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Abstract

Energy consumption and greenhouse emissions across many countries have increased overtime despite widespread energy efficiency improvements. One explanation offered in the literature is the rebound effect (RE), however there is a debate about the magnitude and appropriate model for estimating RE. Using a combined stochastic frontier analysis and two-stage dynamic panel data approach for 55 countries covering 1980-2010, we explore these two issues of magnitude and model. Our central estimates indicate that, in the short-run, 100% energy efficiency improvement is followed by 90% rebound in energy consumption, but in the long-run it leads to a 36% decrease in energy consumption. Overall, our estimated cross-country RE magnitudes indicate the need to consider or account for RE when energy forecasts and policy measures are derived from potential energy efficiency savings.

Keywords: Energy Efficiency, Input Distance Function, Panel Data, Rebound Effects, Stochastic Frontier Analysis.

JEL Classification: C23, D2, Q43.

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1. INTRODUCTION

There appears to be a consensus within the energy policy community about the contributions of energy efficiency improvements towards reducing global energy consumption and greenhouse emissions. Protagonists of energy efficiency improvement often highlight its non-costly nature, arguing that the resulting decrease in energy use may not require higher energy prices or result in slower economic growth. However, a strand of literature starting with early works of Brookes (1979) and Khazzoom (1980) argues that the underlying assumption that energy efficiency improvements yield proportionate reduction in energy consumption is misleading. This view was recently elucidated by Saunders (2013) who argued that overtime; rebound effects (RE) could potentially result in the partial or total erosion of energy savings arising from improved energy efficiency[1].

Since its inception, the RE literature has grown significantly, but controversies remain about its magnitude, mechanisms and the most appropriate approach to measuring it. Clearly, the debate has been more intense regarding macroeconomic RE since it approximates the net effect of different mechanisms that are complex and interdependent, and whose effects may vary over time and across efficiency sources. This possibly explains the scarcity of macroeconomic RE studies as most studies on economy-wide RE are country-specific[2]. Moreover, the few economy-wide studies use different empirical and theoretical approaches, with most of them covering different time periods. As expected, given the differences in methodological approaches and data sets, these studies are non-comparable. In particular, Dimitropoulos (2007) showed that the use of diverse models/methodologies and the lack of a widely accepted rigorous theoretical framework have contributed immensely to the controversies surrounding RE.

Understanding the nature and estimating economy-wide RE is vitally important for a number of reasons. First, the key issues associated with RE, especially global climate change, require top-down analyses of different economies over long time frames, which microeconomic or bottom-up analysis may be inappropriate to handle. This is because effective climate change policies require multilateral co-operation and co-ordination among different countries, thus, there is need for a comparative and consistent measurement of RE across different countries.

[1] Rebound effect is not entirely bad on its own since the resulting increase in energy use contributes towards welfare and expansion of the production possibility space, but given the urgency required in tackling dangerous climate change, it is important to explicitly account for RE (especially when it is large) in global energy forecasts.

[2] A detailed recent meta-analytical survey can be found in Chakravarty et al. (2013).

However, the available pool of studies[3] is inadequate in the context of the broad, extensive and systematic cross-country analysis required to tackle climate change. Secondly, this analysis is crucial given the important role that energy efficiency plays in the derivation of future energy forecasts and in the formulation of wider energy policy measures. Possibly, due to the dearth of reliable and consistent estimates of RE, most of these forecasts and policy measures hardly account for RE, implying that such forecasts may have underestimated future energy consumption, if RE is significant or large. Thirdly, a broad and extensive cross-country analysis of RE, such as this one undertaken here, is crucial to the evolution of more useful debate on RE.

As far as is known, no multi-country study of macroeconomic RE across several countries has been undertaken to provide greater clarity on the RE debate using a sound technique and consistent dataset. This is an important gap in literature given that RE arising from aggregate consumption and production by households and firms are likely to be of great significance and implication (Kydes, 1999).

In this paper, our objective is to provide estimates aggregate RE for a panel of 55 countries between 1980 and 2010 using a two-stage procedure. First, we estimate energy efficiency using Stochastic Frontier Analysis (SFA). Secondly, by employing a dynamic panel framework, and using the efficiency scores from the SFA model, we estimate short-run and long-run RE. To give an insight into our main empirical findings, we find significant RE magnitudes across sampled countries, especially non-OECD countries. However, an encouraging sign is the declining RE magnitudes for some countries over the sample period which possibly indicates the potential for energy efficiency in the future.

The remainder of the paper proceeds as follows. Section 2 presents the modelling approach. Specifically, we present a two-stage estimation approach including the parametric SFA approach for estimating energy efficiency, and a GMM model for estimating short-run and long-run RE. In section 3, the dataset is described in detail. Section 4 presents the empirical results from both models and the resulting rebound effects. We offer our concluding remarks and recommendations in Section 5.

[3] The dearth of macro RE studies for developing countries is more severe. Herring and Roy (2007) argue that macroeconomic RE are likely to be significantly higher in developing countries because their economic growth and development increasingly burden the global environment as they lift millions of people from poverty.

2. MODELLING AND THEORETICAL APPROACH

Our aim is to estimate RE within a macroeconomic production function by accounting for the increase in energy use arising from energy efficiency gain. This efficiency saving is expected to impact energy consumption, resulting in energy conservation which is defined as:

$$\eta^E = \frac{\mathrm{d}\ln E}{\mathrm{d}\,Ef} \tag{1}$$

where E is energy consumption and Ef represents energy efficiency. η^E is also referred to as efficiency elasticity of energy demand, which allows us to derive RE:

$$R = 1 + \eta^E \tag{2}$$

Intuitively, RE represents the size or percentage of the energy efficiency savings that is lost such that if energy consumption E falls by 40% due to a 40% increase in energy efficiency, then $\eta^E = -1$ and $\boldsymbol{R} = 0$. In the same vein, if a 100% increase in energy efficiency yields only a 40% fall in energy consumption, then $\boldsymbol{R} = 0.6$. Given these discussions above, it is easy to see that five rebound conditions are possible (Saunders, 2000; Wei, 2010):

- $\boldsymbol{R} > 1$ or $\eta^E > 0$: '**Backfire**' occurs as energy consumption increases due to improvements in energy efficiency;
- $\boldsymbol{R} = 1$ or $\eta^E = 0$: **Full rebound** as energy demand remains unchanged in the face of energy efficiency gains;
- $\mathbf{0} < \boldsymbol{R} < 1$ or $-1 < \eta^E < 0$: **Partial rebound** as energy consumption falls by a less-than-proportionate rate to efficiency improvements;
- $\boldsymbol{R} = 0$ or $\eta^E = -1$: **Zero rebound** implies a one-to-one or unit relationship between energy consumption and efficiency improvements;
- $\boldsymbol{R} < 0$ or $\eta^E < -1$: **Super conservation** as energy consumption falls by a more-than-proportionate rate with respect to efficiency gains.

