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Does Energy Efficiency Promote Economic Growth?

Evidence from a Multi-Country and Multi-Sector Panel Data Set

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Abstract

This paper examines the causal relationship between energy efficiency and economic growth based on panel data for 56 high- and middle-income countries from 1978 to 2012. Using a panel vector autoregression approach, the study finds evidence of a long-run Granger causality from economic growth to lower energy intensity for all countries. The study also finds evidence of long-run bidirectional causality between lower energy intensity and higher economic growth for middle-income countries. This finding suggests that beyond climate benefits, middle-income countries may also earn an extra growth dividend from energy efficiency measures.

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Does Energy Efficiency Promote Economic Growth? Evidence from a Multi-Country and Multi-Sectoral Panel Data Set

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1 Introduction

Energy efficiency is commonly seen as a key policy option for climate change mitigation. It also has recently been promoted as an industrial policy to boost economic competitiveness. For example, the European Union's 2030 Energy Strategy describes energy efficiency as fundamental in the transition toward a more competitive, secure, and sustainable energy system.[1] And the U.S. government has acknowledged energy efficiency as a key part of its strategy to support trade competitiveness.[2]

There are several potential channels through which energy efficiency policies could spur competitiveness and growth (Deichmann and Zhang, 2013). First, they could encourage innovation and technology development. When firms become more productive by using less energy per unit of output, they could become more cost-competitive in export markets. Second, these policies could create new demand and new markets for energy efficient technologies and products. The ensuing investment could bring new jobs and growth. Third, by enabling government to reduce energy-related expenditures, especially in energy-importing countries, they could allow greater spending in other priority areas that would benefit growth in the long run, such as health and education. Finally, by producing energy savings for households, they could boost disposable income and encourage growth-promoting consumption.

Despite many anecdotal accounts of the relationship between energy efficiency and economic growth, empirical evidence on a causal link is thin. Existing analysis takes a deep dive into specific industries to explore productivity benefits of energy efficiency measures, such as in iron and steel manufacturing (Worrell et al., 2003), paper and steel manufacturing (DOE, 1997), and the glass industry (Boyd and Pang, 2000), At the macro level, numerous studies have investigated the causal relationship between total energy consumption and economic growth (for example Kraft and Kraft 1978 and Costantini and Martini 2010; see also Ozturk 2010 for a detailed review). But there has been no broader examination of the macroeconomic effect of energy efficiency policies.

In this paper, we explore the causal relationship between energy efficiency and GDP growth based on a panel dataset of 56 countries spanning the period from 1978 to 2012. Causality here is confined to Granger causality, in which a variable is said to "Granger-cause" another variable if it serves as a useful predictor of future values of that variable after controlling for several lags. Energy efficiency is proxied by energy intensity, defined as energy use per unit of economic output. Because changes in energy intensity can be driven by both efficiency effects (resulted in lower energy use to produce the same amount of a good) and structural effects (resulted in the tendency of energy intensity to first rise as a country moves from agriculture to industry and then fall as it shifts from industry to services), we

[1] European Commission. "Energy Efficiency and its contribution to energy security and the 2030 Framework for climate and energy policy"

[2] http://trade.gov/press/publications/newsletters/ita_1009/energy_1009.asp

combine macro-level analysis with sector-level analysis of industry and agriculture to control for change in the sectoral composition of the economy.

Previous studies using country-level time-series data or multicountry panel data to test for Granger causality between total energy consumption and growth have been mostly confined to a bivariate model with energy use and GDP as the two variables (Ozturk, 2010). However, inference form bivariate models must be interpreted with caution because of potential omitted variable bias (Lütkepohl, 1982; Zachariadis, 2007). For example, some recent studies have underscored the importance of controlling for energy price, as energy price could have a causal impact on both energy use and output growth (Lee and Lee, 2010; Costantini and Martini, 2010; Belke et al., 2011). In this paper, we specifically control for energy price as an endogenous variable so as to allow more conclusive causal inferences.

We apply a panel vector autoregression (PVAR) approach for the causality analysis. We first test for unit roots in the variables using tests proposed by Pesaran (2007) and Demetrescu et al. (2006). Both these tests allow for cross-section dependence between countries. After establishing unit roots in the variables of interest, we test whether the variables are cointegrated using the panel conintegration test of Pedroni (2004). We find evidence of panel cointegration, which leads us to estimate long-run cointegrating parameters based on generalized methods of moments (GMM). Finally, we use the lagged residuals estimated from the cointegrating regression as an exogenous error correction term in a PVAR.

Our sample covers a diverse set countries of different income levels. Because energy needs differ at different stages of development, we categorize countries into three groups: high income, upper middle income (UMI) and lower middle income (LMI).[3] We find evidence of unidirectional causality from GDP growth to lower aggregate energy intensity and lower industrial energy intensity for high-income countries in the long run. We also find bidirectional Granger causality between economic growth and lower aggregate energy intensity for lower-middle-income countries and between growth and lower industrial energy intensity for upper-middle-income countries, both in the long run. These findings suggest that economic development provides opportunities for countries to become more energy efficient, possibly through capital and technology upgrades (Deichmann and Zhang, 2013). Moreover, the bidirectional causality for lower-middle-income countries and for the industrial sector of upper-middle-income countries implies that energy efficiency could be an instrument for accelerating growth and productivity. In other words, beyond climate benefits, middle-income countries may also earn an extra growth dividend from energy efficiency measures.

The rest of the paper is organized in the following ways: Section 2 describes the data. Section 3 discusses the PVAR approach and presents the results. Section 4 discusses the policy implications and concludes the paper.

[3] The analysis excludes low-income countries because energy price data for these countries are not available.

2 Data and Descriptive Analysis

We use three types of data for the analysis: data on total final energy consumption and the sectoral energy consumption of agriculture and industry from the International Energy Agency (IEA) World Energy Statistics and Balances database; data on GDP and value added of agriculture, services, and industry from the World Bank World Development Indicators (WDI) database; and energy price data from the IEA Energy Prices and Taxes database, the Energy Regulators Regional Association (ERRA) Tariff database, and various government reports and websites. The IEA reports after-tax industry and household electricity and natural gas prices for OECD and selected non-OECD countries. The ERRA database reports after-tax prices for residential and non-residential consumers. We use industry or non-residential electricity price as a proxy for energy price.[4] When electricity price data are not available, we use the industry natural gas price as a substitute. All price and value added data are converted to 2005 U.S. prices.[5] For countries that have gaps in energy price data, we linearly interpolate those missing observations using the growth rate in the corresponding country's Consumer Price Index.[6] Table A1 reports the countries as well as the years for which energy price data are linearly interpolated.

