Energy Economics 60 (2016) 232–243

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Disentangling temporal patterns in elasticities: A functional coefficient panel analysis of electricity demand☆

Yoosoon Chang[a], Yongok Choi[b], Chang Sik Kim[c], J. Isaac Miller[d,*], Joon Y. Park[a,c]

[a] Department of Economics, Indiana University, United States
[b] Department of Financial Policy, Korea Development Institute, Republic of Korea
[c] Department of Economics, Sungkyunkwan University, Republic of Korea
[d] Department of Economics, University of Missouri, United States

ARTICLE INFO

Article history:
Received 5 January 2016
Received in revised form 26 August 2016
Accepted 1 October 2016
Available online 11 October 2016

JEL classification:
C33
C51
C53
Q41

Keywords:
Semiparametric panel regression
Partially linear functional coefficient model
Elasticity of electricity demand

ABSTRACT

We introduce a panel model with a nonparametric functional coefficient of multiple arguments. The coefficient is a function both of time, allowing temporal changes in an otherwise linear model, and of the regressor itself, allowing nonlinearity. In contrast to a time series model, the effects of the two arguments can be identified using a panel model. We apply the model to the relationship between real GDP and electricity consumption. Our results suggest that the corresponding elasticities have decreased over time in developed countries, but that this decrease cannot be entirely explained by changes in GDP itself or by sectoral shifts.

1. Introduction

A diverse literature addresses methods for handling structural change in the coefficients of econometric models, usually by allowing the coefficients to vary over time. Many of these approaches neglect one or both of two important aspects of structural change. First, such models do not typically allow changes in the specification of the functional form itself. Such misspecification may invalidate the economic interpretations of the coefficients when these interpretations are derived from partial derivatives, as is the case with elasticities. Second, few models of coefficient change aim to identify the underlying drivers of that change.

A functional coefficient with multiple arguments, consisting of the regressor itself and each potential driver of parameter change, remedies both of these deficiencies. Specifying the coefficient as an unknown function of the regressor explicitly allows for nonlinearity in the conditional mean of the regressand. The additional arguments further elucidate the underlying causes of the coefficient changes. However, a functional coefficient with more than one argument cannot be effectively estimated — especially when the arguments are highly correlated or share trends.

In order to operationalize such a model and remedy the deficiencies mentioned above, the main novelty of this research is to couple a panel data approach to a nonparametric functional coefficient model. From an econometric point of view, our functional coefficient approach with a nonstationary panel builds on the functional coefficient models of Cai and Li (2008) for stationary panels and Cai et al. (2009) for nonstationary time series. This approach provides several advantages in this context.

First, the addition of the cross-sectional dimension of the data allows effective estimation of an unknown function of two variables. We consolidate the additional arguments into a single time trend to represent structural change. Thus, once the model is estimated, we

☆ The authors are grateful for useful comments from seminar participants at the University of Missouri, Indiana University and the University of Kansas. We also thank Zongwu Cai for helpful discussions. We gratefully acknowledge Kyung-Mook Lim and Doosan Corporation for generous financial support. This work was also supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2014S1A5B8060964).
* Corresponding author.
E-mail address: millerjisaac@missouri.edu (J. Miller).

http://dx.doi.org/10.1016/j.eneco.2016.10.002
0140-9883/

may fix time and examine nonlinearity in the conditional mean. For a fixed regressor or a constant function of the regressor, on the other hand, the model reduces to a more standard model of temporal coefficient change. Such flexibility is not possible using only a time series model.

Second, the allowance of the coefficient to vary over *both* the regressor and time enabled by a panel allows dynamic misspecification, because the nonlinear function itself may evolve over time. Third, a panel provides a much larger number of observations to counter the well-known drawback of the slower rate of convergence of nonparametric estimators.

Once a temporal pattern in the coefficient is established and any nonlinearity is identified, further analysis may unlock distinct components of that pattern. These components could be of interest in their own right. For example, a policy maker considering a stimulus package to a particular economic sector might be interested in the effect on overall electricity consumption — especially in a country with a limited power grid that cannot import electricity, such as Korea or Taiwan, or in which the constituents have substantial concerns about increasing pollution from fossil fuel consumption.

We apply our econometric approach to a panel of observations on electricity consumption across countries with disparate GDP levels. A stylized fact of developed economies is change over time of energy intensity, measured as the ratio of energy consumption to real GDP. Many of these countries have seen a decrease in energy intensity, often referred to as an autonomous energy efficiency increase (AEEI). Such changes have occurred not only with respect to overall energy consumption, but also with respect to consumption of individual energy sources, such as electricity. For example, over the period 1995–2010, our data suggest that this ratio (*electricity* intensity) has decreased by 14–17 % for the US, UK, and Denmark, and decreased by 1–4 % for Japan, Germany, and Belgium, but increased by 46% for Korea.

A common specification for modeling the relationship between electricity and GDP is a fixed coefficient regression of the log of electricity consumption per capita on the log of real GDP per capita and covariates.[1,2] Holding the covariates constant, this specification assumes that the relationship is linear and stable.

Galli (1998), Judson et al. (1999), and Medlock and Soligo (2001) document an inverted U shape in the relationship between log GDP and log energy consumption, which they attribute to changing patterns in electricity consumption as countries develop and especially to shifts in the compositions of national economies from more energy-intensive to less energy-intensive sectors. In other words, the relationship is changing over time.

In similar applications, Galli (1998), Medlock and Soligo (2001), and Richmond and Kaufmann (2006a,b) use panel data with a quadratic term for nonlinearity, while Judson et al. (1999), Luzzati and Orsini (2009), and Nguyen-Van (2010) use more flexible semiparametric panel data approaches to allow for nonlinearity.

To the best of our knowledge, ours is the first study of AEEI that utilizes a panel data model with functional coefficients that allow both for nonlinearity like the models in the studies just mentioned *and* for a coefficient that varies smoothly over time.

Even for a single economic sector, the relationship between log electricity consumption and log income, proxied by log GDP in the household sector, or log electricity consumption and log output, proxied by log GDP in the firm sector, may be linear but with unstable coefficients or may not be linear at all. The often assumed log-linearity of the aggregate household demand function or the aggregate firm conditional factor demand function results from multiplicative indirect utility or production functions.[3] However, changes in utility, technology, policy, or other factors may shift or change these functions over time, inducing time-varying coefficients and even functional misspecification.

While an ideal specification might allow the coefficient on log GDP to be a function of GDP itself, utility, technology, energy policy, sectoral shares, and perhaps other factors, estimating such a model and identifying each of these components would be very difficult given the available data. Instead, we use the panel nonparametric approach to create counterfactuals at fixed levels of development and time periods.

Our model generates a very clear empirical result and one that is expected from the discussion of AEEI's: income elasticities have been declining over time for developed countries.[4] Our counterfactual analysis with time fixed and varying GDP suggests that economic development does not fully explain the declining elasticities in developed countries. The right-hand tail of the inverted U shape is almost flat and has become flatter over time — i.e., there is a threshold beyond which GDP (per capita and relative to other countries) barely affects the elasticity, and both the threshold and the decreasing effect have decreased over time.

Similarly, we construct counterfactuals in which GDP is fixed and time varies and find that the decreasing temporal pattern remains. Reliable sectoral data on electricity consumption for a subset of our panel that includes developed countries over a relatively recent time period allows further analysis of this decrease. We isolate the component of the time-varying elasticities for this subsample that cannot be explained by sectoral reallocations over time, and we find that the decreasing trend in elasticities of these developed countries still remains.

Having accounted for nonlinearity in GDP, as modeled by the Galli (1998) *inter alia*, and for sectoral shifts discussed by Medlock and Soligo (2001) as possible explanations for the evident decreasing pattern in elasticities, we conclude that the salient decrease has been driven by one or more residual influences: utility, technology, policy, or something else proxied by time. It would indeed be difficult to further isolate the effects from these possible drivers given the inherent difficulty in measuring these influences, and we leave this task to future research.

The remainder of the paper is organized as follows. Section 2 provides a short and general motivation of the panel nonparametric approach to modeling economic elasticities. In Section 3, we detail the construction and sources of our electricity panel. We present a basic benchmark model of electricity demand, discuss possible sources of coefficient instability in such a model, and introduce a functional coefficient panel model to better identify these sources. Our empirical results are collected in Section 4, and we conclude with Section 5. Appendix A lists countries used to obtain our empirical results, Appendix B presents the econometric methodology, Appendix C discusses some additional technical details of the methodology and some ancillary empirical results, and Appendix D contains our data and code.

[1] Initiated by Kraft and Kraft (1978), Granger causality is a major focus of the literature on this relationship. However, Granger causality is not a focus of the present analysis.

[2] For brevity, all further references to electricity consumption or GDP should be interpreted to mean electricity consumption per capita or real GDP per capita, unless otherwise specified.