Now we turn to the multi-stage approach to estimating RE. The key objective is the econometric estimation of the efficiency elasticity η^E and we proceed as follows.

Stage One: Energy Efficiency Estimation

Our starting point is the estimation of energy efficiency (Ef) using the stochastic frontier analysis (SFA) (Aigner et al., 1977 and Meeusen and van den Broeck, 1977). The SFA allows for a composed error term which contains a one-sided error term to measure inefficiency in addition to the traditional two-sided error term which captures random noise. A number of studies have estimated efficiency in aggregate energy consumption. One of such is Filippini and Hunt (2011) who demonstrated the need for an econometric estimation of efficiency when estimating aggregate energy efficiency for 29 OECD countries using an energy demand SFA. The parametric estimation of energy efficiency using SFA is underscored by criticisms and inappropriateness of using energy intensity as a proxy for energy efficiency (see Filippini and Hunt, 2011; Saunders, 2013). More recently, Filippini and Hunt (2012) also estimated energy efficiency in residential energy demand for a panel data of 48 U.S states using an input requirement function (IRF).

Although we employ the SFA, this study differs from the studies mentioned above by estimating a production technology using an input distance function (IDF)[4], rather than an IRF. With an IRF, the objective is to radially contract energy use in an input vector for a given level of output, conditional on energy prices and other exogenous factors. By implication, other factor inputs are implicitly assumed to be fixed; hence studies relying on an IRF have arguably estimated short-run energy efficiency. However, an IDF seeks to radially contract energy and the other factor inputs in the input vector for a given level of output. This approach is consistent with long term energy efficiency estimation since in reality one would expect efficiency gains to alter relative/effective prices of factor inputs, resulting in factor substitution as firms adjust input combinations to take advantage of energy efficiency improvements.

Our proposed production technology can be represented by the input requirement set $I(y)$ which represents the set of K inputs $x \in \mathbb{R}^+$ which can produce a set of R outputs $y \in \mathbb{R}^+$ i.e. $I(y) = \{x \in \mathbb{R}^+ : x\ can\ produce\ y\}$. We can obtain an input distance function equation (see Kumbhakar and Lovell (2003): $D_I(\boldsymbol{y}', \boldsymbol{x}', t)$ which takes a value of 1 if a country is efficient (i.e. on the frontier) but is greater than 1 when a country is inefficient $D_I \geq 1$, so that:

[4] Although Zhou et al (2012) estimated a stochastic input distance function for a sample of 21 OECD countries; we note that they employed cross-sectional data for only 2001. Moreover, unlike this study, they did not account for cross-country heterogeneity.

$$\ln D_I\,(\boldsymbol{y}, \boldsymbol{x}, t) - u = 0 \tag{3}$$

where $u \geq 0$. This input distance function is non-increasing in inputs, and non-decreasing and homogeneous of degree one in inputs. By adopting a translog functional form in conjunction with the elements, $i = 1, \ldots, N; t = 1, \ldots, T$, and applying the linear homogeneity property, equation 3 can be written in panel data context[5]:

$$-\ln x_{Kit} \approx TL(\boldsymbol{y}, \boldsymbol{x}/x_K, t)_{it} + v_{it} - u_{it} \tag{4}$$

where $TL(y, x/x_K, t)_{it}$ represents the technology as the translog approximation to the log of the distance function; while v_{it} is the traditional symmetric error term representing sampling, specification and measurement errors, while u_{it} represents the non-negative inefficiency component of the composed error term.

The energy efficiency of each country in each period is then estimated as the conditional expectation of the one-sided error term, $\exp(u)$, given the composed error, $v - u$ so that the energy inefficiency of each country i in period t is given by:

$$TE_{it} = E[exp(u_{it})|\varepsilon_{it}] \tag{5}$$

$$\text{where } \varepsilon_{it} = v_{it} - u_{it} \tag{6}$$

The estimated (in) efficiency evaluates the degree to which a country could decrease the level of energy use relative to the country on the frontier, holding output constant.

Exogenous Variables and Energy Efficiency

The typical production frontier function assumes homogeneity of producers and homoscedasticity of the errors. However, these assumptions can be relaxed by introducing exogenous variables which are different from factor inputs but affect or influence the technical (in) efficiency of firms/countries into the different parts of the SFA model. It is desirable to evaluate the impact of observable country-specific exogenous factors on inefficiency because, in reality; such factors reflect the operating environment and are likely to be partly responsible for energy efficiency performance across countries (Kumbhakar and Lovell, 2003). Moreover, with this approach, it is possible to address the problem of conditional heteroscedasticity in the energy inefficiency term. Hence, we introduce different exogenous variables into the variance of the inefficiency term to capture the impact of structure of

[5] We employ a panel data framework with time-varying inefficiency given the reasonably long timeframe of this study. It is unlikely that energy efficiency will be constant or time-invariant over a long period of time as in this study.

economy, demography, geography, climate on energy inefficiency. In this case the variance of the pre-truncated inefficiency distribution is given as follows:

$$u_{it} \sim \mathcal{N}^{+}(0, \sigma^2_{u_{it}}) \tag{7}$$

$$\sigma^2_{u_{it}} = \exp(\boldsymbol{\gamma}' \boldsymbol{z}_{it}) \tag{8}$$

where $\boldsymbol{z}_{it}$ represents observable exogenous characteristics across countries while $\boldsymbol{\gamma}'$ are parameter estimates obtained in the single stage maximum likelihood ML estimation. In addition, we explore the 'double-heteroscedasticity' model of Hadri (1999) which permits the exogenous variables to affect both the inefficiency component and the idiosyncratic error component of the disturbances, so that in addition to the assumption in (7) and (8), it is possible to have:

$$v_{it} \sim \mathcal{N}(0, \sigma^2_{v_{it}}) \tag{9}$$

$$\sigma^2_{v_{it}} = \exp(\boldsymbol{\delta}' \boldsymbol{z}_{it}) \tag{10}$$

Stage Two: Estimation of Rebound Effects

After estimating energy efficiency using SFA above, we then compute short-run and long-run RE for each country as:

$$R = 1 + \eta^E \tag{11}$$

where η^E is the elasticity of energy consumption with respect to energy efficiency $\frac{d \ln E}{d\, Ef}$; E is energy consumption and Ef is energy efficiency. The task in this second stage is the econometric estimation of η^E_τ, the efficiency elasticity. We estimate short run and long run efficiency elasticity in order to compute SR and LR rebound effects *a la* equation (11). To achieve this, we utilize an Arellano-Bond (1991) autoregressive dynamic-panel energy consumption model estimated by generalized method of moments, GMM, as where the estimated energy efficiency in the first stage is included as a regressor, alongside energy price and national output. The GMM autoregressive dynamic panel model is written as:

$$\ln E_{it} = \beta_i + \delta \ln E_{it-1} + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + \beta_3 Ef_{it} + \beta_4 t + \beta_5 P_{it} Ef_{it} + \beta_6 Y_{it} Ef_{it} + \beta_7 P_{it} Y_{it} + (\alpha_i + v_{it}) \tag{12}$$

where E_{it} is energy consumption, treated as the long-run equilibrium level of energy use by a country in time t. E_{it-1} is the lagged energy consumption while P_{it} is the corresponding real price of energy in time t, Y_{it} represents a country's real GDP at time t; Ef_{it} denotes each country's estimated efficiency from the IDF above in time t. The panel data error term consists of an unobserved country-specific component α_i and an idiosyncratic disturbance term which is assumed to be identically and independently distributed $v_{it} \sim (0, \sigma^2)$.