Our main variable of interest is energy intensity, defined as total final energy consumption divided by GDP. Sector-specific energy intensity is defined as the total final energy consumption of the sector (industry or agriculture) divided by sector value added.

Our yearly dataset consists of an unbalanced panel of 56 countries spanning the period from 1991 to 2012. We categorize the countries as high income, upper middle income, or lower middle income based on the World Bank's income classification and the countries per capita gross national income in 2012. Table 1 lists the countries by their income level in 2012 and by data availability for different measures of energy intensity.

Table 2 reports the summary statistics. Figures 1, 2, 3, and 4 show the trends in average GDP, aggregate and sectoral energy intensity, value added shares, and energy price for each income group over the sample period, respectively. GDP and aggregate energy intensity are strongly trending in opposite directions since 1990. While GDP has steadily increased, the aggregate energy intensity of all income groups has fallen dramatically over the past two decades.[7] The negative correlation between GDP and aggregate energy intensity is highly significant, although it does not indicate causality or the direction of causality. Industrial

[4] We use IEA data on industry electricity prices whenever available. We use ERRA data on non-residential electricity prices when IEA data are not available. The same approach applies to natural gas prices data.

[5] GDP data are based on purchasing power parity.

[6] Our main conclusions are robust to the alternative approach by which missing observations of energy prices are not interpolated.

[7] There was a significant increase in energy intensity in middle-income countries after 1991. This is because many middle-income countries in the sample are transition economies and experienced a sharp contraction in output after the end to centrally planned production. Our main conclusions are robust when we restrict sample to observations between 1991 and 2012.

energy intensity shows a declining trend for middle-income countries especially after mid 1990s while it remains flat for high-income countries. Agricultural energy intensity shows no clear time trend. While the value added share of industry have been on a steady decline for high income countries, the corresponding shares for middle income countries have been increasing until 2010. The value added share of agriculture are declining for all income groups. Finally, the average energy prices for high-income and upper-middle-income countries have more than doubled since 2000. For lower-middle-income countries, it fluctuates around 60 U.S. dollars per MWh between 1991 and 2010 and then declined to 40 USD per MWh in 2012.

3 Model and Results

In this section, we describe procedures for and results of three types of tests: panel unit root test, panel cointegration test and Granger causality test.

3.1 Panel Unit Root Test

Causality tests are very sensitive to the stationarity of the series. Thus we begin by testing for data stationarity using panel unit root tests proposed by Pesaran (2007) and Demetrescu et al. (2006). These tests do not assume that individual time series in the panel are cross-sectionally independently distributed. Furthermore, they can be applied to unbalanced panels and are easy to implement with good power and size properties. The test in Pesaran (2007), the CIPS test, is an extension of the augmented Dickey-Fuller (ADF) test in which the standard ADF test is augmented with first differences of individual series and cross sectional averages of lagged levels. The test proposed in Demetrescu et al. (2006), the DHT test, is based on combining the p-values obtained from a Dickey-Fuller test performed on individual panels. This test is similar to those in Maddala and Wu (1999) and Choi (2001), except that the DHT test uses the modified inverse normal method of Hartung (1999) that is robust to dependence among cross sections.

For the CIPS test, we fit the following cross-sectionally augmented Dickey-Fuller regression:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it} \tag{1}$$

where y_{it} is the observation of the ith country at time t, Δ is the first difference operator, $\bar{y}_{t-1}$ is the first lag of the dependent variable averaged over all panels, and $\Delta \bar{y}_t$ is the first difference of the average. a_i, b_i, c_i, d_i are parameters and e_{it} is the idiosyncratic error. Under the unit root null hypothesis, there is $b_i = 0$ for all i. The alternative hypothesis corresponds to some panels being stationary.

For the DHT test, we fit the following panel version of the augmented Dickey-Fuller test:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + e_{it} \tag{2}$$

where the null hypothesis of unit root is $b_i = 0$ for all i and the alternative hypothesis corresponds to all panels being stationary. The individual Dickey-Fuller p-values are combined to obtain the resulting p-value for the panel unit root test.

To determine the order of integration, we test both the levels and the first differences of the variables. All variables are transformed into logarithms before testing. Table 3 presents the test results applied to the levels of the variables. For all variables (except agricultural energy intensity), the null hypothesis is a random walk with a possible drift, with the alternative hypothesis being stationary around a linear time trend. For agricultural energy intensity, because there was no clear time trend in the series, we test the null hypothesis of a random walk against the alternative of stationary with no time trend. We fail to reject the null hypothesis of a random walk with a possible drift in almost all series. In some cases, we get mixed evidence of nonstationarity when one test rejects the null hypothesis while the other one fails to do so.

Table 4 reports test results applied to the first difference of all variables. We find that both tests reject the null hypothesis of a random walk with a possible drift in the first difference of the variables. The unit root tests provide evidence that all variables are integrated with order one.

3.2 Panel Cointegration Test

Having established the nonstationarity of all variables in the previous section, we now test whether the variables are cointegrated. Specifically, we are interested in testing whether aggregate and sector-level energy intensity are cointegrated with economic growth after controlling for energy price. The existence of cointegration implies Granger causality.

We use the residual-based tests developed by Pedroni (1999, 2004) to test for panel cointegration that allows for a heteregenous cointegrating vector. The null hypothesis is that there is no cointegration among the variables in the individual panels. The alternative hypothesis is that either the variables are cointegrated in all panels with a common autoregressive parameter or the variables are cointegrated in all panels with a country-specific autoregressive parameter. The later case allows for additional heterogeneity among panels.

