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Introducing a large panel dataset of economy-wide real electricity prices and estimating long-run GDP and price elasticities of electricity demand for high-and middle-income panels

Abstract

We assemble a particularly large dataset of real economy-wide electricity prices (2015 US cents per kilowatt hour) by first consumption-weighting electricity prices for industry and residential households. Additional sources were used to extend the price series (i) for 17 OECD countries from 1978 back to 1960 and (ii) for five Asian economies from 1978 back to 1973. Ultimately, the (unbalanced) dataset spans 1960-2019 and consists of the 107 countries for which there are at least 10 observations; 36 countries have at least 40 observations, and another 40 have at least 20 observations. Prices are important to consider when analyzing electricity demand, and price data are not widely available for non-OECD countries. Indeed, we provide a demonstration using a common model for energy/electricity demand that suggests excluding prices imparts an upward bias on the estimation of the GDP/income elasticity of electricity demand. Lastly, the fact that the data are in real prices (as opposed to a real index) means it is suitable for cross-sectional analysis.

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LIDDLE | INTRODUCING A LARGE PANEL DATASET OF ECONOMY RUN GDP [...]

- 1 Increasing the share of energy services that are delivered via electricity is one of two challenges/strategies for mitigating climate change (decarbonizing electricity generation being the other). So, analyzing economy-wide electricity demand is an important research topic. But the availability of price data often constrains such energy demand analyses—particularly the study of demand in non-OECD countries.
 - 2 Hence, we assemble a particularly large dataset of real economy-wide electricity prices (in 2015 US cents per kilowatt hour). This unbalanced electricity price data span 1978–2019 and include 107 countries. A key aspect of the price data is that it is a real price—as opposed to a real index. Thus, it is appropriate for cross-sectional analyses (in addition to panel analyses). Similarly, over-time averages could be compared across countries. An index, in contrast, is not meaningful cross-sectionally (e.g., it is 100 for all countries in the base-year). This short paper introduces the dataset, describes its construction (and its limitations), and displays some of the country series. Then it concludes with an example of the dataset’s usefulness—estimating economy-wide GDP and price elasticities for high- and middle-income panels. This example, suggests that estimating GDP elasticities without the consideration of prices may impart an upward omitted variable bias.
 - 3 We begin with electricity prices for industry and residential households (in 2015 US cents per kilowatt hour and including taxes) from Enerdata’s Global Energy and CO₂ database.¹ We then weight those two prices by their electricity final consumption (data from Enerdata as well).
 - 4 For several countries, we extend this real weighted price via the International Energy Agency’s (IEA) real electricity price index for industry and households² (which typically runs 1978–2019). For 17 OECD countries, a real electricity price index derived from Baade³ is used to extend those countries’ price series from 1978 to 1960. Following the standard procedure for splicing time series, our 1978 price level was extrapolated backward in time by the growth rates in electricity prices reported in the Baade analysis. This approach combined with the Baade data has been used to similarly extend price data in, for example, Adeyemi and Hunt⁴ and Liddle and Huntington.⁵ For five Asian economies, a real electricity price index derived from Pesaran et al.,⁶ which has price data from 1972–1992, was used to extend those economies price series. The Pesaran et al. data were used in a similar fashion in Liddle and Huntington.⁷ (The associated dataset indicates which observations have been extended and by which additional source.)
- Agriculture and transport were not considered in constructing the price series. According to IEA data, agriculture and transport together account for less than five percent of electricity consumption in most countries.
- Potentially, a greater concern is not including data from commercial use. Electricity in commercial buildings is substantial in most countries (representing, on average, 28% of electricity consumption according to IEA data); however, Enerdata does not report prices for commercial buildings. Commercial prices are typically

[end-use-prices/indices-of-energy-prices-by-sector_data-00444-en](#) (accessed 11/11/2021)

³ P. Baade, *International Energy Evaluation System, International Energy Prices 1955–1980* (Service Report, U.S. Department of Energy, 1981/21).

⁴ O. Adeyemi, L. Hunt, “Modelling OECD Industrial Energy Demand: Asymmetric Price Responses and Energy-saving Technical Change”, *Energy Economics*, vol. 29, n° 4, 2007.