It can be seen in (12) that we explore non-linearity in the model by interacting energy efficiency with energy prices and income. This is because the relationship between energy efficiency and energy consumption as well as the other regressors (price and income) is likely to be non-linear. This is an important aspect of modelling energy technical progress, which could be price-induced, endogenous or exogenous; hence, models should be correctly specified accordingly (see Adeyemi and Hunt, 2014). Moreover, the non-linearity assumption allows us to evaluate efficiency elasticity and rebound effects at each given price and income level.

From the parameter estimates of equation 12 above, short-run and long-run efficiency elasticity can be derived as follows:

$$\text{Short-run } \eta_{SR}^{E} \equiv \frac{d \ln E}{dEf} = \beta_3 + \beta_5 P_{it} + \beta_6 Y_{it} \qquad (13)$$

$$\text{Long-run } \eta_{LR}^{E} = \frac{\beta_3 + + \beta_5 P_{it} + \beta_6 Y_{it}}{1-\delta} \qquad (14)$$

Given these, short-run rebound is $R_{SR} = 1 + \eta_{SR}^{E}$ and long-run rebound is $\mathrm{R_{LR}} = 1 + \eta_{\mathrm{LR}}^{\mathrm{E}}$. Ceteris paribus, we expect both SR and LR efficiency elasticities to be negative since improved energy efficiency will most likely reduce the fuel required to deliver a given level of energy service. Therefore, the question of RE centers on the extent to which efficiency gain lowers energy use, so that the magnitude of RE depends on the size of η^E (i.e. the larger η^E, the smaller the RE magnitude).

Autoregressive models are common in studies estimating short-run and long-run elasticities because the response of energy consumption to changes in exogenous influences such as price and income are gradual in nature[6]. Furthermore, the use of PAM stems partly from their simplicity considering that they do not require the imposition of any specification on the model structure. However, the dynamic modeling approach can be generally complicated by issues such as the correlation between lagged values of the dependent variable and the error term, especially the

[6] For instance, due to appliance stock and psychological reasons, households do not immediately change their energy use habits in response to a price increase as such changes may result in some disutility, hence the need for a partial adjustment approach in energy demand modeling.

country-specific heterogeneity component[7] (Nickell 1981). This is because E_{it} is a function of the unobserved country-specific heterogeneity v_i which is time invariant, it then follows that E_{it-1} which is one of the regressors, is correlated with ε_{it}. Moreover, v_i may also be correlated with the other regressors, resulting in endogeneity issues[8]. Furthermore, the presence of the lagged dependent variable as one of the regressors may result in the problem of autocorrelation. Under these circumstances, parameter estimates are biased and inconsistent, particularly for OLS[9].

Thus, the generalized method of moments (GMM) procedure is employed in this study. In the first place, by using the GMM estimator, it is possible to control for cross-country heterogeneity, by the fixed effects term, α_i, including the case where the explanatory variables are correlated with the fixed effects. Secondly, the GMM estimator permits the regressors to be endogenous by exploiting the availability of pre-detemined variables as instruments. This is crucial since energy efficiency is potentially endogenous within the framework proposed here.

Arellano and Bond (1991) derived two GMM estimators, namely one-step and two-step estimators, which allow for heteroscedasticity and autocorrelation in the idiosyncratic errors. In the one step estimator, weighting matrices independent of parameter estimates are used. For the two-step estimator, the moment conditions are weighted by their covariance matrix often regarded as optimal weighting matrices. Thus the two-step estimator yields asymptotic efficiency gains over the one-step estimator, especially in large samples, when there are non-iid errors. In this case, the estimator can handle numerous instruments and it uses the consistent variance co-variance matrix from first step GMM which is robust to panel-specific autocorrelation and heteroskedasticity (Arellano and Bond, 1991). Given the large sample property of our sample and the potential efficiency gain, we employ the two-step estimator, with the finite sample correction due to Windmeijer (2005).

To ascertain the consistency and validity of the model, diagnostic tests namely autocorrelation (AR) test and the Hansen test for over-identifying restrictions are conducted under the null hypothesis of correct model specification and valid over-identifying restrictions.

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[7] This is often referred to as the Nickel bias.

[8] We explored the endogeneity issue by applying the Wu-Hausman test statistic to our dataset. First we regressed energy efficiency on the instruments and other exogenous variables. We then included the residuals from this regression as an additional regressor in the original equation (E=f (P, Y, Eff) which is found to be not statistically significant judging from the t-stat. Hence, this indicates that the data failed to reject the null of no endogeneity (see appendix).

[9] See Roodman (2009 a, b) for detailed discussions on the benefits of the GMM estimator, especially over other estimators such as the FE and 2SLS estimators

3. DATA AND DESCRIPTIVE STATISTICS

The dataset is an unbalanced panel of annual data for 55 countries[10] (including OECD and non-OECD, as listed in the results section) over the period 1980-2010, comprising 1631 observations in total. The number of countries and the length of time are largely determined by the availability of data for different countries[11], as countries with too many missing observations were eliminated. The variables employed in this study are Y, K, L, E, M and z-variables. Y, K and L are all extracted from the Penn World Table (PWT) Version 8.0. Y is represented by "Real GDP at constant 2005 national prices (in mil. 2005U.S$)". K is given by "Capital stock at constant 2005 national prices (in mil. 2005U.S$)". (L), the labour input is "Number of persons engaged (in millions)". E is given by "Total Final Energy Consumption" in thousand tonnes of oil equivalent (ktoe), obtained from the International Energy Agency (IEA) database. M, the Material variable is taken from the Sustainable Europe Research Institute (SERI) materials flow database. It is represented by "used material extraction" in tonnes.

The exogenous variables capturing observable cross-country heterogeneity are also are industrial share of value add, trade openness, population, area size[12] and temperature. Population and trade openness are taken from the Penn World Tables (PWT); Industrial sector shares of value added is downloaded from the World Development Indicators (WDI) database. Land area in square km. is also taken from the WDI. Finally, annual average temperature data are taken from the Tyndall Centre for Climate Change Research database and the UNDP climate change database. These are then spliced with regional temperature data from the UK Met Office for 2007-2010.

