernization—the mechanization of traditional, rural agriculture and the formation of urban manufacturing—cause both urbanization and increased (commercial) energy consumption. Indeed, Liddle and Lung (2014) found more evidence that electricity consumption Granger-caused urbanization rather than the other way around.

Technology. Accounting for technical change is a particularly challenging and very much unresolved issue in energy demand modeling (e.g., Huntington, 2006; Adeyemi and Hunt, 2007). Including cross-sectional averages of energy prices, energy consumption per capita, and GDP per capita—particularly in a mean group context—addresses several of the concerns raised in Adeyemi and Hunt (e.g., modeling heterogeneous responses to socioeconomic and structural conditions).

Climate/temperature. In addition to the challenges/shortcomings of characterizing the climate of large/long countries that comprise several climatic zones with a single annual number, once global warming is accounted for (via cross-sectional averages included in the CCE estimators), temperature would likely fluctuate around a stable mean. Such temporally constant variables (like **institutions** as well) are captured by the fixed effects and mean group specifications.

Population Density. *Urban* population density has been demonstrated to influence transport energy consumption. However, national-level population density is weakly correlated with urban density (Liddle, 2013), and urban density likely differs substantially more cross-sectionally than it differs over time (Liddle, 2013).

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APPENDIX B: TABLES

Table A1: The Energy Price Dataset

	Obser-vations	Coverage	Missing	Source	Classification
Austria	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Belgium	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Cyprus	18	1999–2016		Authors' derivation from Enerdata	OECD_hi
Czech Rep.	39	1978–2016		IEA	OECD_hi
Denmark	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Estonia	22	1995–2016		IEA	OECD_hi
Finland	39	1978–2016		IEA	OECD_hi
France	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Germany	39	1978–2016		IEA	OECD_hi
Greece	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Hungary	39	1978–2016		IEA	OECD_hi
Iceland	24	1993–2016		IEA	OECD_hi
Ireland	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Italy	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Latvia	19	1998–2016		IEA	OECD_hi
Lithuania	22	1995–2016		Authors' derivation from Enerdata	OECD_hi
Luxembourg	39	1978–2016		IEA	OECD_hi
Malta	19	1998–2016		Authors' derivation from Enerdata	OECD_hi
Netherlands	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Norway	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Poland	39	1978–2016		IEA	OECD_hi
Portugal	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Romania	22	1995–2016		Authors' derivation from Enerdata	UMI
Slovakia	39	1978–2016		IEA	OECD_hi
Slovenia	22	1995–2016		IEA	OECD_hi
Spain	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Sweden	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Switzerland	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Turkey	37	1980–2016		IEA	UMI
United Kingdom	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Azerbaijan	20	1997–2016		Authors' derivation from Enerdata	UMI, OIL
Canada	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
United States	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Costa Rica	20	1996–2015		Authors' derivation from Enerdata	UMI
El Salvador	20	1996–2015		Authors' derivation from Enerdata	LMI
Guatemala	20	1996–2015		Authors' derivation from Enerdata	LMI
Honduras	20	1996–2015		Authors' derivation from Enerdata	LMI
Mexico	39	1978–2016		IEA	UMI
Nicaragua	20	1996–2015		Authors' derivation from Enerdata	LMI
Panama	21	1996–2016		Authors' derivation from Enerdata	UMI

	Obser-vations	Coverage	Missing	Source	Classification
Argentina	32	1981–2015	1982, 1993–4	Authors' derivation from Enerdata	UMI
Bolivia	25	1991–2016	2007	Authors' derivation from Enerdata	LMI
Brazil	29	1988–2016		Authors' derivation from Enerdata	UMI
Chile	23	1994–2016		Authors' derivation from Enerdata	UMI
Colombia	25	1991–2016	1993	Authors' derivation from Enerdata	UMI
Ecuador	21	1996–2016		Authors' derivation from Enerdata	UMI
Paraguay	21	1996–2016		Authors' derivation from Enerdata	UMI
Peru	26	1991–2016		Authors' derivation from Enerdata	UMI
Venezuela	34	1981–2014		Authors' derivation from Enerdata	UMI, OIL
Dominican Rep.	21	1994–2014		Authors' derivation from Enerdata	UMI
Jamaica	19	1996–2014		Authors' derivation from Enerdata	UMI
Trinidad and Tobago	21	1996–2016		Authors' derivation from Enerdata	non–OECD, OIL
Bangladesh	33	1973–2016	1993–2003	Authors' deriv. from Enerdata to 2004; extended to 1973 w/Pesaran et al. (1998)	LMI
China	23	1994–2016		Authors' derivation from Enerdata	UMI
Hong–Kong	19	1998–2016		Authors' derivation from Enerdata	OECD_hi
India	44	1973–2016		Authors' deriv. from Enerdata to 1978; extended to 1973 w/Pesaran et al. (1998)	LMI
Indonesia	44	1973–2016		Authors' deriv. from Enerdata to 1980; extended to 1973 w/Pesaran et al. (1998)	LMI
Japan	57	1960–2016		IEA to 1978; extended to 1960 w/ Baade	OECD_hi
Malaysia	37	1973–2016	1993–99	Authors' deriv. from Enerdata to 2000; extended to 1973 w/Pesaran et al. (1998)	UMI
Pakistan	43	1973–2016	1993	Authors' deriv. from Enerdata to 1994; extended to 1973 w/Pesaran et al. (1998)	LMI
Philippines	32	1973–2016	1993–2004	Authors' deriv. from Enerdata to 2005; extended to 1973 w/Pesaran et al. (1998)	LMI
South Korea	44	1973–2016		Authors' deriv. from Enerdata to 1979; extended to 1973 w/Pesaran et al. (1998)	OECD_hi
Sri–lanka	34	1973–2016	1993–2002	Authors' deriv. from Enerdata to 2003; extended to 1973 w/Pesaran et al. (1998)	LMI
Taiwan	44	1973–2016		Authors' deriv. from Enerdata to 1982; extended to 1973 w/Pesaran et al. (1998)	OECD_hi
Thailand	44	1973–2016		Authors' deriv. from Enerdata to 1978; extended to 1973 w/Pesaran et al. (1998)	UMI
Australia	39	1978–2016		IEA	OECD_hi
New Zealand	39	1978–2016		IEA	OECD_hi
Algeria	21	1996–2016		Authors' derivation from Enerdata	UMI, OIL
Morocco	35	1981–2015		Authors' derivation from Enerdata	LMI
Tunisia	24	1993–2016		Authors' derivation from Enerdata	LMI
Ghana	23	1989–2011		Authors' derivation from Enerdata	LMI
Ivory Coast	32	1978–2016	1989–92, 1994, 1996–7	Authors' derivation from Enerdata	LMI
South Africa	39	1978–2016		Authors' derivation from Enerdata	UMI