[3] A large number of studies on household demand, including Halvorsen (1975), Maddala et al. (1997), and Silk and Joutz (1997), *inter alia*, have estimated a fixed coefficient on log income (income elasticity of demand), for which log GDP may be considered a proxy. In the firm sector, GDP may be a proxy for either output or income. Halvorsen (1978) included measures of both output and income in his model of commercial demand, while Berndt and Wood (1975) and Halvorsen (1978) used measures of output in industrial demand.

[4] We will refer to the partial derivative as the *income elasticity*, or simply the *elasticity*, even though it reflects both an income elasticity and an output elasticity in sectorally aggregated data.

2. An overview of our approach

Before introducing a specific model, we illustrate the basic idea of using panel data with a nonparametric approach by considering a single term given by $\beta(r,x)x$, perhaps of an otherwise linear model, where both the regressor x and the regressand $y(r,x)$ are in logs and r represents time. Because x is an argument of the coefficient $\beta(r,x)$, the coefficient is not equal to the partial derivative with respective to the regressor and therefore cannot be interpreted as an elasticity. The elasticity $\epsilon(r,x)=(\partial/\partial x)y(r,x)$, which is given by

$$\epsilon(r,x)=\beta(r,x)+x\beta_x(r,x), \tag{1}$$

where $\beta_x(r,x)$ refers to the partial derivative of $\beta(r,x)$ with respect to its second argument, clearly contains an additional term $x\beta_x(r,x)$. This term is zero only if the coefficient does not vary with the regressor – i.e., if the model is in fact linear in x – or, trivially, if the coefficient does not vary at all. We may estimate both $\beta_x(r,x)$ and $\beta(r,x)$ using our panel approach and compute the income elasticity $\epsilon(r,x)$ at each time r and x from Eq. (1).

In contrast, estimation approaches using individual countries cannot adequately identify the effects of both time and the regressor. With a single-country nonparametric approach, we have only one observation of x at any given time, and therefore, it is impossible to identify the effect of varying x while holding time fixed. In fact, if x is log GDP, as in our electricity consumption model below, there is an almost one-to-one relationship between time and log GDP, since log GDP has a dominant increasing linear time trend. Consequently, we may not be able to identify the time effect with the regressor fixed, either. Our approach encompasses the single-country approach, so we may relate elasticities estimated using our approach to those estimated in studies relying on time series data for a single country.

A time series (single-country) approach that allows the coefficient to vary only over time, such as that of Park and Hahn (1999), actually sets x as a function of time – i.e., $x=x(r)$ – and looks at the coefficient $\beta(r,x(r))$ as a univariate function of time r. In that case,

$$\frac{d}{dr}\beta(r,x(r))=\beta_r(r,x(r))+\dot{x}(r)\beta_x(r,x(r)), \tag{2}$$

where $\beta_r(r,x)$ refers to the partial derivative of $\beta(r,x)$ with respect to its first argument, and $\dot{x}(r)=(d/dr)x(r)$ denotes the instantaneous change in the regressor. As is evident from Eq. (2), the slope of the coefficient $(d/dr)\beta(r,x(r))$ in such a study does not truly represent the rate of time change $\beta_r(r,x(r))$ of the coefficient, which is identified in our approach separately from the secondary temporal effect due to the growth of x. Unless there is trivially no change in the regressor, so that $\dot{x}(r)=0$, or unless the coefficient does not depend explicitly on x and we have $\beta_x(r,x(r))=0$, the temporal effects are not identical. In our model below, in which x is log GDP, we expect the growth rate $\dot{x}(r)$ to be positive. Thus, when $\beta_x(r,x(r))$ is positive (negative), we expect the slope of the coefficient in a single-country study to be larger (smaller) than the rate of time change of our coefficient.

On the other hand, a single-country approach that allows the coefficient to vary only over the regressor is equivalent to setting time r as a function $r=r(x)$, say, of log GDP x. In this case, we have

$$\frac{d}{dx}\beta(r(x),x)=\dot{r}(x)\beta_r(r(x),x)+\beta_x(r(x),x), \tag{3}$$

similarly to Eq. (2), where $\dot{r}(x)=(d/dx)r(x)$ is the reciprocal of the regressor's growth rate. Such an approach allows coefficient changes *only* through regressor changes – i.e., nonlinearity – but omits any temporal changes in the coefficient unrelated to the regressor itself. However, drivers of coefficient instability, such as technology and utility in the case of demand functions, do not need to relate specifically to the regressor (log GDP, e.g.), and therefore cannot be identified by such approaches. If $\beta_r(r,x)$ is positive for all r and x, as we find in our empirical analysis of electricity consumption, and if $\dot{r}(x)$ is positive for all x, we would expect the slope of the coefficient $(d/dx)\beta(r(x),x)$ estimated using a single-country approach to exceed the partial effect $\beta_x(r(x),x)$ estimated using our approach.

Neither of these single-country approaches can separately identify the two arguments of the coefficient. Further, we expect them to systematically underestimate or overestimate the rates of change in the coefficient with respect to its arguments. This bias may have a devastating effect on inferences or predictions from the model. In contrast, a panel approach allows us to create counterfactuals by fixing the regressor and allowing time to vary, identifying $\beta_r(r,x)$, or by fixing time and allowing the regressor to vary, identifying $\beta_x(r,x)$, at each and every combination of time r and regressor x. As a result, the change in elasticity is more accurately analyzed, the individual drivers of this change are better identified, and we may gain a much deeper understanding of the dynamics underlying the structural change.

3. Electricity data, models, and sources of instability

3.1. Data sources and construction

A model of electricity intensity requires at least two series: electricity consumption and GDP. Electricity consumption is measured implicitly by adding net exports to production and subtracting losses from transmission. Production data are available over a longer and wider span than consumption,[5] so we use production as a proxy for consumption. Because electricity must be transmitted by wire and large amounts are not transmitted under water, net exports are a very small percentage of production for most countries. According to data from the World Factbook,[6] 20 of the 89 countries in our sample import or export more than 5% of production and only 7 import or export more than 20%. The Republic of Congo imports 84% of its electricity, but both imports and production are quite small. Paraguay exports 80% of its production, apparently to neighbors Brazil and Argentina. In fact, the absolute value of Paraguay's net trade is nearly the largest of any country's, but this is clearly an outlier.

We collect annual electricity production and GDP over the period 1971–2010 for 184 countries, although not all of these data are ultimately used. Electricity production in gigawatt hours (GWh) is used as a proxy for electricity demand, and almost all of these data originate from Enerdata,[7] except those of a few countries with missing data for 1971 for which we use data from the World Bank. We calculate electricity production per capita using population in thousands. We then create an electricity production index with 2000 as the base year in order to eliminate some of the heterogeneity in per capita production across countries. GDP per capita is constructed from real GDP in 2005 million US dollars at constant purchasing power parities and using population in thousands. GDP per capita is thus expressed in thousands of 2005 US dollars.

We omit 62 countries with some missing electricity production or GDP data. Many of these are former Soviet bloc countries, for which data were missing or unreliable during the beginning of the sample. We then omit 33 countries that appear to have nonsensical (negative or statistically insignificant) cointegrating relationships

[5] Sectoral consumption data are available from the UN Energy Statistics and Enerdata. However, missing subsectoral data are treated as zeros in aggregating to the sectoral level, which generates substantial measurement error, especially as a series becomes missing or ceases to be missing over time.

[6] https://www.cia.gov/library/publications/the-world-factbook/index.html.

[7] http://yearbook.enerdata.net/.

between electricity production and GDP using a conventional fixed coefficient single-country model similar to the benchmark model Eq. (4) below. The countries in this group tend to be poorer countries with less developed markets, and the lack of a cointegrating relationship may reflect the lack of a long-run market equilibrium. After omitting these groups, we are left with 89 countries listed in Appendix A.3.

In order to ameliorate cross-country heterogeneity and generate more stable parameter estimates, we group countries according to GDP per capita in each year. The first group (Gr1) includes the US and any country with a higher GDP per capita. To form the remaining 9 income groups (Gr2–Gr10), we first compute the empirical distribution of the remaining countries. These countries are then assigned to 9 income groups according to the grouping rule given by the percentiles in Table 1. For each group in each year, we weight each country's GDP per capita by its GDP level as a ratio of the group's total GDP level, thus deriving an aggregate measure of GDP per capita for each of the 10 groups in each of the 40 years.

We use a similar procedure to weight the electricity production data, using exactly the same GDP-based weights. We thus have 400 total observations (40 years of 10 country groups) of electricity consumption (proxied by production) and GDP. In this way, the income represented by each group is relatively stable, even though the group members may change each year. The exception is that Gr1 contains the US by definition and is in fact dominated by the US, since the other members tend to be smaller wealthy countries, such as Bermuda and Singapore. Fig. 1 shows the sample paths of the logs of the electricity consumption and GDP series.