We consider the following regression for the test:

$$intensity_{it} = \alpha_i + \delta_i t + \beta_{1i} gdp_{it} + \beta_{2i} price_{it} + \epsilon_{it} \tag{3}$$

where subscript i denotes country and t denotes year. α_i is the individual-specific intercepts or fixed-effects, δ_i is the coefficient on the time trend t, β_{1i} and β_{2i} are the individual slope coefficients. $intensity_{it}$ is aggregate energy intensity and the energy intensity of industry and agriculture. gdp_{it} is the GDP, and $price_{it}$ is energy price. Pedroni (2004) provides two sets of statistics: within-dimension or panel cointegration statistics and between-dimension or group mean panel cointegration statistics. These test statistics differ in how they pool information across panels. In both cases, the residual-based cointegration test involves fitting the following regression of the estimated residuals:

$$\hat{\epsilon}_{it} = \gamma_i \hat{\epsilon}_{it-1} + u_{it} \tag{4}$$

where $\hat{\epsilon}_{it}$ is the estimated residuals after fitting the model in (3).

The within-dimension statistics are constructed by pooling the autoregressive coefficient in (4) across different countries. The null hypothesis in this case is $H_0 : \gamma_i = 1$ whereas the alternative hypothesis is $H_a : \gamma_i = \gamma < 1$. The rejection of the null hypothesis of no cointegration then implies that the variables in all panels are cointegrated with a common autoregressive parameter. The null hypothesis for the between-dimension statistics is the same as that of the within-dimension. However, it differs in the alternative hypothesis which assume country-specific autoregressive parameter given by $H_a : \gamma_i < 1$. The rejection of the null hypothesis in this case implies that the variables in all panels are cointegrated with a country-specific autoregressive parameter. Pedroni (1999) provides seven test statistics for testing cointegration among the variables in a panel setting. The first four are the within-dimension statistics: Panel ν, Panel ρ, Panel t (PP), and Panel t(ADF), where PP and ADF are test statistics of the Phillips-Perron and augmented Dickey Fuller type. The last three statistics are the between-dimension statistics: Group ρ, Group t(PP), and Group t(ADF). We apply these tests to the regression in (3).

Table 5 reports the results of cointegration tests for each of the three country income groups. Almost all test statistics indicate cointegration between different measures of energy intensity and economic growth for high- and upper-middle-income countries, while all do so for lower-middle-income countries.

3.3 Estimation of Long-Run Parameters

The existence of cointegration implies a causal relationship between GDP and energy intensity, but it does not indicate the direction of the causality. Before we proceed with Granger causality tests, we first estimate the parameters of the long-run relationship described in equation (3) using dynamic ordinary least squares (DOLS) to establish the sign of the correlation between GDP, energy intensity, and energy price. The DOLS estimator for univariate time series was proposed in Saikkonen (1991) and Stock and Watson (1993) and extended to a panel setting by Kao and Chiang (2000) and Mark and Sul (2003). Using Monte Carlo simulation, Kao and Chiang (2000) and Wagner and Hlouskova (2010) show that this estimator performs better than the nonparametric fully-modified ordinary least squares estimator in finite samples. Similar to the single-equation DOLS, the panel version adds leads and lags of the regressors to correct for endogeneity of the regressors and serial correlation in the residuals.

Table 6 reports the estimation results. These results show that for all income groups, GDP growth and a higher energy price are correlated with lower aggregate energy intensity. The income elasticity is -0.37 for high-income countries, -0.22 for upper-middle-income countries, and -0.36 for lower-middle-income ones. The price elasticity is -0.10 for high-income countries, -0.02 upper-middle-income countries, and -0.18 for lower-middle-income countries. However, the price effect is not statistically significant for upper-middle-income countries.

Results at the sector level are similar. GDP growth is correlated with a decrease in both industrial and agricultural energy intensity for all income groups. The effect is especially large for agricultural energy intensity in high-income countries, with a 1 percent increase in GDP associated with a 1.20 percent decline in this measure. In general, income elasticity of high-income countries is larger that of middle-income countries. For industrial energy intensity, it is -0.67 for high-income countries, and between -0.14 and -0.50 for middle-income countries.

A higher energy price is associated with lower industrial and agricultural energy intensity for all income groups. Interestingly, sectoral energy intensity is more responsive to energy price changes in middle-income countries than it is in high-income countries. The price elasticity of industrial energy intensity ranges from -0.03 for high-income countries to -0.29 for upper-middle-income countries, and -0.27 for lower-middle-income countries. There is no statistically significant correlation between energy price and agricultural energy intensity in high-income countries. In middle-income countries, the price elasticity ranges from -0.13 in upper-middle-income countries to -0.06 in lower-middle-income countries.

3.4 Granger Causality Tests

In this section, we test for Granger causality using a vector error correction model (VECM). The VEC term represents any deviation from the long-run equilibrium between GDP, energy price and energy intensity described above. Adopting the Engle-Granger method, we use the first lags of the residuals as a proxy for long-run deviations in a VECM. Specifically, we consider the following multivariate panel VECM with the first difference of intensity, GDP, and energy prices as the dependent variables:

$$\Delta intensity_{it} = \theta_{1i} + \sum_{l=1}^{p} \theta_{11,l}\ \Delta gdp_{it-l} + \sum_{l=1}^{p} \theta_{12,l}\ \Delta price_{it-l} + \gamma_1\ \hat{\epsilon}_{it-1} + \nu_{it,1} \tag{5}$$

$$\Delta gdp_{it} = \theta_{2i} + \sum_{l=1}^{p} \theta_{21,l}\ \Delta intensity_{it-l} + \sum_{l=1}^{p} \theta_{22,l}\ \Delta price_{it-l} + \gamma_2\ \hat{\epsilon}_{it-1} + \nu_{it,2} \tag{6}$$

$$\Delta price_{it} = \theta_{3i} + \sum_{l=1}^{p} \theta_{31,l}\ \Delta intensity_{it-l} + \sum_{l=1}^{p} \theta_{32,l}\ \Delta gdp_{it-l} + \gamma_3\ \hat{\epsilon}_{it-1} + \nu_{it,3} \tag{7}$$

where Δ is the first difference operator, θ_{ki} for $k = 1, 2, 3$ are country-specific fixed effects, and $\theta_{kk,l}$ are the coefficients corresponding to the lth lag of the endogenous variables. γ_k are the coefficients of the error correction terms and $\nu_{it,k}$ are idiosyncratic errors.