⁵ B. Liddle, H. Huntington, “Revisiting the Income Elasticity of Energy Consumption: A Heterogeneous, Common Factor, Dynamic OECD & non-OECD Country Panel Analysis”, *The Energy Journal*, vol. 41, n° 3, 2020.

⁶ H. Pesaran et al., *Energy Demand in Asian Developing Economies* (Oxford: Oxford University Press for the World Bank and the Oxford Institute for Energy Studies, 1998).

⁷ B. Liddle, H. Huntington, “Revisiting the Income Elasticity of Energy Consumption: A Heterogeneous, Common Factor, Dynamic OECD & non-OECD Country Panel Analysis”, *The Energy Journal*, vol. 41, n° 3, 2020.

¹ Enerdata, “Global Energy & CO₂ database”. Url : <https://www.enerdata.net/research/energy-market-data-co2-emissions-database.html> (accessed 11/11/2021).

² OECD iLibrary, “IEA Energy Prices and Taxes Statistics”. Url: <https://www.oecd-ilibrary.org/energy/data/>

LIDDLE | INTRODUCING A LARGE PANEL DATASET OF ECONOMY RUN GDP [...]

between residential and industry prices and, usually, much closer to residential prices than industry. For example, in the US, commercial electricity prices ranged from 18% to 6 % lower than residential prices over 1990-2019 (data from Energy Information Administration). IEA has relative price data (residential, commercial, industry) for a few OECD and non-OECD countries. For most of these countries, residential prices are the highest, industry prices the lowest, and commercial prices on average are roughly the same as or within 20% of residential prices. For the countries where this was not the case, commercial prices tended to be the highest and residential prices the lowest. Correspondingly, for several of these

latter countries (India, Nepal, Pakistan), commercial buildings comprised a relatively small share of total electricity consumption (10-15%), and for Iran, commercial prices were very similar to industry prices. Thus, we believe that the exclusion of commercial electricity prices on average should not bias the economy-wide price estimates.

All told this real electricity price (unbalanced) dataset spans 1960-2019 and consists of the 107 countries for which there are at least 10 observations; 36 countries have at least 40 observations (with 17 of those having the full 60), and another 40 have at least 20 observations. Table 1 lists the country coverage.

Country	Obs.	Coverage	Country	Obs.	Coverage
Austria	0	1960-2019	Guyana	15	1994-2006, 2010, 15
Belgium	0	1960-2019	Paraguay	26	1994-2019
Bosnia-Herzegovina	0	2010-2019	Peru	29	1991-2019
Bulgaria	8	2002-2019	Suriname	14	1994-2006, 2010
Croatia	15	2005-2019	Uruguay	21	1999-2019
Cyprus	21	1999-2019	Venezuela	34	1981-2014
Czech Rep.	42	1978-2019	Dominican Rep.	20	1994-2012, 2014
Denmark	60	1960-2019	Haiti	16	1994-2007, 2010, 15
Estonia	25	1995-2019	Jamaica	21	1994-2014
Finland	42	1978-2019	Trinidad & Tobago	28	1991-2007, 2009-2019
France	60	1960-2019	Bangladesh	16	2004-2019
Germany	42	1978-2019	Cambodia	19	2000-2018
Greece	60	1960-2019	China	18	1995-96, 2003-2019
Hungary	42	1978-2019	Hong-Kong	20	2000-2019
Ireland	60	1960-2019	India	47	1973-2019
Italy	60	1960-2019	Indonesia	47	1973-2019
Latvia	23	1997-2019	Japan	60	1960-2019
Lithuania	28	1992-2019	Lao PDR	16	2004-2019
Luxembourg	42	1978-2019	Malaysia	20	2000-2019
Malta	29	1991-2019	Nepal	14	2000-2013
Netherlands	60	1960-2019	Pakistan	20	2000-2019
Norway	60	1960-2019	Philippines	10	2005-2014
Poland	42	1978-2019	Singapore	18	2002-2019
Portugal	60	1960-2019	South Korea	47	1973-2019
Romania	26	1994-2019	Sri-lanka	16	2003-2018
Serbia	20	2000-2019	Taiwan	47	1973-2019
Slovakia	42	1978-2019	Thailand	47	1973-2019
Slovenia	28	1992-2019	Vietnam	16	1999-2003, 2009-2019
Spain	60	1960-2019	Australia	42	1978-2019
Sweden	60	1960-2019	New Zealand	42	1978-2019
Switzerland	60	1960-2019	Algeria	30	1990-2019
Turkey	42	1978-2019	Egypt	27	1982-1992, 2004-2019
United Kingdom	60	1960-2019	Morocco	30	1990-2019
Azerbaijan	23	1997-2019	Tunisia	30	1990-2019
Kazakhstan	21	1996-2016	Burkina Faso	26	1994-2019
Moldova	11	2008-2018	Cameroon	12	2008-2019
Russia	15	2004-7, 2009-19	Ethiopia	14	2006-2019
Ukraine	10	2010-2019	Ivory Coast	38	1975-88, 1993,95, 1998-2019
Uzbekistan	11	2001-3, 2012-19	Kenya	12	2008-2019
Canada	60	1960-2019	Mauritania	19	2000-2018