Finally, in the second stage where an energy consumption function is estimated, we use energy prices P_{it} which is taken from the IEA Energy Prices and Taxes database (Indices of End-use Prices for industry and households in the case of OECD countries, 2005=100) and energy price index taken from the International Labor Organization (ILO) database for the non-OECD countries. These are normalized to 2005 base year for consistency. The descriptive statistics of all the variables defined above are presented in Table 1 below.

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[10] As much as data availability permitted, we have sampled from the widest and most policy-relevant population, especially considering some arguments in literature that the rebound effect is most serious for developing economies, given their relatively higher growth rates and limited level of technological advancement.

[11] In particular, energy price data.

[12] A more appropriate explanatory variable for area and population is residential population density as a larger country may have lots of nonresidential areas and low energy consuming activities. However, we were unable to find any dataset on "residential area". Moreover, we believe that our approach is consistent with earlier works on the impact of country size (via area size and population) on macroeconomic performance (see Milner and Westaway, 1994; Weyman-Jones and Milner, 2003). Further, other studies (e.g Hunt and Filippini, 2011) have shown that population and area size are explanatory variables for energy demand. In our case, the statistical significance of these variables indicates that they influenced energy use performance.

TABLE 1: DESCRIPTIVE STATAISTICS

1631 Observations	Variable	Mean	SD	Min	Max
Variables minimized i.e. inputs					
Capital (million U.S2005$)	K	2884690.73	6755249	43697.65	75301295.05
Labour (million people)	L	36.77	103.11	.067	781.38
Energy (ktoe)	E	102473.8	228512.7	1742.55	1581622
Materials (tons)	M	347359.5	989507.7	1603.44	16176128
Variable held constant i.e. output					
GDP (million U.S2005$)	Y	727134.7	1553914	13361.71	13144400
Environmental variables					
Population (million people)	z_1	82.94	204.41	0.94	1330.14
Area size (km^2)	z_2	1552501	2966275	670	16389950
Industrial sector share (% of GDP)	z_3	33.66	8.99	9.19	78.66
Temperature (degree Celsius)	z_4	15.67	8.45	-8.74	28.88
Trade Openness	z_5	65.32	48.07	6.69	433.05
Variables used in 2nd stage					
Energy price index (2005=100)	p_E	79.59	30.76	0.02	192.06

4. EMPIRICAL RESULTS

4.1 Estimates of achieved energy efficiency from SFA Model

We estimate four models: time-decay, pooled conditional mean, pooled conditional variance model and the conditional variances/double heteroskedatic model. We performed a range of diagnostics to reach our preferred model[13]. In particular, in order to avoid arbitrary assumptions, we checked for heteroscedastic error structure across our panel data using the LR test procedure recommended by Wiggins and Poi (2001). The LR test, which approximately follows a chi-square distribution by nesting the homoscedastic model in the heteroscedastic model under the null hypothesis of homoscedasticity, clearly indicated the presence of heteroscedasticity in the model.

This guided our attempt to address this heteroscedasticity problem using the double-heteroscedasticity model proposed by Hadri (1999). Further, we tested this preferred model as an unrestricted model against other alternative model specifications using the LR and Wald tests, with both tests strongly rejecting the restrictions. We further checked the theoretical appropriateness of the models by observing the curvature properties of the model. Based on our diagnostics, we conclude that our dataset favours the double condtional heteroscedasticity model (Hadri 1999) where exogenous variables influence both the inefficiency term and the two-sided error term. Therefore, our subsequent analysis is based on this preferred model.

The output and inputs and environmental variables are in mean-corrected logarithms, Estimates of the first-order coefficients and the inefficiency effects from the different models are presented in Table 2. All the estimated first-order coefficients on inputs and outputs have the appropriate signs and they are all statistically significant, implying that the model is generally consistent with our underlying assumption of a production technology. This conclusion is supported by regularity tests for economic properties which indicate that the preferred model largely satisfies the curvature properties[14]. For the inefficiency effects, we find all the coefficients on the environmental variables to be statistically significant and they all have a positive effect on the estimated inefficiency.

[13] Maximum-likelihood estimations of the model were obtained using STATA 12. We conducted some sensitivity experiment by dropping some of the heterogeneous variables in turn to evaluate the impact on the estimated efficiency. We only observed slight variations in the efficiency scores and therefore ranks. In particular, we consistently found the same set of countries to be most efficient across all the models. Similarly, we find this to be the case for the least efficient countries too, indicating that the slight variations are of no substantial consequence. Interested readers can obtain the full range of experimented models and diagnostics from the authors.

[14] Monotonicity is confirmed at 100% of our data points for output; 97% for Capital; 96% for Labour and 83% for Materials. The concavity condition is satisfied at the sample mean, and at 88% of the data points.

TABLE 2: FIRST STAGE SFA MODEL RESULTS

Variable	Parameter	Model 1 Time-decay	Model 2 Pooled conditional mean	Model 3 Single conditional heteroscedasticity	Model 4 Double conditional heteroscedasticity
Constant	α_0	1.069***	2.142***	0.230***	0.344***
		(0.04)	(0.05)	(0.02)	(0.01)
$ln\,Y$	α_Y	-0.657***	-0.383***	-0.954***	-0.849***
		(0.02)	(0.01)	(0.01)	(0.01)
$ln\,K$	β_K	0.418***	0.0742***	0.443***	0.428***
		(0.01)	(0.01)	(0.01)	(0.01)
$ln\,L$	β_L	0.437***	0.639***	0.0423***	0.202***
		(0.02)	(0.01)	(0.01)	(0.01)
$ln\,M$	β_M	0.053***	0.038***	0.114***	0.064***
		(0.01)	(0.01)	(0.01)	(0.01)
t	θ_1	-0.008***	-0.001	0.002	-0.001
		(0.00)	(0.00)	(0.00)	(0.00)
Parameters					
in μ or σ_u					
pop	π_{pop}		0.618***	0.363**	0.787***
			(0.01)	(0.1)	(0.1)
$area$	π_{area}		0.022***	0.755***	0.435***
			(0.00)	(0.1)	(0.04)
ind	π_{ind}		0.409***	8.405***	4.113***
			(0.04)	(1.38)	(0.55)
$temp$	π_{temp}		-0.009***	-0.005	0.031***
			(0.00)	(0.01)	(0.01)
$open$	π_{open}		0.101***	1.319***	0.750***
			(0.01)	(0.3)	(0.2)
t			-0.001	-0.025	-0.028***
			(0.00)	(0.02)	(0.01)

t^2		-0.003***	-0.003	-0.0003
		(0.00)	(0.00)	(0.00)
LLF	1970.17	1175.15	334.75	479.92
η	0.004***			
μ	0.931***			
γ	0.989***	1.00***		
LR Stat			312.47	290.34
Wald			112.03	735.70

*Standard errors in parentheses. *, **, *** denote statistical significance at the 5, 1 and 0.1% levels, respectively*

Table 3 presents the average energy efficiency score and rank for every country over the whole sample period. The estimated energy efficiency of each country gives a relative measure or indication of change in energy efficiency over the sample period vis-à-vis the constructed IDF frontier. A key observation in Table 3 is that the estimated energy efficiency scores appear reasonable, particularly in terms of the countries' distance to the estimated frontier. It can be seen that the OECD countries are closer to the frontier, while developing countries such as China, Brazil, India and Russia are found to be farthest from the frontier. This is to be expected in a way, given the huge technological gaps between them and the OECD countries.