Because all variables are nonstationary I(1), we take first differences to make the system of equations (5)-(7) stable. However, using lagged differences of the dependent variable in this system introduces a bias, and a standard fixed-effects estimator would be inconsistent (Arellano and Bond, 1991). To obtain consistent estimators, we estimate panel GMM proposed by Holtz-Eakin et al. (1988); Arellano and Bond (1991). The panel GMM estimator uses further lagged differences of the dependent variable as instruments to remove endogeneity arising from lagged regressors. In our application, we use second and third lags of the dependent variables as instruments.

A VECM allows testing for both short- and long-run causality. In the system of equations (5)-(7), the coefficients $\theta_{kk,l}$ represent the short-run effect of the endogenous variables. A standard Wald test on these coefficients can be used to test for short-run Granger causality. Specifically, we test the null hypothesis $H_0 : \theta_{kk,l} = 0$ for $l = 1, \ldots, p$. In equation (5), rejecting the null hypothesis $\theta_{11,1} = 0$ implies that GDP growth Granger-causes change in energy intensity in the short run. In other words, the first lag of the GDP growth is a significant predictor of changes in energy intensity. Similarly, rejecting the null hypothesis $H_0 : \theta_{21,1} = 0$ in equation(6) implies that GDP is responding to short-term shocks to energy intensity. The joint significance of the coefficients $\theta_{11,1}$ and $\theta_{21,1}$ implies bidirectional causality in which the two variables Granger-cause each other in the short run, while the rejection of only one of the hypotheses implies unidirectional causality.

We can test for long-run Granger causality between variables in our model by examining the significance of the coefficient γ_k, which represents the speed of adjustment to the long-run equilibrium in response to any shocks to the system. We test the null hypothesis $H_0 : \gamma_k = 0$ for $k = 1, \ldots, 3$. The rejection of the null hypothesis implies long-run Granger causality running from the error- correcting term to the respective dependent variable. For example, the significance of γ_1 in equation (5) implies that changes in energy intensity adjust in the long run to any temporary deviations from economic growth. Similarly, the significance of γ_2 in equation (6) implies that changes in energy intensity directly drive economic growth in the long run.

Tables (7)-(9) report the estimated coefficients of the error correction terms and the chi-squared statistics for the test of Granger causality. We find evidence of long-run causality from GDP and energy price to energy intensity for all income groups. For lower-middle-income countries, we also find evidence of long-run causality from energy intensity and energy price to GDP growth. This implies that in these countries, GDP in the long run responds to shocks to energy intensity and energy prices.

In the short run, we find bidirectional causality between aggregate energy intensity and economic growth in high-income countries. We find no Granger causality between energy intensity and economic growth for middle-income countries.

Tables 7-9 show the results of Granger causality tests at the sector level. For all income groups, there is long-run causality from GDP and energy price to industrial energy intensity. We also find Granger causality from industrial energy intensity and energy price to GDP for upper-middle-income countries in the long run, and for high- and lower-middle-income countries in the short run. Finally, there is evidence that GDP and energy price Granger-cause agricultural energy intensity for upper-middle-income countries in the long run.

As noted, an aggregate analysis at the country level may not reflect variation in sectoral composition. As a robustness check to control for the effect of structural change on energy intensity, we include in the system of equations (5)-(7) an additional variable measuring the ratio of industrial and services value added to GDP. The second panel to the right in Tables 7-9 report corresponding long- and short-run Granger causality test results. Our main conclusions on the direction of causality between GDP and energy intensity remain the same under this alternative specification. This is consistent with findings in the literature on the decomposition of energy intensity indicating that most of the gains in energy productivity over the past few decades can be attributed to genuine efficiency improvements while structural change in the mix of economic activities has had less influence (Zhang, 2013).

4 Conclusion

Energy efficiency is recognized as playing an important part in climate change mitigation. However, the long-term relationship between energy efficiency and growth has not been fully understood. Using panel data for 56 countries from 1991 to 2012, this paper presents a first effort to shed light on this question. We employ panel unit root tests, panel cointegration analysis, and a multivariate panel vector autoregression framework to investigate the long- and short-run causal relationship between energy intensity (used as a proxy for energy efficiency) and GDP for a mix of high and middle-income countries. Because changes in energy intensity can be driven by both changes in sectoral composition and improvements in efficiency, we combine macro-level analysis and analysis of the industrial and agricultural sectors to differentiate the effects of these two processes on energy intensity.

Our main results indicate unidirectional long-run causality running from economic growth and higher energy prices to lower energy intensity. This conclusion holds for all income groups and at the sector level. This finding corroborates the intuition that higher energy prices provide incentives for increasing energy efficiency, while economic development and demand growth provide opportunities for achieving efficiency gains by replacing old plants and technologies with new ones.

More interestingly, we find evidence of bidirectional long-run Granger causality between energy intensity and economic growth for middle-income countries, implying a feedback between GDP and energy intensity. This finding suggests that encouraging energy efficiency could support higher economic growth in the long run. Thus beyond climate benefits, energy efficiency could also provide long-term economic growth benefits.