Since both demand and supply of any good are functions of its price, energy prices are often used in models of energy consumption. Annual household electricity prices per kilowatt hour measured in 2005 US cents at constant purchasing power parities are available for a range of countries from Enerdata. We create a price index with 2000 as the base year. Using price necessitates a slightly different modeling strategy, because price data are available for only 25 of the 89 countries and no earlier than 1978 for these countries.

Table A.1 (Appendix A) shows the number of countries in each group and each year for which we have price data. Gr1–Gr4 contain at least 2 of the 25 countries in each year, so we use the *same* groups defined above with the same group members for GDP and electricity production, but just omit Gr5–Gr10. We construct price data similarly to GDP and electricity production data for Gr1–Gr4, except that, because we have fewer group members with price, we re-weight using each country's GDP level as a ratio of the group total excluding those countries with no price data. We therefore have 132 total observations (33 years of 4 country groups) of electricity consumption (production), GDP, and price. The right panel of Fig. 2, to be discussed in more detail below, shows the sample paths of the log price series for these groups.

Table 1
Income grouping rules. For each year, Gr1 is defined to be the US and countries with a higher GDP per capita than the US. Countries in Gr2–Gr10 are determined by the percentiles of the annual distribution of GDP per capita of the remaining countries.

Group	Percentiles of GDP per capita
Gr2	[88,100]
Gr3	[77,88)
Gr4	[66,77)
Gr5	[55,66)
Gr6	[44,55)
Gr7	[33,44)
Gr8	[22,33)
Gr9	[11,22)
Gr10	(0,11)

3.2. A benchmark model of total electricity consumption

A general model of the ratio of electricity consumption to GDP is of course linear when the data are expressed in logs. Assuming fixed coefficients, such a model for a single country that also includes price may be written as

$$y_t = \alpha + \beta x_t + \gamma p_t + \varepsilon_t, \tag{4}$$

for $t = 1, \ldots, T$ years, where y_t, x_t, and p_t represent logs of the electricity consumption, GDP, and electricity price series discussed above. This fixed coefficient model may be interpreted as a model of electricity demand, in which GDP is a proxy for income, and β may thus be interpreted as the income elasticity of electricity demand.[8,9]

However, we note several obstacles to this interpretation of β. On the left-hand side, we use production data as a proxy for a country's demand. Recall that actual consumption is measured implicitly by adding net exports and subtracting transmission losses. As long as the omitted variables, net exports and transmission losses, do not have unit roots or deterministic trends, the regression is still cointegrating so that β is estimated consistently.

Further obstacles to associating β with an income elasticity may arise on the right-hand side from using GDP (output) as a proxy for income. By definition, GDP contains electricity sales as a final good and any net exports of electricity. We do not expect the percentage of GDP comprised of such sales to be very large for most countries.[10]

Countries with historically unreliable data may present a more subtle problem. Forecasters of GDP of centrally planned economies, for example, have traditionally found electricity consumption to be a good predictor of GDP. Our estimates could be biased for countries in which electricity consumption is used – other than as a final good in the definition of GDP – to construct the publicly available measure of GDP. However, many of these countries have been excluded from our sample due to missing data.

Finally, we note again that β itself is not strictly an *income* elasticity, because electricity is consumed by both households and firms. As a proxy for income, GDP is an input into an aggregate household utility function, making the coefficient an income elasticity in the household sector. However, GDP is an output of an aggregate production function, of which energy is a factor of production, making the coefficient an output elasticity in the firm sector. Even within the firm sector, different technologies across firms induce different coefficients, and studies conducted at the sectoral level have uncovered substantial differences in elasticities across economic sectors within a given country. The coefficient β in a sectorally aggregated single-country model thus reflects all of these elasticities.

[8] Such a model usually includes additional covariates that act as demand shifters. Going back to Halvorsen 's (1978) monograph on energy demand and earlier, demand shifters have been used with varying degrees of success. Perhaps the most obvious ones that we omit are a measure of seasonality to account for electricity use in heating and cooling and the price of a close substitute. Since we examine annual data, such a seasonal measure is unnecessary. In a fairly homogeneous market, natural gas or fuel oil may be the predominant substitute for electricity in heating applications. However, these data may not be as informative globally. With a wide range of countries and climates, a substantial amount of heating is unnecessary in some countries. Technological differences across time and across countries may further weaken the impact of the price of a heating substitute. Moreover, data availability in this panel precludes the use of such prices.

[9] The joint determination of electricity price and consumption means that γ cannot be interpreted as a price elasticity of demand, and that estimates of γ will likely be inconsistent. We do not expect such a problem for estimates of β, since there appears to be no co-movement between price and GDP in our data, as shown in Fig. 2.

[10] The ratio is about 2% for the US, e.g., using data from the Energy Information Administration (EIA): http://www.eia.gov/electricity/; and the Federal Reserve Bank of St. Louis: http://research.stlouisfed.org/fred2/.

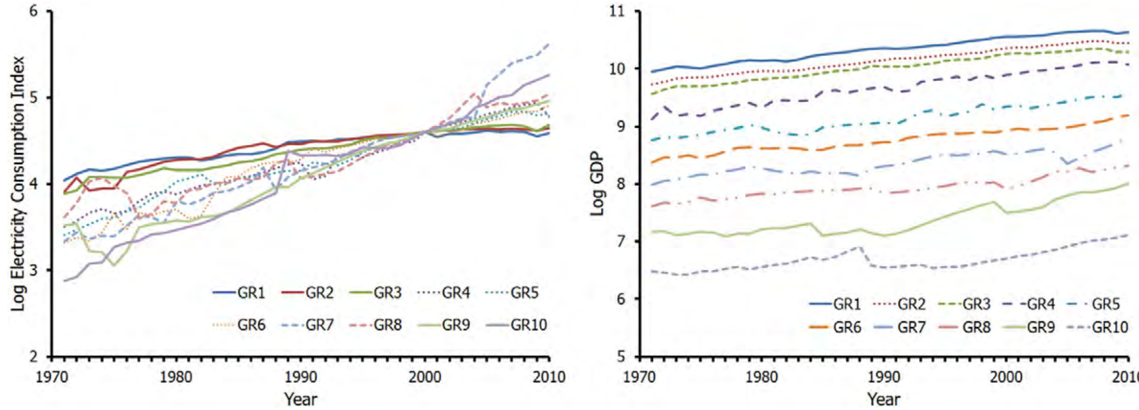

Fig. 1. Time series plots of log electricity consumption indices with 2000 as the base year and log real GDP per capita for ten groups Gr1–Gr10.

3.3. Coefficient variation from sectoral shifts and GDP

A cost of using sectorally aggregated data is that, strictly speaking, the coefficient β is not a single elasticity as just mentioned. Aggregating data across sectors implies some type of aggregation of the coefficients for those sectors. Even if the coefficients for each sector are time-invariant, the aggregation weights may change as the focus of real economic activity shifts from one sector to another over time.

Medlock and Soligo (2001) explicitly tie sectoral shifts to economic development and argue for an econometric specification flexible enough to allow for nonlinearity in the relationship between energy demand and GDP. Denoting log GDP by x, those authors let $\beta = \beta(x) = \beta_0 + \beta_1 x$ so that $\beta(x)x$ is quadratic in x. The left-hand tail of the inverted U shape of the quadratic allows an increase in energy intensity at low income levels as countries build their industrial bases. In line with earlier authors, such as Brookes (1972), those authors emphasize the process of dematerialization, which drives sectoral dominance from energy-intensive heavy industry to light industry, and then eventually to the less energy-intensive commercial sector. Dematerialization is tied to high income levels, and the right-hand tail of the inverted U shape allows a decline in energy intensity as countries prosper. The nonlinearity in β for countries that have developed rapidly may be quite pronounced, as Galli (1998) notes for Korea and Taiwan.

Although GDP may be a good proxy for sectoral composition in some cases, temporal sectoral shifts do not have to be tied to economic development. For example, consider the sectoral reallocation of Eastern European countries in the 1990's following the demise of Soviet-style communism. From the starting point of high growth and an intensive industrial focus with little emphasis on energy efficiency under that system, the process of dematerialization was rapid in those countries that tried to adapt quickly, while the pace of economic development lagged behind.

More generally, increased globalization may drive countries to specialize in certain industries in order to compete. Sectoral shifts resulting from such specialization may indeed be correlated with economic development, such as in the case of specialization in manufacturing exports by Japan, Korea, Taiwan, and China. Alternatively, economic growth due to specialization might not be followed by dematerialization if a country does not diversify its main economic driver, as is often the case with exporters of basic resources, such as oil or minerals.