TABLE 3: AVERAGE ENERGY EFFICIENCY SCORES AND RANKINGS

Country	Efficiency Score	Rank
Argentina	0.631	48
Australia	0.782	40
Austria	0.941	17
Belgium	0.950	13
Brazil	0.564	49
Canada	0.875	31
Chile	0.884	29
China	0.317	55
Czech Republic	0.869	32
Denmark	0.962	2
Dominican Republic	0.958	3
Egypt	0.915	24
Finland	0.936	18
France	0.816	38
Germany	0.825	35
Greece	0.956	5
Hungary	0.927	19
India	0.462	53
Indonesia	0.463	52
Iran	0.640	47
Ireland	0.956	6
Israel	0.957	4
Italy	0.901	27
Japan	0.880	30
Kuwait	0.952	9
Libya	0.852	34
Malaysia	0.703	42
Mexico	0.825	36
Morocco	0.915	23
Netherlands	0.950	12
New Zealand	0.953	8
Nigeria	0.680	45
Norway	0.946	15
Pakistan	0.540	51
Philippines	0.685	44
Poland	0.643	46
Portugal	0.949	14
Russia	0.383	54

Saudi Arabia	0.860	33
Singapore	0.952	10
Slovak Republic	0.951	11
South Africa	0.699	43
Spain	0.897	28
Sri Lanka	0.916	22
Sweden	0.945	16
Switzerland	0.965	1
Syria	0.820	37
Tanzania	0.903	26
Thailand	0.560	50
Tunisia	0.917	21
Turkey	0.955	7
UAE	0.910	25
United Kingdom	0.921	20
U.S	0.808	39
Venezuela	0.723	41

4.2 Dynamic panel data model for determinants of achieved efficiency

The results[15] of the estimated dynamic panel data two-step GMM model[16] are given in Table 4. Overall, most of the parameter estimates having the expected signs and within credible magnitude range.The coefficient on the lagged dependent variable in the Arellano-Bond results is 0.923, significant at the 0.001 level. While this appears close to unity, Bond (2002) and Roodman (2009) have shown that this coefficient needs only to be less than unity, as the requirements for its consistent estimation are relatively weak.

The interaction terms indicate that, c*eteris paribus*, higher energy prices stimulated energy-augmenting technological progress so that a higher energy price results in a greater energy-reducing efficiency effect[17]. Moreover, by accounting for the interaction between price and efficiency, it is possible to disentangle price effects from other exogenous efficiency effects thereby reducing the problem of overestimating the efficiency elasticity.

[15] We use the xtabond2 in STATA12. Although T is fairly large (31 years), we restrict our set of lags to 2-3 lags given that more lags will result in a huge number of instruments and the attendant weakening of the instruments validity tests (see Roodman, 2009a).

[16] Given that energy efficiency gains could be exogenous or endogenous as shown by effects of energy prices, regulations and policies, tastes etc. on energy efficiency, we explore a model with interaction between energy efficiency and the other regressors. Results show that these assumptions are accepted by the data.

[17] This has been partly demonstrated by asymmetric price responses of energy demand where reductions in energy consumption via technical progress due to higher prices are not fully reversed in the face of lower prices.

This possibly explains why the time trend is statistically insignificant as it is possible that the interaction terms have picked up some of the exogenous/time effects, causing this statistical insignificance.

TABLE 4: GMM DYNAMIC PANEL AUTOREGRESSIVE MODEL RESULTS

	Dep. variable Energy Consumption (E)
Lagged E	0.923***
	(0.06)
p_E	-0.0751*
	(0.04)
y	0.0780
	(0.06)
ef	-0.474**
	(0.22)
t	0.000709
	(0.00)
$p_E * ef$	-0.353**
	(0.15)
$y * ef$	0.148**
	(0.07)
$p_E * y$	-0.0323**
	(0.02)
constant	0.0551***
	(0.02)
Hansen Test (p-value)	0.606
Ar(1) (p-value)	0.003
Ar(2) (p-value)	0.448

*Windmeijer corrected standard errors in parentheses. *, ** and *** represents significant level at 10%, 5% and 1% respectively*

For the system-GMM to be reliable, it is required that we fail to reject both null hypotheses on the Hansen test of over-identification and the AR test for serial correlation which is applied to the residuals in differences. From Table 4, notice that the p-values on the AR tests indicate first-order serial correlation, but no serial correlation at the second-order. This is consistent with a priori expectation since first-order serial correlation is expected in differences because Δv_{it} is related to Δv_{it-1} through the shared v_{it-1} term. Hence, to check for first-order serial correlation in levels, the second-order correlation in differences is checked as this will detect correlation between the v_{it-1} in Δv_{it} and the v_{it-2} in Δv_{it-2}. The Hansen test statistic indicates that we are unable to reject the null hypothesis of overall exogeneity of the instruments used in the GMM estimation, implying that the instruments are valid.

4.3 Rebound Effects Estimates

The estimated energy efficiency elasticities from the results in Table 5 are -0.10 in the SR and -1.36 in the LR. These yield SR and LR rebound effects of 90% and -36% respectively, at the sample mean. The LR rebound estimate suggests that energy efficiency gain is likely to generate a more than proportionate reduction in energy use (a 1% energy efficiency gain will result in a 1.36% reduction in energy consumption), a situation referred to as *super conservation* in the RE literature.

The smaller LR rebound estimate is consistent with the expectation that in the LR, learning/innovation/knowledge formation are likely to better help energy end-users to "lock-in" more energy efficiency savings. This LR result also possibly reflects the impact of the continuous global awareness and policy efforts of the climate change agenda. Turner (2009) found similar results whereby the energy increase pressures arising from rebound are partially or wholly offset by negative income, competitiveness and disinvestment effects, which also occur in response to falling energy prices. These effects were found to reduce domestic energy supply, leading to a contraction in the capital stock in these sectors, which in turn led to smaller long-run economy-wide rebound effects[18].