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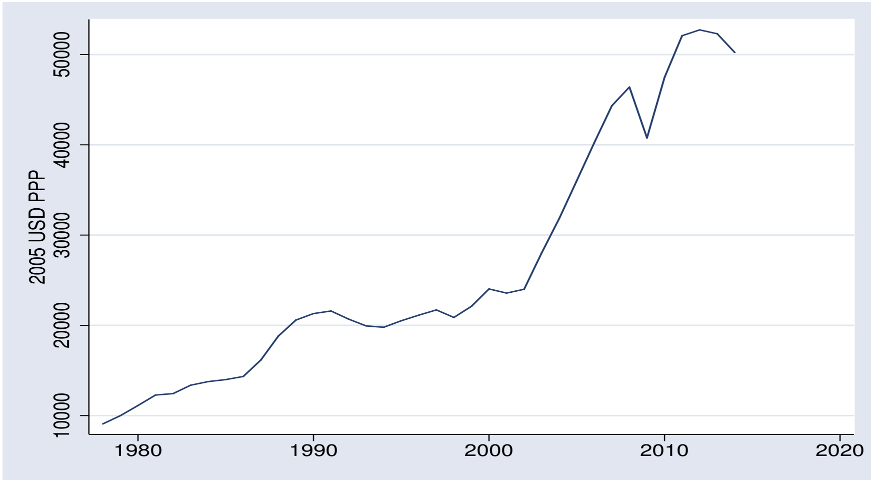
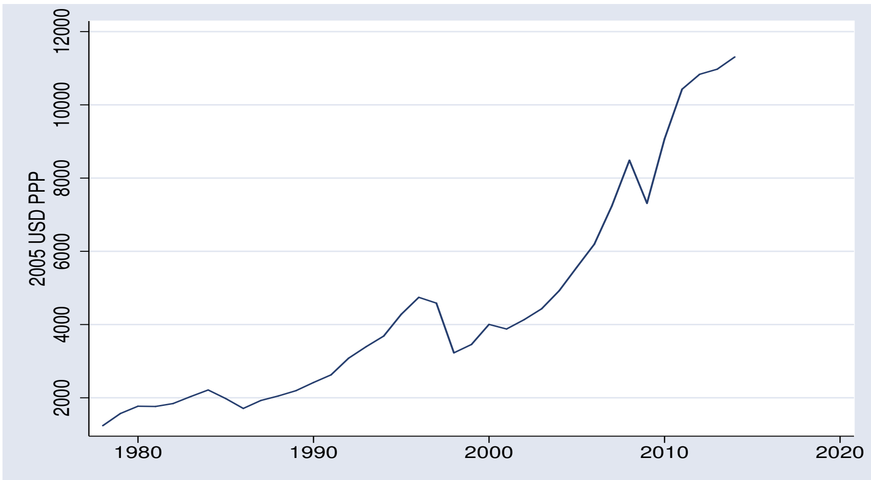
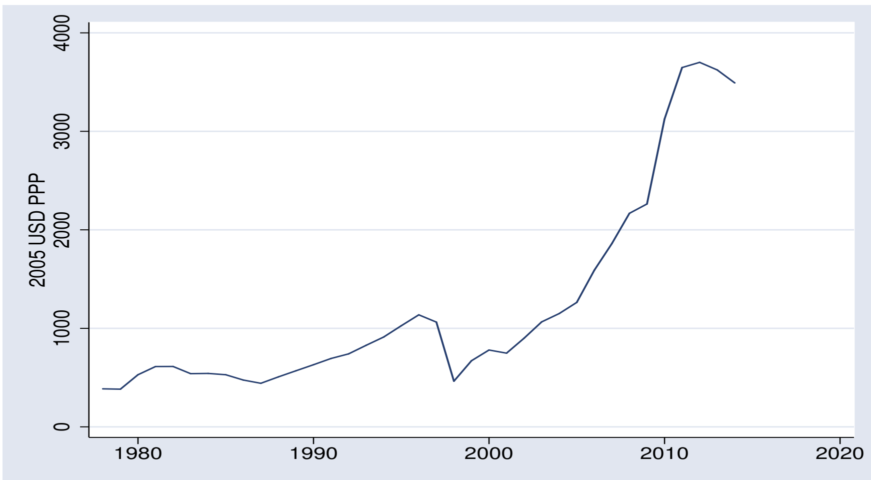