3.4. Coefficient variation from other sources

Shifts in utility, technology, and energy policy may also drive coefficient change. In this case, a nonlinear function of GDP may not adequately capture such instability. Consider a residential consumer's choice between a cheaper durable that uses more electricity (lower fixed cost and higher total variable cost) and a more expensive durable that uses less electricity (higher fixed cost and lower total variable cost). Suppose that the expected total cost of each durable is equal, so that household income is irrelevant to the choice between them. For a given increase in household income after which such a choice becomes possible, the choice between which durable to consume – and thus the income elasticity of electricity demand – may be influenced by both technology and utility. Technology determines whether in fact such a trade-off is possible, while the diffusion

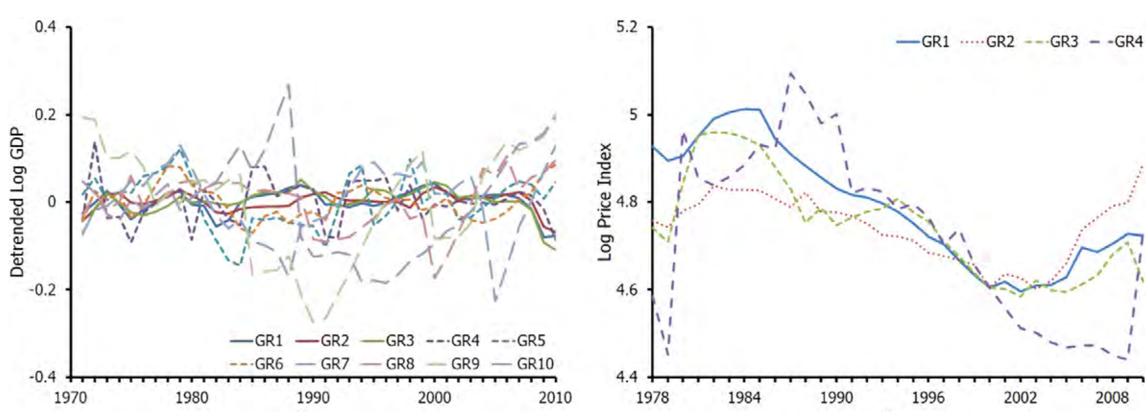

Fig. 2. Time series plots of detrended log real GDP per capita for ten groups Gr1–Gr10 and log real electricity prices for four groups Gr1–Gr4, respectively, in the left and right panels.

of knowledge about the negative externalities associated with using exhaustible resources may influence utility.

In industry, consider the example of the rise of electric arc furnaces in steelmaking. While electric arc furnaces do not require the large amounts of coal needed for basic oxygen furnaces and decrease overall energy usage, they increase the need for electricity to obtain the same amount of output.[11] A further example is provided by increased computerization across all firm sectors, increasing productivity while most likely increasing reliance on electricity for power even while enabling more efficient usage of it.

Utility and technology are difficult to identify, because these terms refer to the functional forms and unknown parameters of the respective functions. In addition, energy policies have certainly affected how firms and households use electricity, thus influencing the elasticity. Policy is difficult to quantify beyond simple binary policy changes, and policies are not necessarily comparable across countries.

Because these additional drivers are difficult to measure, researchers often allow a function of time to capture residual influences on coefficient instability. For example, Webster et al. (2008) use a linear time trend to capture AEEI, although Kaufmann (2004) argues against such a specification. A more flexible alternative is offered by Chang and Martinez-Chombo (2003) and Chang et al. (2014), who model the coefficient β as a flexible function of time, such that $\beta = \beta(r)$ with r denoting time. As noted in Section 2, such an approach may systematically overestimate or underestimate the coefficient if it is also a function of GDP.

3.5. Econometric model specification

In order to segregate the influence of GDP from other time-varying factors and avoid the systematic biases discussed in Section 2, we consider a model in which $\beta = \beta(r,x)$ is a function of both GDP and time. We refer to $\beta(r,x)$ as the *income coefficient of electricity demand*, or *income coefficient* for short. Specifically, we extend the time-series model in Eq. (4) to a panel model given by

$$y_{it} = \alpha' c_{it} + \beta(t, x_{it}) x_{it} + \gamma p_{it} + u_{it}, \tag{5}$$

for $i = 1, \ldots, N$ groups of countries, where c_{it} represents an $N \times 1$ vector of group binaries to capture cross-sectional heterogeneity, and α is an $N \times 1$ vector of group fixed effects. Because electricity price data pose a major constraint on data collection, it will also be useful to rewrite the model in Eq. (5) as

$$y_{it} = \alpha' c_{it} + \beta(t, x_{it}) x_{it} + v_{it}, \tag{6}$$

where $v_{it} = \gamma p_{it} + u_{it}$.

A detailed comparison of these specifications is presented in Appendix B.2. Note that the regressions introduced in Eqs. (5) and (6) both involve variables having deterministic and stochastic trends and are interpreted as describing long-run relationships. In fact, tests for the presence of deterministic and stochastic trends, shown in Tables C.1 and C.2 (Appendix C), strongly and unambiguously show that (x_{it}) has both a stochastic trend and a linear time trend, while (p_{it}) has only a stochastic trend, for a majority of $i = 1, \ldots, N$. Time series plots of (p_{it}) and linearly detrended (x_{it}) shown in Fig. 2 provide additional evidence.

On the other hand, as shown in Fig. B.1 (Appendix B), it appears that the fitted residuals from both regressions Eqs. (5) and (6) have no time trends, and in particular, the series of fitted residuals from regression Eq. (5) is stationary. Therefore, we interpret regression Eqs. (5) and (6) as representing semiparametric long-run relationships with stationary and integrated errors respectively.[12] Clearly, regression Eq. (5) may be regarded as a semiparametric cointegrating regression if (u_{it}) is stationary. Regression Eq. (6) is also meaningful, since (x_{it}) has a linear trend, providing a stronger signal than the noise generated by an integrated error (v_{it}). Although it is misspecified, we may estimate $\beta(r,x)$ consistently from regression Eq. (6).[13]

All else equal, we expect regression Eq. (5) to provide a better estimate of $\beta(r,x)$ than regression Eq. (6) when $\gamma \neq 0$. In our case, this is not necessarily true, since the observations we may use to fit regression Eq. (5) are only a fraction of the entire sample, due to the severely restricted availability of price data. Using regression Eq. (6) to estimate $\beta(r,x)$ incurs some bias. However, at the same time, we may drastically reduce the sample variance of the estimator of $\beta(r,x)$ by using observations on more years and many more countries and estimating $\beta(r,x)$ from regression Eq. (6).

Overall, regression Eq. (6) may yield an estimator of $\beta(r,x)$ with a smaller mean squared error than regression Eq. (5), if the reduction in sample variance due to the utilization of observations on more countries over a longer time span exceeds the magnitude of the squared bias resulting from the omitted variable problem in regression Eq. (6). Indeed, we show in Appendix B.2 that regression Eq. (6) provides an improved estimator of $\beta(r,x)$ in terms of the bootstrap mean squared error.

4. Empirical results

We estimate the nonlinear panel data models in Eqs. (5) and (6) semiparametrically, allowing the most flexible form for the functional coefficient $\beta(r,x)$ and allowing us to glean substantial information about the dynamics of the functional coefficient using our aggregated but cross-sectionally diverse data. Our estimation procedure is detailed in Appendix B.1.

4.1. Estimated income coefficients

The first step of the partially linear estimation procedure entails estimating α and γ. Table 2 shows the estimation results for the parametric parts of the models with and without price, by running least squares on Eq. (B.4) (with price) for model Eq. (5) and on Eq. (B.6) (without price) for model Eq. (6). Note that our data are nonstationary and that standard results for stationary data are not applicable. We therefore calculate asymptotic variances using a bootstrap method described in detail in Appendix C.3. The estimated price elasticity $\hat{\gamma}$ of electricity demand is negative and significant, and the estimates of the group effects are in general not negligible. In regression Eq. (6), the standard errors for the group effects have mostly larger standard errors and are generally insignificant, which is expected from the inconsistency of the estimator.

The top two panels of Fig. 3 show the income coefficient estimates from model Eq. (5) with price. The top left panel shows income coefficient estimates for the exact data points observed (Gr1–Gr4 over 33 years, $t = 1978, \ldots, 2010$) while the top right panel shows estimates evaluated over a grid of log real GDP per capita ranging from 9.3 ($10,938) to 10.7 ($44,356). The income coefficient estimates using model Eq. (6) without price are plotted in the bottom two panels of the figure, using all 10 country groups and $t = 1971, \ldots, 2010$. In this case, the bottom right panel shows estimates

[11] "Energy Trends in Selected Manufacturing Sectors: Opportunities and Challenges for Environmentally Preferable Energy Outcomes," U.S. Environmental Protection Agency (March 2007): http://www.epa.gov/sectors/pdf/energy/report.pdf.