To compute point estimates of RE outside the sample mean (i.e. for each country and overtime), we calculate the point efficiency elasticity for each year across the entire sample. In particular, our point estimates

[18] Birol and Keppler (2000) and Turner (2013) elucidated that the lack of attention to these energy supply issues in rebound analysis has led to the neglect of supply-side responses to demand-side rebound pressures. It is in this context that our macroeconomic rebound analysis embodies/captures these wider supply-side issues which yield smaller long-term rebound.

indicate that our modeling approach demonstrates the entire rebound possibilities, ranging from super-conservation to backfire. The computed RE magnitudes are quite substantial, ranging from an average of 18% for Dominican Republic to 117% for Russia over the entire sample period[19]. Our results also show some variation in rebound estimates overtime and across the sample countries (see appendix). Interestingly, overall, we find slightly different RE magnitudes and patterns between OECD and non-OECD countries. For instance, it is observed that RE magnitudes for non-OECD countries (with an average of 56%) are generally bigger those for OECD countries (with average 49%)[20] while for the 7 OPEC countries in our sample we estimate an average RE of 60%.

Also, we find for most OECD countries, generally increasing rebound magnitudes in the 1980s which stabilized in the 90s before declining in the 2000s. We also observed a spike in rebound levels around 2008/09 for most of the OECD countries, with the obvious suggestion being the recession which might have curbed RE around that period[21]. Interestingly, for the U.S, our estimates are consistent with results in Saunders (2013) who adopted a sectoral approach to estimating economy-wide RE for the U.S over 1960-2005. Saunders estimated aggregated SR and LR RE at 126% and 62% respectively, providing a band for our average U.S RE of 96% over the sample period. Further, we estimate average RE of 55% for Spain, compared to Freire Gonzalez (2010) who estimated RE at 35%-49% respectively for household energy services in Catalonia (Spain) over the period 1999-2006. In terms of computable general equilibrium (CGE) studies, Allan et al. (2007) estimated UK RE for the year 2000 at 30-50% while we estimated average UK RE over the sample period at 65%.

In general, we find evidence of backfire in mostly non-OECD countries (Iran, Russia, Tanzania, India, Indonesia, Philippines, South Africa and Venezuela) with the U.S and Israel being the only OECD countries where we found backfire at some data points/for some given years. Overall, a very encouraging sign from our analysis is the generally declining RE trend[22] across many countries in this study, to the extent that *super conservation* was observed for Sri Lanka and Syria towards the end of our sample period 2009-10.

5. CONCLUSION AND RECOMMENDATION

[19] We restricted the dataset and estimations to OECD countries in order to examine the sensitivity of the rebound estimates to the sample. We found that, on average, the restricted rebound estimates was 8% lower than the whole sample estimates which indicates that the estimates are not too far apart. See Appendix 3 for a comparison of the estimates.

[20] We observe even lower rebound levels for EU-OECD countries.

[21] It is also noteworthy that the emissions targets from the Kyoto agreement come into effect around 2008.

[22] Although the declining RE trend is an encouraging sign for the future, current RE levels are still significantly high to pose serious challenges to energy and climate policy plans.

RE is one of the most debated issues in energy economics literature. A great deal of this debate derives from the lack of clarity on its nature and a consistent range for its estimate. This paper has attempted to estimate economy-wide RE for 55 countries, and to the best of our knowledge, it is the first attempt to evaluate RE for several countries over a reasonably long timeframe. First we derive energy efficiency by adopting a specification that allows for estimation of energy efficiency across different heterogeneous economies within the panel SFA framework. Secondly, we estimate aggregate SR and LR efficiency elasticity of energy using a GMM energy consumption model. We then compute rebound effects from these efficiency elasticities.

We estimate SR and LR rebound effect across sampled countries at 90% and -36% respectively. While the SR estimate shows significant RE, the LR indicates the potential for energy efficiency to significantly lower energy consumption in the future[23]. In particular, the country-wise estimates show larger RE magnitudes (and in some cases back-fire) for developing countries. This is consistent with the reasoning that developing countries are on a growth trajectory that requires greater energy consumption, to the extent that energy efficiency savings are easily "re-spent" to fuel further growth. Policy-wise, this finding should alert policy that RE in developing countries will potentially represent one of the most challenging energy and climate policy issues in the future. More importantly, despite the declining RE over the period under consideration, our results indicate that RE magnitudes are still large enough to be considered when constructing future energy scenarios.

One limitation which we seriously attempted to address is that some important z-variables, especially those on energy efficiency policies and regulations could have been included. However, the challenge was the limited data and changing energy policy stance overtime[24]. In addition, we also add that our results cannot of course establish complete causality, but we have demonstrated, with a high degree of confidence, the dimensions of the rebound effect using well-established modelling procedures.

Finally, this study does not in any way attempt to downplay the role of energy efficiency measures and policies, but rather argues that energy policies in general are likely to be more effective with the incorporation of

[23] Based on the LR estimate it is clear that energy efficiency improvement will remain an important policy measure, but the large rebound magnitudes suggest a need for an array of policy instruments to "lock-in" such efficiency gains and prevent their erosion by rebound effects.

[24] For instance the most comprehensive subsidy information can be found on the OECD-IEA Fossil Fuel Subsidies database, which covers only 39 countries and spans a period of 5 years (2007-2011). Further, there is also the challenge that even when some descriptive energy policy information was available for OECD countries, we found changing policy stance over a period of time, where for instance, some policy measures were only implemented for a few years and discontinued thereafter, such that even dummy variables would overstate the impact of such discontinued policies overtime. However, it is the case that the country fixed effects included in our DPD instrumental variables estimation will pick up additional country specific effects including inter-country differences in energy policies.

RE. A greater understanding of RE drivers is required to further assist policy makers. Ideally a sectoral analysis of RE for residential, industrial and electricity sectors across different countries should follow in order to decompose macro RE into its underlying sources.