(a) High income

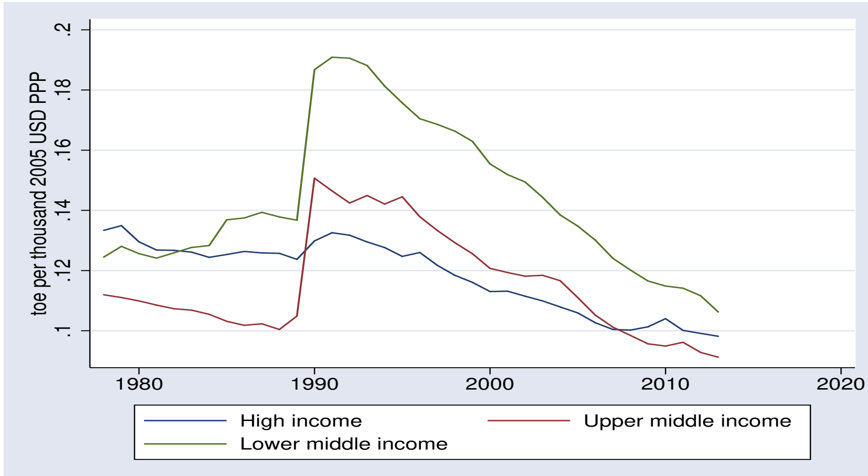


(b) Upper middle income

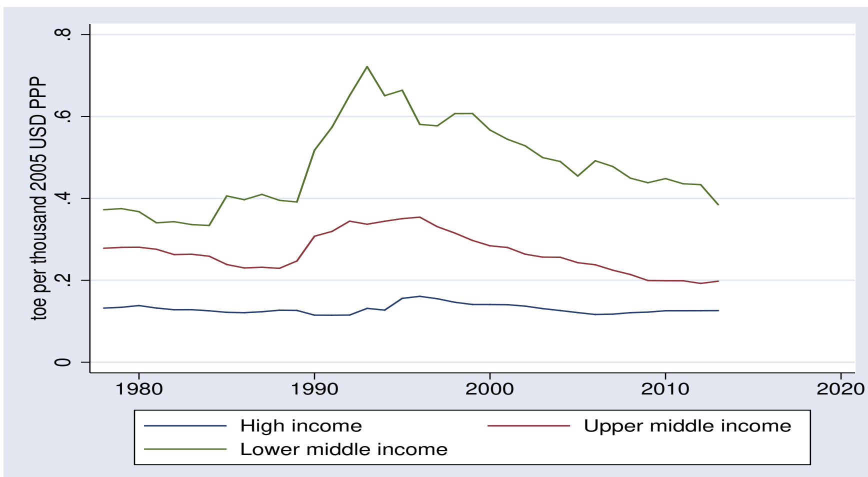


(c) Lower middle income

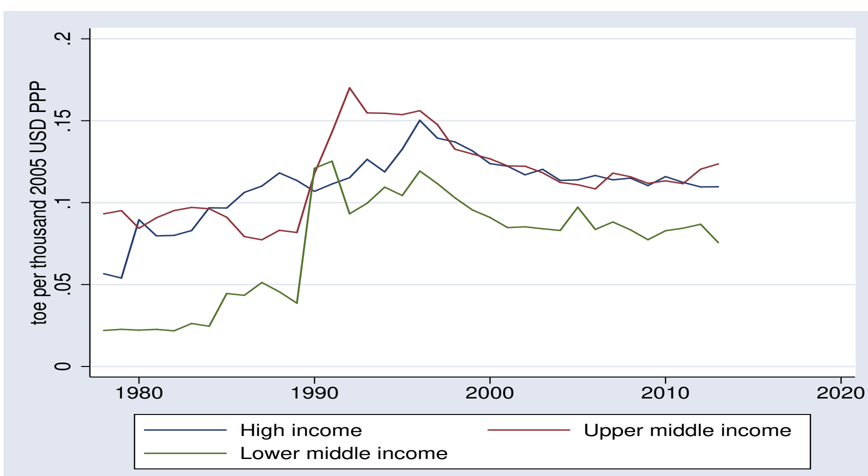
Figure 1: Average per capita GDP



(a) Aggregate energy intensity

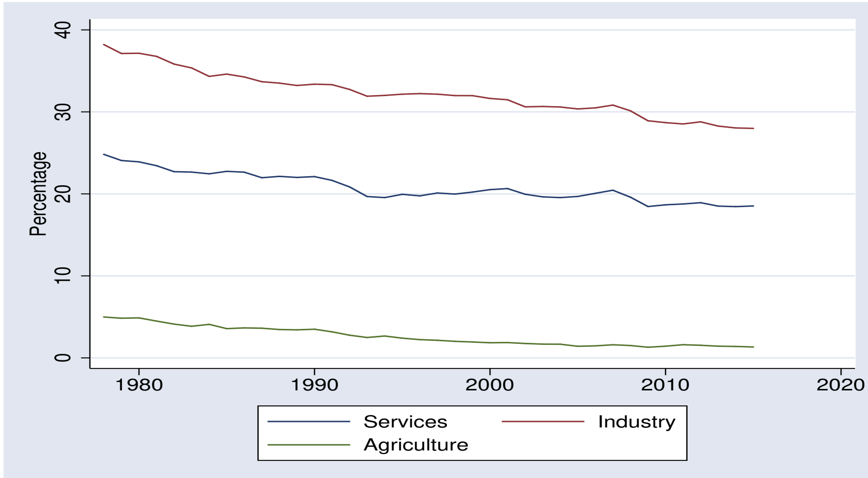


(b) Industrial energy intensity

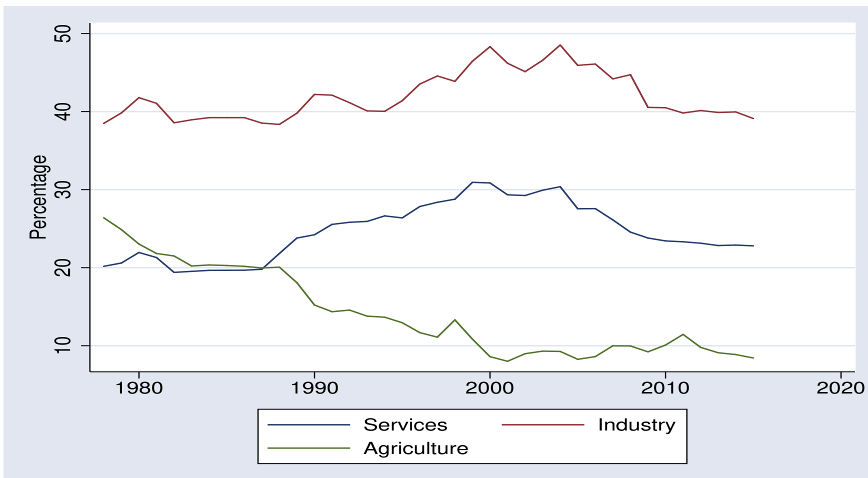


(c) Agricultural energy intensity

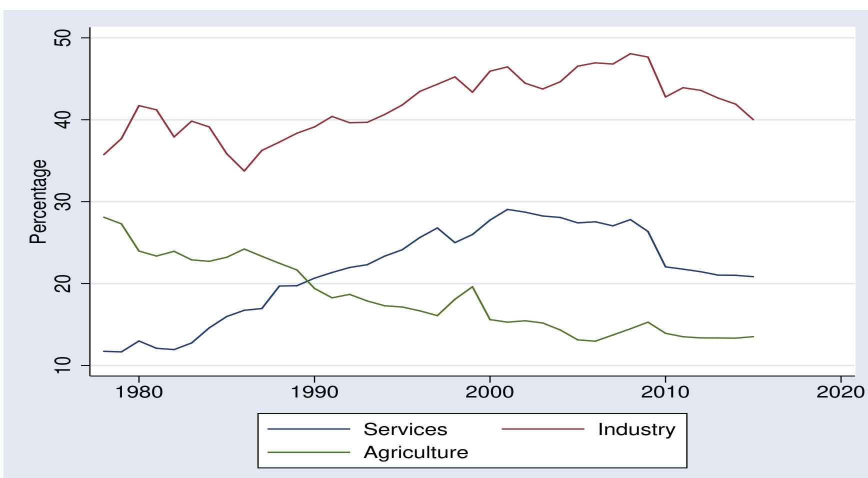
Figure 2: Average aggregate and sectoral energy intensities