[12] Unfortunately, no formal test exists for the stationarity and integratedness of the error terms in regressions like Eqs. (5) and (6).

[13] An integrated time series is of order $\sqrt{T}$, and it is therefore asymptotically negligible compared with a linear time trend growing at the rate of T. However, the parameter α cannot be estimated consistently in regression Eq. (6) unless $\gamma = 0$.

Table 2
First-step estimation results. Least squares parameter estimates from regressions given by Eq. (B.4), with prices included but Gr5–Gr10 excluded, and by Eq. (B.6), with prices excluded but Gr5–Gr10 included. Standard errors calculated using the bootstrap method described in Appendix C.3.

	With price		Without price	
	Estimate	s.e.	Estimate	s.e.
γ	− 0.114	0.055		
α_1	−2.232	1.479	1.217	1.745
α_2	−2.092	1.460	1.276	1.714
α_3	−2.063	1.446	1.284	1.692
α_4	−1.781	1.451	1.338	1.652
α_5			1.563	1.623
α_6			1.669	1.580
α_7			1.836	1.557
α_8			1.972	1.446
α_9			1.961	1.385
α_{10}			2.079	1.324

evaluated over a grid of log real GDP per capita ranging from 6 ($403) to 11 ($59,874).

The most salient feature of the income coefficient estimates from either model Eqs. (5) or (6) is that they are not constant functions of time and GDP, as a traditional fixed coefficient model assumes. The income coefficient estimates in the models with and without price appear to be flatter for richer countries than for poorer countries, emphasizing the importance of a sample with diverse GDP levels to evaluate the coefficient dynamics over time and GDP. Comparing the bottom left panel with the top left panel makes clear the increase in sample size from dropping price. Comparing the smoothness of the bottom right panel with the top right panel gives some idea of the efficiency gain from the larger sample.

Though not exactly the same, the topologies of the income coefficient estimates from regressions Eqs. (5) and (6) are qualitatively very similar. On the other hand, the estimates from regression Eq. (6) based on a larger data set identify the income coefficient over a wider range of time and GDP. Furthermore, the estimates we obtain from regression Eq. (6) show a clearer pattern of variation of the income coefficient over the time and GDP, compared to the estimates from regression Eq. (5).

Although a comparison of the vertical axes suggests that a scalar bias may exist from estimating the model without price, our detailed comparison in Appendix B.2 conclusively demonstrates, to the contrary, that the severe restriction on the sample imposed by using price data generates a much larger variance. The evident vertical difference thus results more from variance than from bias, and the small bias incurred by using model Eq. (6) is therefore more acceptable. With this comparison in mind, we henceforth restrict our attention to model Eq. (6) (without price).

In order to examine the temporal patterns in the coefficients more closely, Fig. 4 shows a two-dimensional representation of the bottom right panel of Fig. 3 for fixed years and levels of GDP. Specifically, the left panel of Fig. 4 illustrates $\hat{\beta}(r,x)$ holding time r fixed, while the right panel illustrates $\hat{\beta}(r,x)$ holding log GDP x fixed.

Holding time r constant, $\hat{\beta}(r,\cdot)$ appears to be mostly increasing in GDP during the 1970's and 1980's ($\hat{\beta}_x(r,\cdot) > 0$), but mostly decreasing in GDP during the 1990's and 2000's ($\hat{\beta}_x(r,\cdot) < 0$). In 1971, for example, the estimated coefficient for a hypothetical country with a log real GDP per capita of 7 ($1097) is 0.18, while it increases 56% to 0.28 for a country with a log real GDP per capita of 10 ($22,026) the same year. In 1990, the coefficients of the two countries are estimated to be the same, 0.30, up to rounding error. The estimate decreases 21% from 0.43 for the poorer country to 0.34 for the richer country in 2010. In light of the role played by this term in Eqs. (1) and (2), the elasticities and temporal change in elasticities could be quite a bit larger or smaller than those previously estimated using more restrictive models.

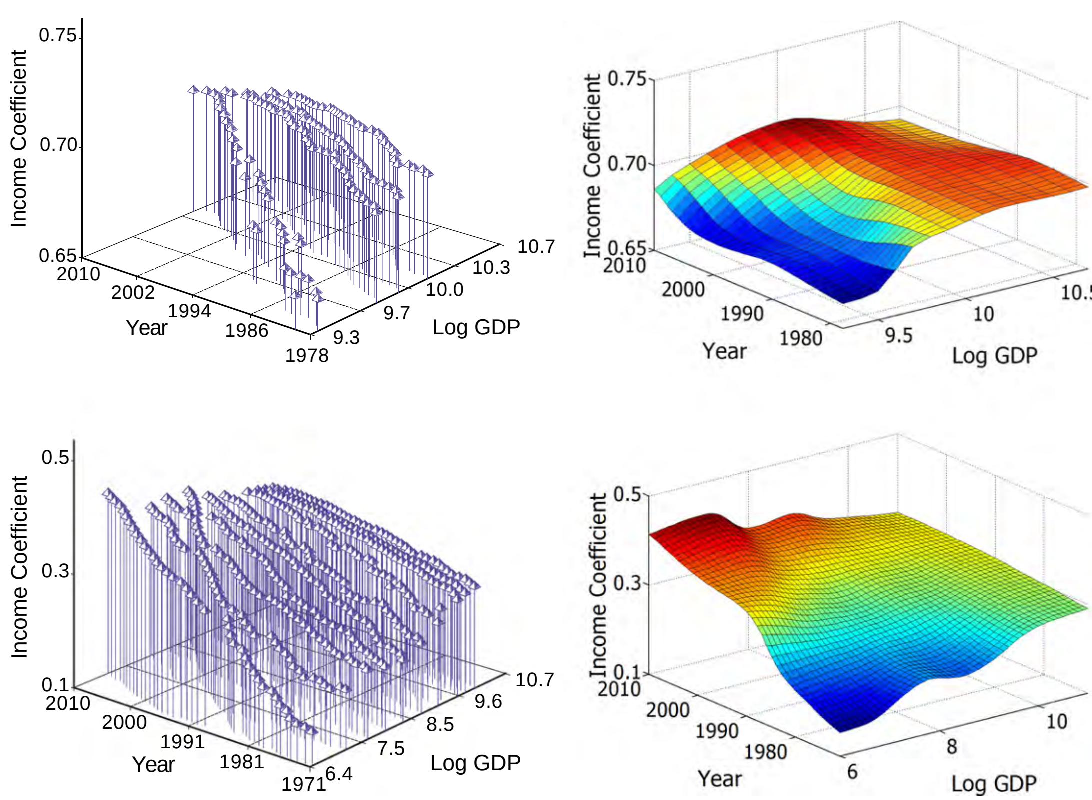

Fig. 3. Surface plots of estimated income coefficient using Eq. (B.5) with price for model Eq. (5) (top panels) and Eq. (B.7) without price for model Eq. (6) (bottom panels), plotted at actual data (left panels) and interpolated over a grid (right panels). Actual data are Gr1–Gr4 over 1978–2010 (top left) and Gr1–Gr10 over 1971–2010 (bottom left). Grid points range from 9.3 ($10,938) to10 .7 ($44,356) using data from Gr1–Gr4 (top right), and from 6 ($403) to 11 ($59,874) using data from Gr1–Gr10 (bottom right).

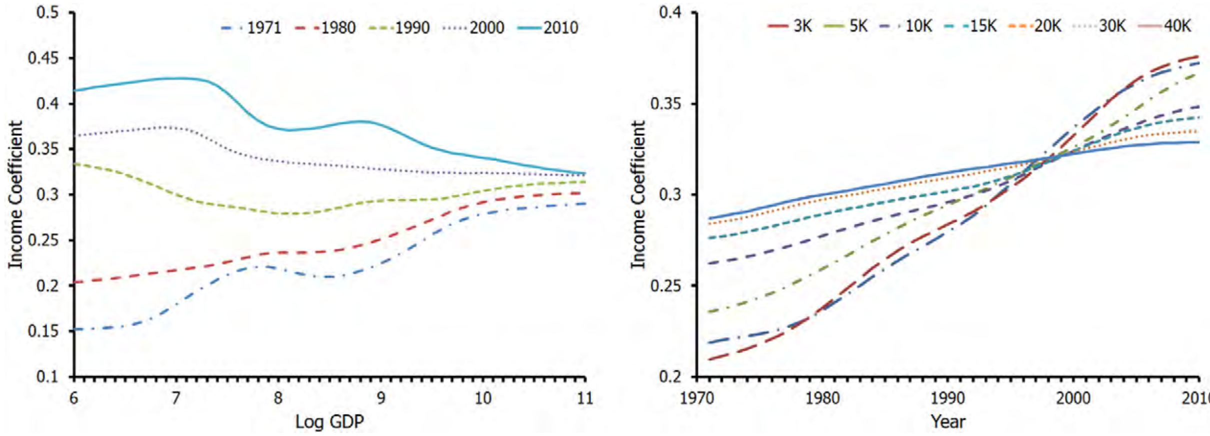

Fig. 4. Cross sections of income coefficient estimates at selected years and time series of income coefficient estimates at selected income levels, estimated using Eq. (B.7) without price.