LIDDLE | INTRODUCING A LARGE PANEL DATASET OF ECONOMY RUN GDP [...]

United States	60	1960-2019	Mauritius	18	2000-2017
Costa Rica	26	1994-2019	Niger	19	2001-2019
El Salvador	23	1994-2015, 2018	Nigeria	11	2009-2019
Guatemala	23	1994-2015, 2018	Senegal	17	2003-2019
Honduras	23	1994-2015, 2017	South Africa	42	1978-2019
Mexico	42	1978-2019	Uganda	11	2001-2011
Nicaragua	23	1994-2015, 2017	Iran	49	1971-2019
Panama	26	1994-2019	Israel	34	1986-2019
Argentina	18	2002-2019	Jordan	30	1990-2019
Bolivia	28	1991-2006, 2008-19	Lebanon	26	1994-2019
Brazil	32	1988-2019	Qatar	10	2010-2019
Chile	26	1994-2019	Saudi Arabia	42	1978-2019
Colombia	28	1991-2, 1994-2019	Syria	19	1990-2005, 2007-09
Ecuador	26	1994-2019			

Table 1: Real economy-wide electricity price dataset coverage.

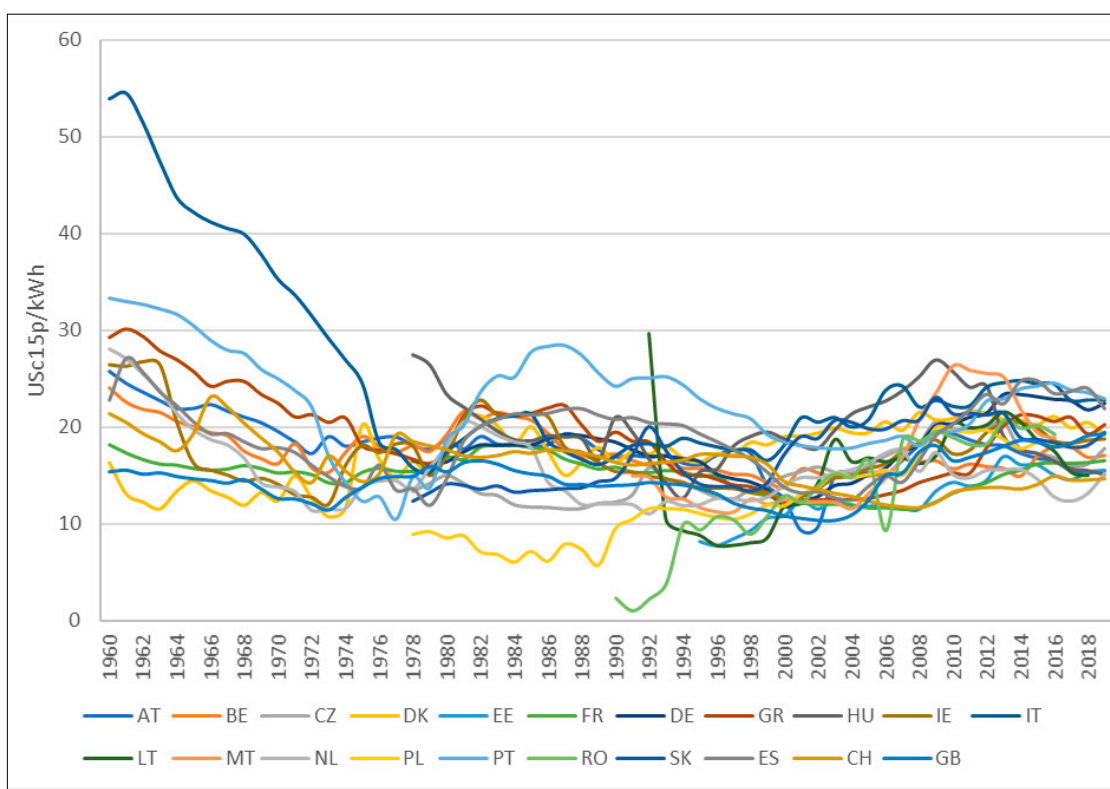


Figure 1: Economy-wide real electricity prices for many European countries, 1960-2019 (unbalanced).

- 8 We conclude the introduction of the data by displaying some of the price series. Figure 1 shows the real electricity prices (in 2015 US cents/kWh) for most European countries from 1960-2019. Two patterns stand out in Figure 1: (1) there has been a high degree of convergence in prices among European countries; and (2) electricity prices no longer follow the pattern of international oil prices.
- 9 The international oil price tended to decline slightly during the 1960s, then rose through the 1970s because of Middle Eastern oil supply