(a) High income



(b) Upper middle income



(c) Lower middle income

Figure 3: Average sectoral value added shares

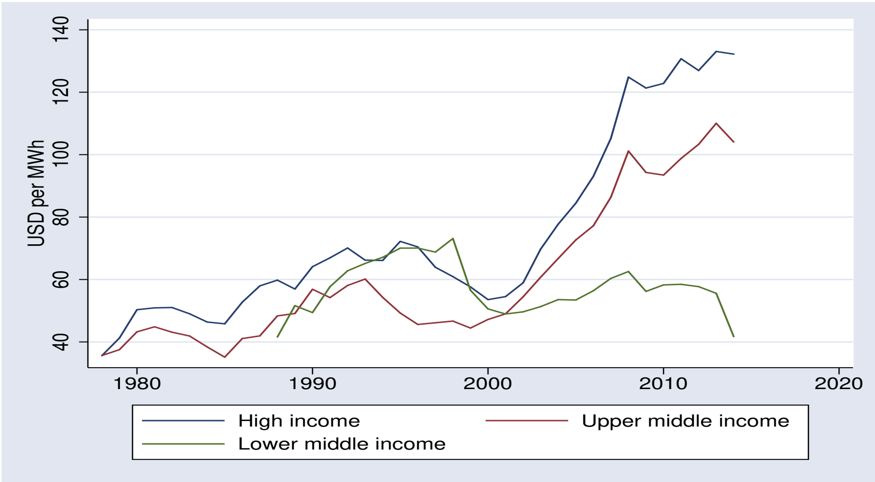


Figure 4: Average energy prices

Table 1: List of countries

	Aggregate energy intensity
High income	Australia, Austria†, Belgium†, Canada, Chile, Croatia, Cyprus†, Czech Republic, Denmark, Estonia, Finland†, France, Germany, Greece†, Hong Kong, Ireland, Israel, Italy, Japan, Korea, Luxembourg†, Netherlands†, New Zealand, Norway†, Poland, Portugal, Russia, Singapore, Slovak Republic, Slovenia, Spain, Sweden†, Switzerland, United Kingdom, United States
Upper middle income	Albania, Bosnia and Herzegovina, Brazil, Bulgaria, Hungary, Jordan, Kazakhstan, Macedonia†, Malaysia, Mexico, Romania†, Serbia, South Africa, Thailand, Turkey, Venezuela
Lower middle income	Armenia, Georgia, India, Indonesia, Moldova, Mongolia†, Ukraine
	Industrial energy intensity
High income	Australia, Austria†, Belgium†, Canada, Chile, Croatia, Cyprus†, Czech Republic, Denmark, Estonia, Finland†, France, Germany, Greece†, Hong Kong, Ireland, Israel, Italy, Japan, Korea, Luxembourg†, Netherlands†, New Zealand, Norway†, Poland, Portugal, Russia, Singapore, Slovak Republic, Slovenia, Spain, Sweden†, Switzerland, United Kingdom, United States
Upper middle income	Albania, Brazil, Bulgaria, Hungary, Jordan, Kazakhstan, Macedonia†, Malaysia, Mexico, Romania†, Serbia, South Africa, Thailand, Turkey, Venezuela
Lower middle income	Armenia, Georgia, India, Indonesia, Moldova, Mongolia†, Ukraine
	Agricultural energy intensity
High income	Australia, Austria†, Belgium†, Canada, Chile, Croatia, Cyprus†, Czech Republic, Denmark, Estonia, Finland†, France, Germany, Greece†, Hong Kong, Ireland, Israel, Italy, Japan, Korea, Luxembourg†, Netherlands†, New Zealand, Norway†, Poland, Portugal, Russia, Slovak Republic, Slovenia, Spain, Sweden†, Switzerland, United Kingdom, United States
Upper middle income	Albania, Bosnia and Herzegovina, Brazil, Bulgaria, Hungary, Jordan, Kazakhstan, Macedonia†, Malaysia, Mexico, Romania†, Serbia, South Africa, Thailand, Turkey, Venezuela
Lower middle income	Armenia, Georgia, India, Indonesia, Moldova, Mongolia†, Ukraine

Note: † denotes countries for which gaps in energy price observations are linearly interpolated using Consumer Price Index for multiple years.

Table 2: Summary statistics

GDP	Mean	Std. Dev.	Min	Max	No. of Obs.
High income	22476.39	17834.08	1330.75	116664.3	1269
Upper middle income	4036.65	3053.55	218.49	15,649.72	503
Lower middle income	1060.31	955.16	97.16	4387.70	340
Aggregate energy intensity	**Mean**	**Std. Dev.**	**Min**	**Max**	**No. of Obs.**
High income	0.12	0.06	0.005	0.404	2104
Upper middle income	0.11	0.08	0.006	0.52	1378
Lower middle income	0.14	0.10	0.036	0.75	1095
Industrial energy intensity	**Mean**	**Std. Dev.**	**Min**	**Max**	**No. of Obs.**
High income	0.13	0.07	0.01	0.52	1106
Upper middle income	0.27	0.24	0.004	1.70	1173
Lower middle income	0.48	0.57	0.002	4.76	915
Agricultural energy intensity	**Mean**	**Std. Dev.**	**Min**	**Max**	**No. of Obs.**
High income	0.11	0.10	0.0003	0.75	1106
Upper middle income	0.11	0.14	0.0001	1.27	1181
Lower middle income	0.07	0.15	0.00007	1.16	915
Energy price	**Mean**	**Std. Dev.**	**Min**	**Max**	**No. of Obs.**
High income	75.86	11.64	42.17	327.78	1056
Upper middle income	64.88	33.25	12.22	169.64	309
Lower middle income	56.47	24.87	7.36	166.71	154

Note: The unit of per capita GDP is 2005 USD PPP. The unit of aggregate and sectoral energy intensities is toe per thousand 2005 USD PPP. The unit of energy price is USD per MWh.

Table 3: Panel unit root tests in levels

			CIPS		
Income group	GDP	Aggregate	Industry	Agriculture	Price
High income	-1.70	-2.31	-2.15	-1.94 (rw)	-2.92^{***}
No. of Obs.	1645	1615	903	856	1050
Upper middle income	-2.52	-2.44	-2.37	-2.14 (rw)	-2.77^{**}
No. of Obs.	570	562	463	443	309
Lower middle income	-2.39	-2.65	-2.90^{**}	-2.08	-1.83
No. of Obs.	211	211	210	210	132
			DHT		
High income	5.53	2.03	3.20	-0.19 (rw)	3.12
Upper middle income	0.55	1.19	0.62	-0.92 (rw)	1.16
Lower middle income	-0.87	0.96	0.30	-0.38	1.13

Note: ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively. (rw) indicates a null hypothesis of random walk. In all other cases, the null hypothesis is a random walk with a drift. Number of observations for DHT test are the same as reported for the CIPS test.