The coefficients appear to be increasing over time with GDP held constant: $\hat{\beta}_r(r,x) > 0$ for each (r,x). The increase over time may reflect global diffusion of electronic technology in all sectors over the last four decades. In every country, both households' and firms' reliance on machinery and appliances that require electricity has increased. An increase in the income of a household in 1971 might have induced a large purchase of a durable good that did not require much electricity, resulting in a relatively small coefficient. On the other hand, an increase in the income of a household in 2010 might have induced a large electronics purchase, making that household's demand for electricity more sensitive to income changes and resulting in a relatively larger coefficient.

The increase over time appears to be much steeper for poorer countries than for richer countries. For example, the coefficient of a hypothetical country with real GDP per capita held constant at $3000 increases 68% from 0.22 in 1971 to 0.37 in 2010, and the change for a country with constant real GDP per capita of $10,000 is similar: a 54% increase from 0.24 to 0.37. In contrast, for a country of $30,000, the coefficient estimate increases only 18%, from 0.28 to 0.33.

As relatively cheap electronic technology diffuses to poorer countries, their households demand more electricity to power these devices and their firms require more electricity to be globally competitive. Especially in markets in which the electricity price is heavily regulated and electronics are imported from abroad, we may expect the ratio of electricity usage relative to GDP per capita of these countries to grow disproportionately faster than that of richer countries.

4.2. Identifying the effects of GDP and time

Using the formula in Eq. (B.8) based on that in Eq. (1) to calculate elasticities, the left panel of Fig. 5 shows the time paths of the elasticities of the four groups with the highest GDP's per capita. Even though we aggregated individual countries into groups in order to avoid some heterogeneity in estimation, we can evaluate the elasticity of an individual country with non-missing GDP data. The right panel of Fig. 5 shows the time paths of the elasticities of four countries: China, Korea, Japan, and the US.

The most obvious pattern that emerges suggests that elasticities of developed countries have been declining over time. Indeed, this finding reflects that of Brookes (1972), *inter alia*. From 1971 to 1993, the estimated elasticities decline from 0.55 to 0.41, 0.74 to 0.46, 0.87 to 0.49, and 0.76 to 0.45 for Gr1, Gr2, Gr3, and Gr4 respectively. From 1993, when the elasticities of these four groups are similar, to the end of the sample, the elasticities decrease similarly across Gr1, Gr2, Gr3, and Gr4 to 0.15, 0.13, 0.12, and 0.15 respectively.

Looking at individual countries, Japanese and US elasticities exhibit declines, 0.88 to 0.12 and 0.56 to 0.15 respectively, similar to those observed for the richest four groups. Indeed, these two

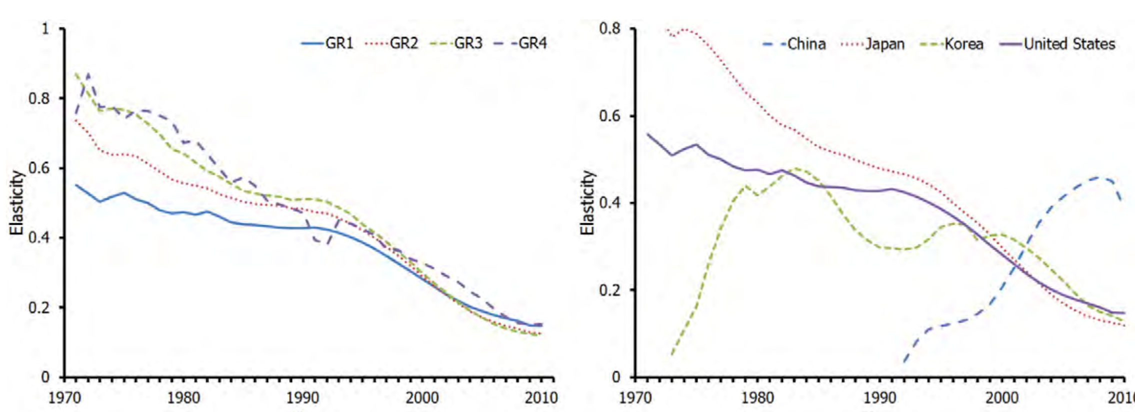

Fig. 5. Estimated elasticities of four richest income groups: Gr1–Gr4, and four selected countries: China, Japan, Korea, and the US. Elasticities estimated using Eq. (B.8), with $\beta(r,x)$ and $\beta_x(r,x)$ estimated using Eq. (B.7) without price.

countries are members of these groups throughout the sample. Korea and China both clearly exhibit over *time* the inverted U shape over *GDP* discussed above — not surprising in light of their dramatic increases in GDP over time.

Korea has been a member of the top five groups only since 1983, when its estimated elasticity peaks at 0.48 compared to 0.47 for the US in the same year. At about that time, there is a clear switch from an increasing to a decreasing pattern similar to that of Japan and the US and dropping to 0.13 by the end of the sample, suggesting dematerialization of Korea's economy.

A similar pattern appears for China. Because it was so poor prior to 1991, we do not estimate an elasticity in order to avoid an empty bin problem for the nonparametric estimator. Since then, China's elasticity appears to have increased, surpassing those of the other three countries after 2002, peaking at 0.47 in 2008, and then declining slightly to 0.39 by the end of the sample.

The Chinese pattern appears similar to the Korean pattern, only shifted by about two and a half decades, with a peak elasticity comparable to Korea's peak elasticity of 0.48 in 1983. China's elasticity of 0.39 in 2010, two years after its peak, marks a sharper decline than that of Korea, 0.45, two years after its peak, suggesting the possibility that dematerialization in China is moving at a faster pace than in Korea a quarter of a century earlier.

The panel analysis allows us to construct meaningful counterfactuals, because for a fixed time period we estimate a range of coefficients that vary with GDP, and for a fixed country or GDP level we estimate a range of coefficients that vary over time. Fig. 6 shows the elasticities over income groups but for fixed years (left panel) and over time but for fixed incomes (right panel).

Looking at the left panel, we clearly observe prior to the 1990's the inverted U shape noted by previous authors, with its peak shifting over time from Gr3, down to Gr4 and below. The inverted U shape appears to break down by about 1991 and even inverts to an uninverted U shape by 2006, when the elasticities appear to *decrease* from Gr8 until about Gr6. This inversion may reflect the diffusion of electronic technology made possible both by the proliferation of such technology and by the internationalization of trade patterns during this period.

The elasticities are nearly flat across the four richest groups Gr1–Gr4 since about 1996. Such a pattern suggests that once a country attains a threshold level of development, GDP no longer seems to play an important role in determining the elasticity. Temporal patterns unrelated to GDP seem to matter much more for countries in these groups.

Median countries (primarily those in North Africa, Central America, and poorer countries in Asia and Europe) have less wealthy households, and firms use a larger share of electricity. As these countries industrialize, more sensitive industrial demand plays a larger role until household demand catches up, which seems to happen at about the income level of Gr4, which includes at different times Ireland, Israel, Korea, Mexico, and Portugal, among others.

Having effectively ruled out GDP as a major driver of electricity intensity in developed countries, we now examine the right panel of Fig. 6. We do not plot years for which we have either no data or only data for Bermuda in excess of \$30,000 and \$40,000 in order to avoid biasing estimates by overweighing a small and atypical country that relies on only a few economic sectors. Specifically, the beginnings of these plots, 1985 and 1997 respectively, correspond to the real GDP per capita of Norway surpassing these thresholds. (That of the US surpasses \$30,000 in 1988 and \$40,000 in 2004.) With GDP fixed, decreasing temporal patterns clearly remain. The general decline suggests the importance of alternative drivers of the coefficient instability.

It is interesting to compare the elasticities against the backdrop of the Kyoto Protocol, which was signed in 1997 and went into effect in 2005, marking a major milestone in awareness of the negative externalities associated with consuming fossil fuels. We expect such awareness to reduce the income elasticity, as richer countries may choose to pollute less, following the downward slope of a hypothetical environmental Kuznets curve. According to the left panel of Fig. 6, such a decrease appears *prior* to 1996, when the downward slope in the elasticity with respect to income declined over time due to a decrease in the peak elasticity across income groups. In this light, we may perhaps interpret the Kyoto Protocol not so much as a binding agreement to shape future environmental sensitivity, but rather as the culmination of shifting attitudes up to that time.