disruptions. After reaching a peak in 1982, oil prices declined and remained relatively low for more than two decades before rising beginning in 2004. By 2008, oil prices reached a level similar to their previous peak, but declined rapidly during 2014-2015 and have stayed relatively low since.

Figure 2 displays electricity prices for three Scandinavian countries (Finland, Norway, and Sweden) that have particularly low electricity prices because of the share of renewable energy (between 80% and 100% from renewable

sources) and for several non-European OECD countries. Like those Scandinavian countries, Canada, New Zealand, US, and, until recently, Australia have had relatively low electricity prices. Electricity prices in Japan still appear to mimic international oil prices; whereas, this is no longer the case for US.

11 Lastly, Figure 3 contains the price paths for five rapidly growing Asian countries/economies. As above, local electricity prices have mostly broken from international oil prices, and electricity prices are particularly low for Korea and Chinese Taipei (two countries that have higher per capita electricity consumption than many European and other OECD countries).

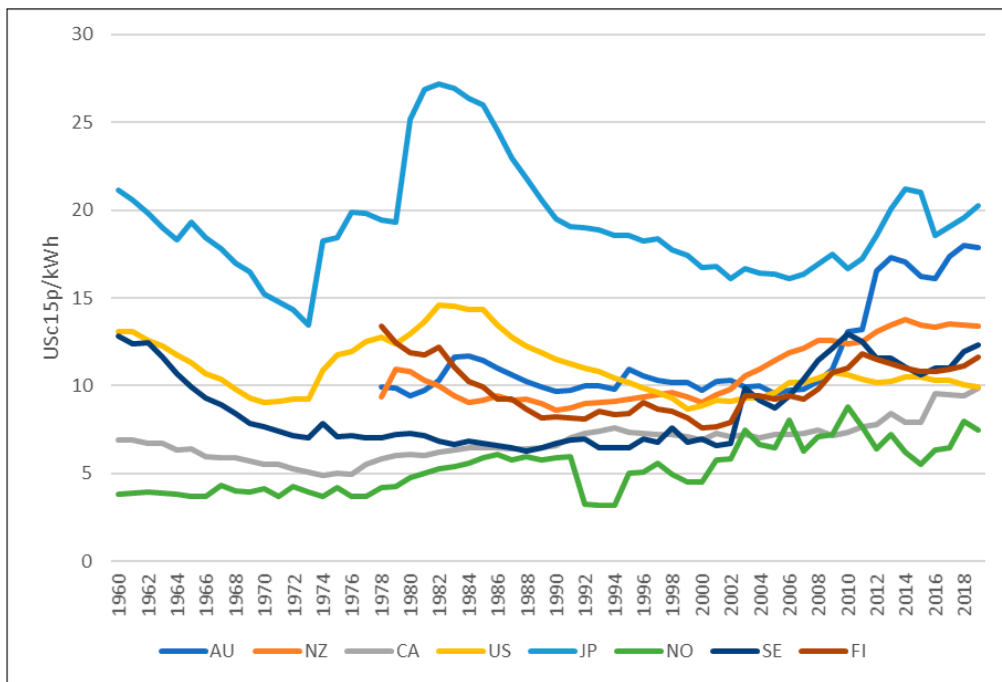


Figure 2: Economy-wide real electricity prices for eight OECD countries with relatively low electricity prices, 1960-2019 (unbalanced).