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APPENDIX 1: ANNUAL POINT ESTIMATES OF REBOUND EFFECTS

Country	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Argentina	30%	29%	29%	29%	29%	28%	29%	46%	54%	45%	38%	45%	61%	69%	71%	78%	71%	71%	83%	73%	56%	60%	62%	59%	52%	44%	38%	39%	25%	39%	33%
Australia	48%	47%	46%	44%	44%	44%	48%	50%	54%	55%	53%	51%	52%	52%	54%	54%	54%	55%	57%	57%	54%	55%	56%	57%	56%	53%	52%	54%	50%	53%	54%
Austria	27%	24%	24%	26%	26%	26%	31%	34%	36%	37%	37%	39%	39%	40%	41%	40%	39%	39%	41%	44%	42%	43%	43%	43%	40%	39%	38%	38%	36%	38%	34%
Belgium	37%	33%	31%	32%	32%	32%	41%	45%	48%	47%	45%	45%	46%	45%	47%	48%	47%	47%	49%	49%	46%	46%	47%	46%	44%	42%	41%	41%	37%	42%	41%
Brazil	86%	81%	83%	83%	84%	85%	97%	96%	97%	94%	89%	90%	77%	78%	78%	78%	80%	82%	84%	84%	84%	86%	88%	79%	73%	63%	55%	52%	50%	48%	47%
Canada	65%	61%	57%	56%	57%	58%	61%	63%	65%	66%	64%	63%	63%	64%	66%	67%	67%	67%	69%	68%	66%	65%	66%	64%	63%	60%	60%	61%	57%	64%	63%
Chile	108%	100%	92%	82%	77%	70%	66%	62%	55%	49%	45%	42%	39%	38%	45%	47%	46%	48%	50%	49%	42%	38%	38%	36%	35%	33%	32%	32%	30%	35%	33%
China	83%	83%	84%	86%	87%	87%	87%	88%	84%	76%	74%	70%	65%	62%	64%	65%	66%	68%	69%	70%	89%	89%	89%	89%	88%	87%	86%	87%	86%	87%	88%
Czech Republic														32%	33%	36%	38%	38%	38%	37%	33%	35%	37%	37%	37%	35%	34%	35%	33%	33%	32%
Denmark	29%	24%	24%	27%	30%	30%	35%	35%	36%	35%	38%	37%	38%	37%	40%	40%	38%	38%	38%	37%	33%	34%	34%	34%	35%	33%	32%	33%	31%	34%	31%
Dominican Rep	21%	20%	18%	20%	21%	20%	20%	21%	21%	19%	17%	15%	17%	17%	16%	14%	14%	14%	14%	13%	12%	26%	26%	22%	20%	17%	16%	15%	13%	22%	21%
Egypt	94%	96%	98%	98%	101%	95%	92%	92%	90%	89%	82%	68%	54%	48%	46%	46%	46%	45%	46%	48%	46%	46%	47%	47%	42%	41%	39%	37%	31%	28%	25%
Finland	26%	24%	26%	27%	29%	30%	37%	38%	40%	41%	38%	37%	37%	34%	37%	37%	34%	35%	36%	36%	34%	35%	35%	32%	32%	31%	31%	33%	29%	29%	28%
France	57%	55%	54%	54%	55%	54%	61%	63%	66%	66%	67%	68%	69%	68%	69%	70%	69%	69%	71%	71%	68%	69%	70%	70%	70%	67%	66%	66%	63%	66%	64%
Germany	68%	65%	65%	67%	67%	67%	74%	76%	78%	76%	77%	78%	79%	80%	79%	81%	81%	81%	83%	82%	79%	79%	78%	76%	76%	72%	70%	70%	67%	69%	68%
Greece	22%	20%	23%	23%	24%	23%	26%	29%	33%	37%	32%	31%	31%	31%	34%	36%	36%	37%	41%	42%	36%	38%	41%	42%	40%	38%	37%	37%	34%	38%	31%
Hungary	50%	46%	47%	45%	48%	48%	36%	36%	36%	39%	26%	27%	30%	33%	35%	36%	35%	32%	32%	31%	30%	33%	34%	32%	33%	31%	29%	27%	24%	25%	25%
India	87%	84%	79%	77%	74%	72%	70%	69%	109%	109%	108%	104%	101%	99%	98%	97%	95%	92%	90%	89%	82%	78%	75%	75%	75%	74%	74%	73%	71%	75%	75%
Indonesia	108%	106%	96%	85%	76%	73%	72%	72%	73%	72%	99%	99%	97%	93%	92%	92%	92%	92%	84%	81%	79%	73%	63%	56%	55%	53%	51%	51%	49%	48%	48%
Iran	89%	84%	82%	81%	79%	78%	71%	63%	61%	63%	63%	154%	143%	137%	133%	124%	112%	101%	90%	77%	69%	65%	61%	57%	54%	53%	53%	49%			
Ireland	14%	10%	9%	9%	11%	11%	14%	18%	20%	21%	22%	23%	25%	26%	28%	30%	29%	31%	36%	37%	37%	38%	40%	38%	36%	33%	31%	32%	28%	30%	
Israel	224%	193%	138%	90%	76%	26%	21%	30%	35%	35%	31%	33%	34%	37%	39%	40%	37%	37%	39%	36%	36%	38%	36%	34%	33%	31%	31%	31%	31%	34%	33%
Italy	68%	65%	63%	62%	63%	64%	71%	72%	73%	73%	70%	68%	69%	68%	69%	69%	69%	69%	71%	71%	68%	68%	68%	68%	68%	66%	63%	64%	61%	63%	62%
Japan	58%	57%	56%	59%	60%	62%	66%	69%	72%	74%	75%	76%	77%	77%	77%	79%	80%	79%	81%	81%	81%	80%	81%	81%	81%	79%	77%	77%	73%	77%	77%
Kuwait							27%	28%	25%	28%	23%	15%				27%	28%	28%	28%	26%	24%	24%	25%	27%	28%	28%	31%	32%	32%	31%	32%
Libya							16%	14%	17%	19%	25%	22%	25%	28%	29%	32%	33%	36%	35%	36%	37%	32%	29%	32%	32%	24%	26%	27%	27%	24%	23%
Malaysia	26%	23%	23%	24%	23%	23%	24%	26%	27%	27%	27%	28%	30%	31%	33%	34%	36%	36%	34%	35%	36%	36%	36%	38%	39%	39%	38%	38%	37%	37%	37%
Mexico	79%	69%	67%	58%	59%	62%	60%	65%	63%	66%	67%	66%	65%	66%	68%	68%	68%	68%	70%	68%	66%	66%	65%	63%	62%	62%	62%	63%	62%	63%	62%
Morocco	33%	30%	30%	27%	25%	22%	21%	19%	20%	19%	33%	32%	30%	28%	28%	24%	23%	22%	23%	22%	22%	22%	22%	22%	22%	22%	22%	21%	22%	22%	23%
Netherlands	51%	46%	44%	45%	44%	45%	52%	56%	58%	58%	57%	56%	57%	55%	56%	57%	56%	56%	57%	57%	54%	54%	54%	54%	53%	50%	49%	49%	48%	49%	51%