Both panels of Fig. 5 and the right panel of Eq. 6 suggest a different interpretation, however. The decline in many of the elasticities presented in these figure steepens during the 1990's. The fact that the decrease remains when holding income fixed (right panel of Fig. 6) suggests that there is more to the story than an environmental Kuznets curve. Clearly, other temporal factors matter, and the timing of the evident break around the time of the signing of the Kyoto Protocol is very suggestive that sensitivity of electricity consumption to increases in GDP could be related to that agreement. Note that Korea reverses an increase in its elasticity in about 1997 and its subsequent decrease steepens in about 2005, suggesting that – at least in the case of Korea – the signing and enforcement of the Kyoto Protocol may have indeed affected future (as well as reflecting past) environmental awareness.

The right panel of Fig. 5 contains elasticities of two countries for which the constraints of the Kyoto Protocol are not binding: China

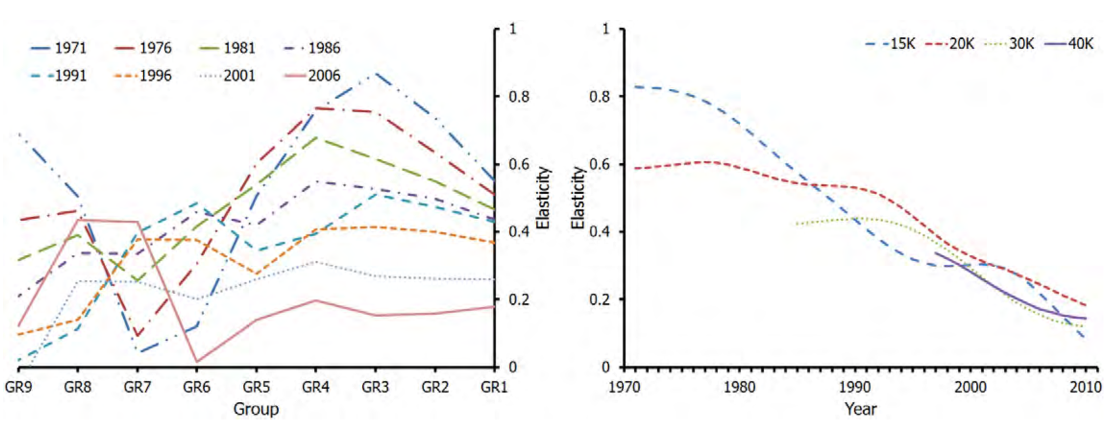

Fig. 6. Cross sections of elasticity estimates at selected years and time series of elasticity estimates at selected income levels. Elasticities estimated using Eq. (B.8), with $\beta(r,x)$ and $\beta_x(r,x)$ estimated using Eq. (B.7) without price.

Table 3
Share regressions: selected countries. Regression of estimated elasticities on time trend and sectoral shares. Statistical significance shown for one-sided test of $H_0 : \pi_o = 0$ and two-sided tests of $H_0 : \pi_j = 0$ for $j = r, c, i$, denoted by *** for 1% significance, ** for 5% significance, and * for 10% significance.

France		Germany		Italy		Japan	
1990-2010		1990–2010		1990–2010		1971–2010	
Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimates	s.e.
−0.466***	0.032	−0.508***	0.040	−0.373***	0.063	−0.794***	0.115
1 .127**	0.484	0.712**	0.320	2.466***	0.453	0.078	0 .534
0 .532	0.487	0.914**	0.376	−0.249	0.446	1.804***	0 .644
0 .235**	0.105	0.154	0.175	−0.020	0.077	0.977***	0 .141
Korea		**Spain**		**United Kingdom**		**USA**	
1979–2010		1990–2010		1990–2010		1973–2010	
Estimates	s.e.	Estimates	s.e.	Estimates	s.e.	Estimates	s.e.
−0.912***	0 .102	−0.590***	0.009	−0.574***	0.013	−0.230*	0.163
0 .554	1.088	1.095***	0.250	−0.011	0.244	−1.878***	0.534
2 .924***	0.637	0 .729***	0.170	2 .821***	0.385	1 .795*	0.951
0 .044	0.184	0.312***	0.043	−0.622***	0.132	1 .766***	0.567

is exempt and the US did not ratify the agreement. To the extent that we can attribute the decline in elasticities to changing attitudes about emissions, there is a huge difference between these two countries. As a developing country, China continues to increase electricity intensity of its economy through 2008. Similarly to Korea, Japan, and Gr2–Gr4, the US shows a substantial change at about the same time, following a decline almost as steep as Korea and Japan. The decline in elasticities for Korea, Japan, and Gr2–Gr4 were such that the elasticities fell below that of the US by 2008, when emissions targets became binding. Interestingly, the slope of Japan's elasticity appears to flatten out shortly before the end of the sample, leading up to Japan's announcement shortly thereafter (in 2011) that it would not engage in additional second-round emissions cuts.

The proliferation of electronic devices (computers, cell phones, etc.) suggests an alternative explanation for the steepening of the decline in the elasticities of developed countries in Figs. 5 and 6 that starts in the 1990's. Use of such devices has skyrocketed over time. The increased usage has perhaps rendered demand for electricity to power these devices less sensitive to income and has perhaps sped the process of dematerialization in developed countries by decreasing reliance on the industrial sector for economic growth. Of course, these two explanations, the Kyoto Protocol and proliferation of electronics, need not be mutually exclusive. Additional research would be required to further disentangle them.

4.3. *Identifying the effects of sectoral shifts*

Previous authors tied sectoral shifts to GDP by way of sectoral dominance at different stages of economic development. However, sectoral shifts alone may drive changes in the aggregate elasticity, since different economic sectors do not generally have the same elasticities. For countries with reliable sectoral data, we may test the null that sectoral shifts explain the apparent decrease in the estimated elasticities by regressing them onto the sectoral shares and a simple time trend. The null corresponds to a zero coefficient on the time trend, while the one-sided alternative on that coefficient is negative. Although the test may have low power against more complicated temporal patterns, we expect that the test will distinguish trends as striking as the negative trends depicted in Figs. 5 and 6.

The regression we run to test this hypothesis is given by

$$\hat{\epsilon}_t = \pi_o(t/T) + \pi_r s_t^r + \pi_c s_t^c + \pi_n s_t^n + \varepsilon_t$$

where $\hat{\epsilon}_t = \hat{\epsilon}(t, x_t)$ denotes the fitted values of the elasticity $\epsilon(t, x_t)$ from model Eq. (6) for a particular country,[14] and s_t^r, s_t^c, and s_t^n denote shares of electricity consumption by the residential, commercial, and industrial sectors of that country. Letting $\pi = (\pi_o, \pi_r, \pi_c, \pi_n)'$, its least squares estimator $\hat{\pi}$ has a limiting distribution given by

$$\sqrt{T}\,(\hat{\pi} - \pi) \to_d \mathbb{N}\left(0, (\text{plim}S_T)^{-1}\Omega(\text{plim}S_T)^{-1}\right)$$

under general conditions, where $S_T = T^{-1}\sum_{t=1}^{T} s_t s_t'$, $s_t = (t/T, s_t^r, s_t^c, s_t^n)'$, and Ω is the asymptotic variance of $T^{-1/2}\sum_{t=1}^{T} s_t\varepsilon_t$ – i.e., $T^{-1/2}\sum_{t=1}^{T} s_t\varepsilon_t \to_d \mathbb{N}(0, \Omega)$. A consistent estimator of Ω can be easily obtained from a consistent estimator of the long-run variance of $(s_t\varepsilon_t)$.[15,16]

Table 3 shows the results of the regressions for eight countries with reliable sectoral consumption data over sub-periods of our main sample. In order to avoid the measurement error in sectoral data from our main data source noted in Section 3.1, we collect data from national statistical agencies for this purpose.[17] The table specifically shows results using data from the US, two large Asian economies, Japan and Korea, for which sectoral data may be obtained, and the five largest economies in the European Union: France, Germany, Italy, Spain, and the UK.

All eight countries show $\hat{\pi}_o < 0$, and significantly so. Holding sectors constant, there still appears to be a downward trend in elasticities, and we reject the null of no trend against a downward trend

[14] Here and subsequently, we suppress the subscript i for notational simplicity, since this part of our analysis is based on a single country.

[15] We use a standard long-run variance estimator with a triangular window and a bandwidth chosen by Andrews (1991) automatic bandwidth selection procedure with a maximum of four lags.

[16] A consistent estimator of Ω can also be obtained from a consistent estimator of the long-run variance Ω° of $(s_t{\circ}\varepsilon_t)$, $s_t{\circ}\varepsilon_t = (\varepsilon_t, s_t^r\varepsilon_t, s_t^c\varepsilon_t, s_t^n\varepsilon_t)'$. Indeed, if we let $\Omega = (\omega_{ij})$ and $\Omega^\circ = (\omega_{ij}{}^\circ)$, then we have $\omega_{11} = \omega_{11}{}^\circ/3$, $\omega_{1j} = \omega_{j1} = \omega_{1j}{}^\circ/2$ for all $j \neq 1$, and $\omega_{ij} = \omega_{ij}{}^\circ$ for all $i, j = 2, 3, 4$. However, such an indirect estimator of Ω is not necessarily positive definite, and appears to work significantly worse in finite samples.