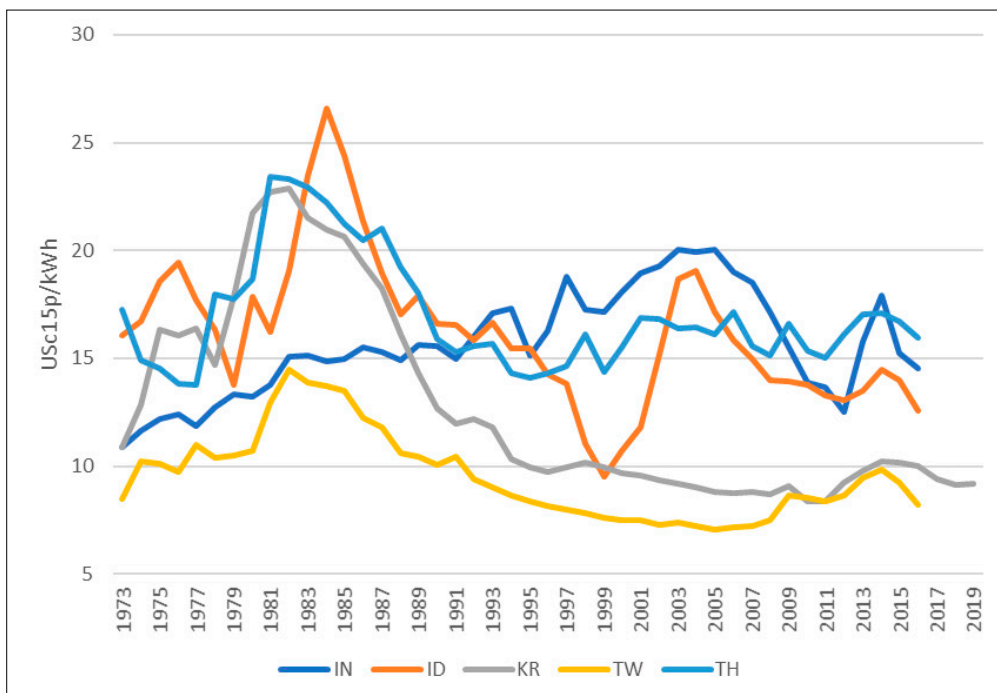


Figure 3: Economy-wide real electricity prices for five Asian countries/economies, data span 1973-2019 (unbalanced).

An Example: Estimating Economy-wide GDP and Price Elasticities

12 As is standard in the energy demand literature, we estimate per capita electricity consumption as a function of per capita GDP (income) and electricity prices:

$$\ln Electricity_{it} = \alpha_i + \beta_1^2 \ln GDP_{it} + \beta_1^3 \ln price_{it} + \varepsilon_{it} \quad (1)$$

13 where t represents the time dimension and i the country dimension; α is a cross-sectional specific constant; the β s are cross-sectional specific coefficients to be estimated; and ε_{it} is the error term. It also is common to allow for the gradual adjustments—differences between short-run and long-run effects—to analyze a dynamic model:

$$\ln Electricity_{it} = \alpha_i + \beta_1^1 \ln Electricity_{it-1} + \beta_1^2 \ln GDP_{it} + \beta_1^3 \ln price_{it} + \varepsilon_{it} \quad (2)$$

14 For this dynamic, partial adjustment model, the long-run GDP and price elasticities, respectively, are:

$$\frac{\beta_1^2}{(1 - \beta_1^1)} \quad \text{and} \quad \frac{\beta_1^3}{(1 - \beta_1^1)} \quad (3)$$

15 One also can consider more complex dynamics—i.e., additional lags of the GDP and price terms (see Liddle and Huntington 2020 for a detailed discussion of dynamic panel energy models). Because of data limitations in panel estimations, we limit ourselves to only one lag for GDP and price:

$$\ln Electricity_{it} = \alpha_i + \beta_1^1 \ln Electricity_{it-1} + \beta_1^2 \ln GDP_{it} + \beta_1^3 \ln price_{it} + \beta_1^4 \ln GDP_{it-1} + \beta_1^5 \ln price_{it-1} + \varepsilon_{it} \quad (4)$$