New Zealand	11%	10%	11%	12%	13%	14%	20%	21%	22%	23%	24%	25%	24%	26%	27%	28%	28%	27%	29%	31%	28%	29%	30%	29%	27%	24%	21%				
Nigeria	57%	61%	57%	60%	73%	76%	53%	55%	70%	72%	76%	76%	88%	91%	50%	43%	52%	56%	59%	41%	40%	48%	49%	55%	44%	36%	39%	42%	44%	40%	35%
Norway	39%	37%	37%	36%	37%	38%	42%	43%	42%	43%	41%	39%	40%	40%	40%	40%	39%	40%	42%	43%	42%	41%	42%	36%	39%	39%	36%	41%	38%	40%	36%
Pakistan	81%	82%	82%	82%	81%	80%	80%	80%	79%	75%	73%	68%	67%	64%	61%	57%	55%	50%	45%	48%	44%	44%	45%	44%	44%	43%	40%	39%	34%	29%	29%
Philippines	125%	118%	114%	109%	93%	83%	86%	86%	85%	83%	76%	67%	65%	63%	61%	61%	60%	57%	56%	54%	51%	47%	46%	45%	43%	38%	35%	35%	33%	32%	31%
Poland	65%	60%	62%	61%	64%	63%	66%	65%	62%	66%	59%	55%	52%	52%	54%	57%	58%	58%	59%	57%	53%	52%	52%	51%	50%	48%	48%	49%	45%	47%	45%
Portugal	20%	19%	17%	15%	15%	14%	17%	20%	23%	26%	29%	29%	29%	29%	30%	32%	34%	35%	36%	39%	39%	39%	41%	39%	38%	35%	33%	33%	32%	35%	32%
Russia													361%	253%	195%	155%	140%	129%	125%	112%	98%	89%	79%	75%	71%	66%	62%	59%	55%	53%	52%
Saudi Arabia							76%	64%	65%	55%	57%	60%	77%	78%	78%	59%	60%	60%	60%	45%	46%	45%	45%	47%	48%	49%	64%	71%	75%	76%	73%
Singapore	7%	7%	8%	10%	13%	13%	17%	22%	25%	27%	27%	27%	30%	32%	34%	33%	32%	33%	33%	36%	30%	28%	32%	32%	33%	31%	26%	28%	21%	26%	27%
Slovak Republic														22%	25%	30%	31%	29%	31%	29%	25%	26%	27%	23%	22%	21%	20%	22%	20%	21%	22%
S.Africa	117%	114%	109%	104%	103%	100%	94%	91%	87%	84%	79%	75%	70%	65%	63%	60%	59%	56%	54%	52%	50%	48%	46%	44%	43%	42%	41%	39%	33%	38%	37%
Spain	50%	43%	43%	42%	42%	44%	48%	51%	54%	56%	56%	55%	55%	54%	55%	57%	57%	58%	61%	61%	59%	61%	62%	63%	63%	60%	59%	61%	57%	60%	58%
Sri Lanka	97%	86%	85%	76%	71%	70%	70%	70%	66%	62%	59%	55%	54%	49%	45%	44%	42%	41%	41%	41%	36%	31%	28%	24%	22%	18%	11%	4%	0%	0%	0%
Sweden	50%	47%	45%	46%	46%	47%	52%	52%	53%	51%	47%	46%	47%	46%	47%	49%	47%	47%	48%	48%	45%	44%	45%	42%	41%	40%	38%	38%	34%	35%	34%
Switzerland	27%	26%	27%	29%	30%	30%	38%	40%	42%	41%	42%	42%	44%	42%	43%	43%	42%	41%	44%	43%	40%	42%	43%	43%	42%	40%	38%	39%	36%	42%	39%
Syria	106%	90%	81%	78%	77%	75%	66%	62%	56%	46%	47%	45%	38%	38%	30%	19%	20%	22%	23%	22%	22%	23%	20%	18%	19%	19%	19%	18%	9%	0%	
Tanzania	176%	165%	158%	147%	135%	125%	120%	111%	108%	98%	85%	78%	72%	64%	51%	41%	32%	26%	22%	20%	18%	18%	14%	14%	12%	9%	7%	6%	4%	5%	4%
Thailand	65%	60%	60%	60%	61%	58%	56%	57%	58%	60%	61%	61%	62%	62%	62%	62%	62%	58%	51%	52%	50%	48%	48%	48%	48%	48%	46%	47%	53%	56%	54%
Tunisia	32%	29%	23%	19%	17%	15%	15%	14%	14%	14%	29%	27%	26%	24%	23%	22%	22%	21%	21%	20%	21%	20%	20%	19%	18%	16%	14%	14%	13%	12%	9%
Turkey	111%	96%	68%	60%	47%	49%	51%	56%	64%	61%	58%	57%	56%	61%	59%	62%	58%	57%	59%	55%	54%	49%	50%	53%	56%	54%	55%	56%	52%	52%	52%
UAE							25%	30%	30%	30%	32%	31%	31%	39%	40%	40%	42%	42%	43%	43%	42%	42%	39%	39%	39%	38%	37%	40%	42%	41%	41%
UK	58%	55%	55%	56%	57%	58%	62%	64%	67%	68%	68%	68%	68%	68%	68%	69%	69%	69%	70%	69%	68%	70%	71%	71%	71%	68%	65%	65%	61%	61%	61%
USA	81%	80%	80%	82%	84%	86%	93%	94%	96%	97%	95%	97%	98%	100%	101%	102%	102%	103%	107%	108%	103%	103%	106%	103%	100%	96%	94%	93%	90%	97%	95%
Venezuela	213%	205%	204%	202%	196%	192%	193%	188%	183%	163%	152%	145%	152%	134%	113%	103%	86%	62%	46%	36%	37%	37%	35%	34%	36%	37%	38%	38%	38%	36%	43%

APPENDIX 2: STEPS IN THE HAUSMAN-WU TEST

First Regression: Basic Panel Energy Demand Model

	(1) lne
lnp	-0.112***
	(-9.15)
lny	0.917***
	(122.72)
eff	-1.447***
	(-25.27)
_cons	-2.11e-08
	(-0.00)
N	1631

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Second Regression: Energy Efficiency Model

	(1) eff
lnp	0.0805***
	(10.69)
lny	-0.0527***
	(-19.64)
t	0.000251
	(0.61)
p*eff	-0.0109
	(-0.30)
y*eff	0.311***
	(19.62)
p*y	0.0144**
	(3.16)
_cons	0.0216***
	(5.12)
N	1631

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Third Regression: Energy Demand Model with Residuals from Second Efficiency Model

	(1) lne
lnp	-0.118***
	(-7.99)
lny	0.921***
	(95.15)
eff	-1.365***
	(-11.08)
uhat	-0.105
	(-0.76)
_cons	-2.10e-08
	(-0.00)
N	1631

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX 3: AVERAGE REBOUND SENSITIVITY TO DATA SAMPLE

	Restricted Sample	Whole Sample	Difference
Australia	44%	52%	8%
Austria	32%	36%	4%
Belgium	35%	43%	8%
Canada	51%	63%	12%
Denmark	28%	34%	6%
Finland	26%	33%	7%
France	57%	65%	8%
Germany	63%	74%	11%
Greece	30%	33%	3%
Ireland	22%	26%	4%
Italy	57%	67%	10%
Japan	66%	74%	8%
Netherlands	43%	53%	10%
New Zealand	18%	23%	5%
Norway	32%	40%	8%
Portugal	28%	29%	1%
Spain	49%	55%	6%
Sweden	34%	45%	11%
Switzerland	34%	39%	5%
United Kingdom	56%	65%	9%
US	81%	96%	15%

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