[17] EuroStat (European Union): http://epp.eurostat.ec.europa.eu/; KEPCO (Korea): http://cyber.kepco.co.kr/kepco/EN/main.do; FEPC (Japan): http://www5.fepc.or.jp/tokei-eng/; EIA (US): http://www.eia.gov/electricity/.

for all eight of these countries.[18] We note that $|\pi_o|$ for the US is smaller but with a larger standard error than for the other countries. Fig. 5 provides a possible explanation. Electricity intensity declined more slowly in the US than in Japan and in Gr2–Gr4. The 1990's marked a substantial change in the decrease in all of these elasticities, but the break seems more pronounced for the US. A smaller slope to begin with and a larger break at that time may underlie the smaller point estimate with the larger standard error for the US.

Overall, it is clear that although sectoral shares account for some of the temporal decrease in elasticities in some of the countries, they do not entirely account for this pattern in any of these countries. While this finding does not necessarily contradict the empirical findings of previous authors, it suggests that those findings are incomplete. Additional drivers, such as utility, technology, and policy, must account for the decline in elasticities over time.

5. Summary and conclusion

A general contribution of the paper is to demonstrate how to use a panel nonparametric approach to identify nonlinearity and specific drivers of coefficient instability in an econometric model. To the best of our knowledge, a functional coefficient model that allows for both of these features has not been applied to a panel consisting of nonstationary time series previously.

Our functional coefficient nonparametric approach allows us to study the coefficient under counterfactuals — e.g., as one functional argument changes and the other stays fixed. Relative to a functional coefficient of time and the regressor itself, as in our model, we show that more commonly utilized functional coefficients that take into account only time (to model structural instability) or only the regressor (to model nonlinearity) systematically overestimate or underestimate the effect of a change in the argument.

More specifically, when applied to a model of electricity consumption, our model both echoes findings in the extant literature and uncovers new information. We identify a clear, decreasing pattern in aggregate income/output elasticities of electricity demand over time for the wealthiest countries, which is broadly consistent with interpretation of economic dematerialization in the literature. In particular, we find decreases in the elasticities for Japan (0.88 to 0.12) and the US (0.56 to 0.15) over the whole sample, and in those of Korea (0.48 to 0.13) and China (0.47 to 0.39) since their respective peaks in 1983 and 2008. The increases prior to these peaks show a ramping up of electricity-intensive industrial growth in these two economies before they diversify into less electricity-intensive sectors. Our modeling approach allows similar analyses of other countries or even countries with hypothetical income growth paths.

Moving beyond the general decline in elasticities already noted in this literature, our econometric methodology allows the identification of some of the sources of this decrease. We detect the inverted U shape in GDP expected from research by previous authors, but only until the 1990's, when this pattern appears to break down, and only up to an apparent GDP threshold in recent years. We attribute the breakdown in the 1990's to increased environmental awareness and technology diffusion. Beyond the GDP threshold, GDP appears to have little or no effect on the elasticities of the richest countries (top third) in recent years. In contrast to the inverted U shape postulated in the literature, a linear specification may be adequate for these countries during this period.

Although declining elasticities are often associated with dematerialization, further analysis of our estimated elasticities shows that sectoral shifts alone are insufficient to explain the downward movement in elasticities for a selected number of these countries: France, Germany, Italy, Japan, Korea, Spain, the UK and the US. In other words, once we account for changes in GDP and changes in consumption by sector, the downward trend remains. As a result, we find that dematerialization noted in the literature is insufficient to explain the downward trend by itself. Such a result suggests, for example, that policies aimed at de-industrialization or economic diversification may not be as effective at increasing overall energy efficiency as the aggregate data suggest.

We are left with residual explanations, such as consumer utility, consumer and producer technology, and policy. Because the downward trend in the elasticities is common to developed countries, a transnational driver such as technology or preferences is more likely responsible than any national policy. In contrast to a discontinuous jump in autonomous energy efficiency that might result from a one-time legally-binding policy mandate, the gradual decline is more consistent with evolving technology and preferences.

On the other hand, an apparent break in the rate of decline in elasticities during the 1990's could be interpreted either in light of the boom in electronics technology, which started in the mid 1990's, or the Kyoto Protocol, which was signed in 1997 and required participants to implement efficiency measures by 2005. To the extent that our research informs policy making, it suggests the importance of transnational policy such as the Kyoto Protocol or the more recent 2015 Paris Agreement to improve autonomous energy efficiency.

Further research is needed for the potentially difficult task of identifying the effects of these remaining drivers.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.10.002.

References

Andrews, D.W.K., 1991. Heteroskedasticity and autocorrelation consistent covariance matrix estimation. Econometrica 59, 817–858.
Berndt, E.R., Wood, D.O., 1975. Technology, prices, and derived demand for energy. Rev. Econ. Stat. 57, 259–268.
Brookes, L.G., 1972. More on the output elasticity of energy consumption. J. Ind. Econ. 21, 83–94.
Cai, Z., Li, Q., 2008. Nonparametric estimation of varying coefficient dynamic panel data models. Economet. Theor. 24, 1321–1342.
Cai, Z., Li, Q., Park, J.Y., 2009. Functional-coefficient models for nonstationary time series data. J. Econ. 148, 101–113.
Chang, Y., Kim, C., Miller, J.I., Park, S., Park, J.Y., 2014. Time-varying long-run income and output elasticities of electricity demand. Energy Econ. 46, 334–347.
Chang, Y., Martinez-Chombo, E., 2003. "Electricity Demand Analysis Using Cointegration and Error-Correction Models with Time Varying Parameters: The Mexican Case". Department of Economics, Rice University. mimeo
Galli, R., 1998. The relationship between energy intensity and income levels: forecasting long term energy demand in Asian emerging countries. Energy J. 19, 85–105.
Halvorsen, R., 1975. Residential demand for electric energy. Rev. Econ. Stat. 57, 12–18.
Halvorsen, R., 1978. Econometric Models of U.S. Energy Demand New York: Lexington. MA: D.C. Heath and Company.
Judson, R.A., Schmalensee, R., Stoker, T.M., 1999. Economic development and the structure of the demand for commercial energy. Energy J. 20, 29–57.
Kaufmann, R.K., 2004. The mechanisms for autonomous energy efficiency increases: a cointegration analysis of the US energy/GDP ratio. Energy J. 25, 63–86.
Kraft, J., Kraft, A., 1978. On the relationship between energy and GDP. J. Energy Dev. 3, 401–403.
Luzzati, T., Orsini, M., 2009. Investigating the energy–environmental Kuznets curve. Energy 34, 291–300.

[18] Some additional intuition about sectoral shifts may be gleaned from other coefficient estimates. We expect that income elasticities of residential demand are lower than the output elasticities in the firm sectors (see Chang et al., 2014) . As the residential share increases, we should expect the elasticity to decrease. However, the coefficient $\hat{\pi}_r$ does not have to be negative for this to hold. First, if the increase in the elasticity is linear, it is already accounted for by $\hat{\pi}_0$, which is negative for all eight countries. Second, an increase in the residential share must be accompanied by a decrease in one or both of the other shares.

Maddala, G.S., Trost, R.P., Li, H., Joutz, F., 1997. Estimation of short-run and long-run elasticities of energy demand from panel data using shrinkage estimators. J. Bus. Econ. Stat. 15, 90–100.
Medlock, K.B., Soligo, R., 2001. Economic development and end-use energy demand. Energy J. 22, 77–105.
Nguyen-Van, P., 2010. Energy consumption and income: a semiparametric panel data analysis. Energy Econ. 32, 557–563.
Park, J.Y., Hahn, S.B., 1999. Cointegrating regressions with time varying coefficients. Economet. Theor. 15, 664–703.
Richmond, A.K., Kaufmann, R.K., 2006a. Energy prices and turning points: the relationship between income and energy use/carbon emissions. Energy J. 27, 157–180.
Richmond, A.K., Kaufmann, R.K., 2006b. Is there a turning point in the relationship between income and energy use and/or carbon emissions? Ecol. Econ. 56, 176–189.
Silk, J.I., Joutz, F.L., 1997. Short and long-run elasticities in US residential electricity demand: a co-integration approach. Energy Econ. 19, 493–513.
Webster, M., Paltsev, S., Reilly, J., 2008. Autonomous efficiency improvement or income elasticity of energy demand: does it matter? Energy Econ. 30, 2785–2798.