	Obser-vations	Coverage	Missing	Source	Classification
Iran	36	1980–2015		Authors' derivation from Enerdata	UMI, OIL
Israel	27	1990–2016		Authors' derivation from Enerdata	OECD_hi
Jordan	21	1995–2015		Authors' derivation from Enerdata	LMI
Lebanon	20	1995–2016	1996–7	Authors' derivation from Enerdata	UMI
Saudi Arabia	28	1978–2016	1981–3, 1985–6, 1988–91, 1993–4	Authors' derivation from Enerdata	non–OECD, OIL

Notes: OECD_hi=OECD/high income country; UMI=upper middle income (by World Bank definition circa 2018); LMI=lower middle income (by World Bank definition circa 2018); non-OECD=non-OECD country, includes all UMI and LMI; OIL=oil and natural gas dominate economy/exports.

Table A2: Averaged Absolute Value Correlation Coefficients and Pesaran (2004) CD test, 78 Countries, unbalanced.

Variables	CD-test	Abs. corr. coeff.
Ln(GDP)	258*	0.78
Ln(TFC)	98*	0.57
Ln(Price)	121*	0.63

Notes: * p-value < 0.001. Null hypothesis is cross-sectional independence.

Table A3: Pesaran (2007) Panel Unit Root Test Results. 78 Countries, unbalanced.

	Constant without trend				Constant with trend			
	Number of lags							
Variables	**0**	**1**	**2**	**3**	**0**	**1**	**2**	**3**
Ln(GDP)	0.952	0.998	1.000	1.000	1.000	1.000	1.000	1.000
Ln(TFC)	0.014	0.155	0.681	0.996	1.000	1.000	1.000	1.000
Ln(Price)	0.000	0.012	0.039	0.662	0.033	0.701	0.806	1.000

Notes: P-values shown. Null hypothesis is the series is I(1).

Table A 4: Additional Regressions. Long-run Elasticities.

Panel (N)	OECD (37)	Non-OECD (41)	UMI (23)	LMI (16)	OECD (37)	Non-OECD (41)	OECD (33)	Non-OECD (26)	UMI (14)	LMI (11)
Estimator	CCE	CCE	CCE	CCE	CCEP	CCEP	DCCE	DCCE	DCCE	DCCE
Dynamics	Static	Static	Static	Static	ADL (1,1,1)	ADL (1,1,1)	EC	EC	EC	EC
GDP	0.68****	0.77****	0.78****	0.77****	0.81***	0.53***	0.62****	0.54**	0.88**	0.28
	[0.55 0.81]	[0.63 0.92]	[0.56 1.00]	[0.56 0.98]	[0.31 1.31]	[0.17 0.88]	[0.34 0.91]	[0.052 1.03]	[0.015 1.75]	[–0.25 0.81]
Price	–0.11***	–0.066**	–0.071***	–0.090*	–0.26**	–0.063*	–0.22***	–0.082	0.020	–0.20**
	[–0.19 –0.029]	[–0.12 –0.015]	[–0.12 –0.022]	[–0.19 0.0068]	[–0.46 –0.054]	[–0.13 0.0092]	(0.075)	(0.070)	(0.12)	(0.084)

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets. N=cross sections. UMI=upper middle income. LMI=lower middle income. CCE=mean group with cross-sectional average terms. CCEP=fixed effects with cross-sectional average terms. DCCE=CCE with additional two lags of all cross-sectional average terms. EC=error correction model.

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