16 Now, the long-run GDP and price elasticities are estimated via:

$$\frac{\beta_1^2 + \beta_1^4}{(1 - \beta_1^1)} \quad \text{and} \quad \frac{\beta_1^3 + \beta_1^5}{(1 - \beta_1^1)} \quad (5)$$

17 In choosing an estimation method, there are several issues one must consider for this type of long, macro-panel data (for a more detailed discussion of each of these issues in the context of panel energy demand modeling, again, see Liddle

and Huntington 2020). First, it is likely that elasticities will be different across countries. Hence, we use a mean group estimator (MG) that first estimates coefficients from cross-sectional specific regressions and then averages those estimated individual-country coefficients to arrive at panel coefficients. Two other well-known statistical issues for macro-panels are cross-sectional dependence and non-stationarity. Thus, we include in the regression cross-sectional averages of the dependent and independent variables (following the Pesaran 2006 Common Correlated Effects—CCE—approach) to account for cross-sectional dependence and help produce stationary residuals.

In addition to addressing cross-sectional dependence, these cross-sectional average terms represent unobserved common factors, e.g., technology. Also, CCE is robust to nonstationarity, cointegration, breaks, and serial correlation. However, the CCE estimator is not consistent in dynamic panels since the lagged dependent variable is not strictly exogenous; thus, the Dynamic Common Correlated Effects (DCCE) estimator of Chudik and Pesaran⁸ includes additional lags of the cross-sectional means to become consistent again.

One last statistical issue is that dynamic models estimated with panel data are subject to a downward bias, called the dynamic panel or Nickell bias (static models, naturally avoid this bias). Since the dynamic panel bias is on the order of $1/T$ (Nickell 1981), it can be mitigated by having several time observations. Beck and Katz (2009) claimed that with at least 20 time observations, bias correction is counter-productive; whereas, Judson and Owen (1999) were more conservative, recommending bias correction unless there are at least 30 time observations. Bruno (2005) determined that in unbalanced panels (i.e.,

⁸ A. Chudik, H. Pesaran, “Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressions”, *Journal of Econometrics*, vol. 188, no 2, 2015, 393-420. The Dynamic Common Correlated Effects estimator is implemented by Stata command `xtmg`—which was developed by Markus Eberhardt.

LIDDLE | INTRODUCING A LARGE PANEL DATASET OF ECONOMY RUN GDP [...]

Panel	High-income: 35x1960–2019			Middle-income: 34x1973–2018	
	ADL (1,1,1)	ADL (1,0,0)	Static	ADL (1,0,0)	Static
GDP	0.544*** [0.187 0.901]	0.629**** [0.427 0.832]	0.551**** [0.375 0.727]	0.578**** [0.359 0.798]	0.732**** [0.502 0.963]
Price	-0.119* [-0.241 0.00299]	-0.0941*** [-0.148 -0.0404]	-0.0720*** [-0.113 -0.0311]	-0.0409 [-0.103 0.0212]	-0.0365 [-0.0814 0.00836]
GDP w/o price	0.695** [0.101 1.288]	0.810**** [0.556 1.064]	0.611**** [0.448 0.773]	0.703**** [0.488 0.919]	0.783**** [0.528 1.037]

Table 2: Long-run economy-wide electricity demand elasticity estimates.

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. 95% confidence intervals shown in brackets. Long-run estimates calculated directly from mean group panel results via Equations 3 and 5 (standard errors computed via the Delta method). ADL (1,1,1), ADL(1,0,0), and Static models represented by Equations 4, 2, and 1, respectively. Static models estimated via CCE; dynamic models estimated via DCCE and include two lagged terms each of the three cross-sectional average terms. For the middle-income panel, that the one period lags of GDP and Price were jointly equal to zero could not be rejected (i.e., ADL(1,0,0) model preferred and thus, the ADL(1,1,1) model not shown). Results from the same regression run without any price terms also shown (GDP w/o price).

like our panels), the bias declines with average cross-sectional size (i.e., the bias is not determined entirely by the shortest series).

20 We construct two unbalanced panels: one consisting of high-income countries and the other middle-income countries (according to World Bank classifications). So, we collect electricity consumption per capita data (in kWh per capita) and GDP per capita data (in constant 2010 US\$ at PPP) from IEA. Ultimately, the only data constraint are the availability of the price data. The unbalanced high-income panel has 35 countries⁹ and spans 1960–2019. All of those countries have at least 21 years of price data, 17 have the full 60 years, and the average number of price observations is 48. The unbalanced middle-income panel has 34 countries¹⁰ and spans 1973–2018. All of those countries have at least 20 years of price data, four have the full 46 years, and the average number of price observations is 30.6.

⁹ Those countries are: Australia, Austria, Belgium, Canada, Chinese Taipei, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Israel, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and USA.

¹⁰ Those countries are: Algeria, Azerbaijan, Bolivia, Brazil, Chile, Columbia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, India, Indonesia, Iran, Ivory Coast, Jamaica, Jordan, Kazakhstan, Lebanon, Morocco, Mexico, Nicaragua, Panama, Paraguay, Peru, Romania, Saudi Arabia, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uruguay, and Venezuela.

Thus, even according to the conservative rule of thumb of Judson and Owen, dynamic panel bias should be minimized at least.

21 Because of the lack of available price data for non-OECD countries, we know of no previous panel-based analyses of economy-wide electricity demand (that included both GDP and electricity prices) focusing on such countries. There have been a few such previous panel-based analyses that used OECD/EU data. Lee and Lee (2010) considered a panel of 25 OECD countries that spanned 1978–2004 and used a static model employing first-generation methods (i.e., methods that ignore potential cross-sectional dependence). Their GDP elasticity was significant and rather large at 1.08, but their price elasticity was very small and highly insignificant (-0.01). Lee and Chiu (2011) considered nearly the same panel, but used methods that allowed for nonlinearities and change over time (but still no consideration of cross-sectional dependence). Lee and Chiu found an average GDP elasticity of 0.36 and an insignificant price elasticity around -0.23. Recently, Arcabic et al. (2021) analyzed a sample of EU countries considering quarterly data over 2003–2018 and used a method that approximated smooth structural breaks with a Fourier function. For their preferred specification, they calculated an average long-run income elasticity of around 0.3 and an average long-run price elasticity of less than -0.04.

LIDDLE | INTRODUCING A LARGE PANEL DATASET OF ECONOMY RUN GDP [...]

- 22 Our long-run elasticity results are displayed in Table 2. For the high-income panel, we show results from all three models (i.e., Equations 1, 2, and 4). For the middle-income panel, we do not show the results from the model using Equation 4 since the hypothesis that the one period lags of GDP and Price (i.e., β^4 and β^5 from Equation 4) were jointly equal to zero could not be rejected.
- 23 The GDP elasticities are all highly significant and similar both among the different models and for the high- and middle-income panels (particularly so when the dynamic model is considered). The GDP elasticities suggest that GDP will grow faster than per capita electricity consumption. Also, all of the GDP elasticity estimates are significantly below unity (one is not contained in their 95% confidence intervals). Thus, electricity intensity (electricity consumption/GDP) will decline with economic growth. The price elasticities are all small and negative. They are, however, statistically significant for the high-income panel.
- 24 Comparing our high-income panel results to the previous analyses, our price elasticity estimates (while significant) are between those of Lee and Chiu and Arcabic et al. While our GDP elasticity is larger than both of Lee and Chiu and Arcabic et al., it is substantially smaller than that of Lee and Lee. It is important to note that our time span is considerably larger than the previous three papers. Furthermore, while Lee and Chiu and Arcabic et al. allowed for some flexibility in terms of nonlinearities and temporal heterogeneity, neither of those papers adjusted for cross-sectional dependence.
- 25 Lastly, in considering the results from the models run without price information, we can draw several important conclusions. Each of the GDP elasticity estimates without prices considered are larger than the corresponding estimate when prices were considered; most of the estimates without prices were less precise (their confidence intervals were larger) than estimates with prices, and most of the estimates without prices were not statistically different from unity (one was within the confidence interval). These differences occurred even though the price elasticities themselves were very small, and in the case of the middle-income panel statistically insignificant. Thus, including prices in panel electricity demand estimations may improve the precision of the GDP elasticity estimates, and not including prices can lead to (an apparent upward) omitted variable bias in those GDP elasticity estimates. Thus, this rather large database of economy-wide electricity real prices should prove valuable to future analyses.

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