Table 4: Panel unit root tests in first differences

			CIPS		
Income group	Δ GDP	Δ Aggregate	Δ Industry	ΔAgriculture	Δ Price
High income	-5.35^{***}	-7.22^{***}	-5.25^{***}	-5.43^{***}	-5.11^{***}
Upper middle income	-4.84^{***}	-5.99^{***}	-5.90^{***}	-6.33^{***}	-4.11^{***}
Lower middle income	-4.66^{***}	-5.52^{***}	-5.55^{***}	-4.85^{***}	-3.10^{***}
			DHT		
High income	-16.46^{***}	-24.92^{***}	-17.78^{***}	-21.08^{***}	-13.43^{***}
Upper middle income	-9.82^{***}	-17.50^{***}	-16.45^{***}	-20.44^{***}	-7.14^{***}
Lower middle income	-6.33^{***}	-11.04^{***}	-11.38^{***}	-11.96^{***}	-1.47^{***}

Note: ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively. Number of observations are the same as reported in Table 3.

Table 5: Panel cointegration test

	High income		
Test statistic	Aggregate	Industry	Agriculture
Panel ν	-4.16^{***}	-1.09	3.61^{***}
Panel ρ	-2.17^{**}	-2.05^{**}	-24.74^{***}
Panel t - PP	5.45^{***}	2.95^{***}	-2.89^{***}
Panel t - ADF	1.73^{*}	0.97	-2.70^{***}
Group ρ	-50.20^{***}	-68.37^{***}	-149.56^{***}
Group t - PP	-2.64^{***}	-5.80^{***}	-14.14^{***}
Group t - ADF	-0.76	-2.66^{***}	-4.60^{***}
	Upper middle income		
Test statistic	Aggregate†	Industry	Agriculture
Panel ν	2.95^{***}	5.55^{***}	7.48^{***}
Panel ρ	-3.74^{***}	-2.94^{***}	-15.27^{***}
Panel t - PP	-1.77^{*}	0.56	-3.87^{***}
Panel t - ADF	-0.83	1.27	-2.81^{***}
Group ρ	-10.79^{***}	-7.22^{***}	-28.74^{***}
Group t - PP	-3.13^{***}	-0.86	-8.03^{***}
Group t - ADF	-2.17^{**}	-0.27	-7.13^{***}
	Lower middle income		
Test statistic	Aggregate	Industry	Agriculture
Panel ν	-1.30	-1.54	-0.29
Panel ρ	1.66^{*}	0.02	-3.64^{***}
Panel t - PP	2.75^{***}	0.85	-3.08^{***}
Panel t - ADF	2.84^{***}	3.84^{***}	-1.88^{*}
Group ρ	1.97^{**}	1.04	-4.08^{***}
Group t - PP	1.82^{*}	1.24	-3.10^{***}
Group t - ADF	1.51	3.11^{***}	-2.67^{***}

Note: ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively. † denotes no deterministic terms and ‡ denotes a constant and a trend term.

Table 6: Estimation of long-run cointegration parameters

	High income		Upper middle income		Lower middle income	
Intensity	GDP	Price	GDP	Price	GDP	Price
Aggregate	-0.37^{***}	-0.10^{***}	-0.22^{***}	-0.02	-0.36^{***}	-0.18^{***}
Industry	-0.67^{***}	-0.03^{*}	-0.14^{***}	-0.29^{***}	-0.50^{***}	-0.27^{**}
Agriculture	-1.20^{***}	-0.04	-0.16^{***}	-0.13^{***}	-0.16^{***}	-0.06^{*}

Note: ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

Table 7: Granger causality - Aggregate energy intensity

Income group	Without control for structure			With control for structure		
	GDP/Price ↓ Aggregate	Aggregate/Price ↓ GDP	GDP/Energy ↓ Price	GDP/Price ↓ Aggregate	Aggregate/Price ↓ GDP	GDP/Aggregate ↓ Price
Long run						
High income	-1.19^{***}	0.31^{**}	0.61	-1.05^{***}	0.12	0.15
	(0.28)	(0.15)	(0.65)	(0.21)	(0.11)	(0.67)
Upper middle income	-1.33^{***}	-0.01	0.31	-1.31^{***}	-0.13	-0.36
	(0.28)	(0.21)	(0.92)	(0.28)	(0.19)	(0.77)
Lower middle income	-0.88^{***}	-0.97^{**}	-3.30^{**}	-0.87^{***}	-0.65	-2.73^{*}
	(0.31)	(0.47)	(1.56)	(0.31)	(0.44)	(1.44)
Short run†						
High income	7.74^{**}	15.79^{***}	1.45	9.38^{***}	4.23	3.03
Upper middle income	0.42	0.35	0.40	0.31	0.19	0.52
Lower middle income	1.18	0.09	1.01	0.59	1.28	3.83

Note: ↓ denotes direction of Granger causality. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.
† represents the chi squared statistic for the test of Granger causality. Standard errors are reported in parentheses.

Table 8: Granger causality - Industrial energy intensity

Income group	Without control for structure			With control for structure		
	GDP/Price ↓ Industry	Industry/Price ↓ GDP	GDP/Industry ↓ Price	GDP/Price ↓ Industry	Industry/Price ↓ GDP	GDP/Industry ↓ P
Long run						
High income	-1.70***	-0.01	0.66	-1.57***	0.04	0.75
	(0.34)	(0.11)	(0.54)	(0.33)	(0.10)	(0.57)
Upper middle income	−1.40***	−0.17**	−1.17***	−1.32***	−0.15**	−1.17***
	(0.19)	(0.08)	(0.43)	(0.22)	(0.08)	(0.45)
Lower middle income	-1.52***	−0.07	−0.64	−1.57***	−0.05	−0.23
	(0.25)	(0.09)	(0.27)	(0.27)	(0.10)	(0.39)
Short run†						
High income	4.64*	16.42***	3.36	2.44	3.46	1.43
Upper middle income	1.49	0.04	1.13	0.15	0.30	0.26
Lower middle income	6.11**	0.35	2.33	8.00**	1.00	5.42*

Note: ↓ denotes direction of Granger causality. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively. † represents the chi squared statistic for the test of Granger causality. Standard errors are reported in parentheses.

Table 9: Granger causality - Agricultural energy intensity

Income group	Without control for structure			With control for structure		
	GDP/Price ↓ Agriculture	Agriculture/Price ↓ GDP	GDP/Agriculture ↓ Price	GDP/Price ↓ Agriculture	Agriculture/Price ↓ GDP	GDP/Agriculture ↓ Price
Long run						
High income	-0.65^{***}	-0.03	0.05	-0.62^{***}	-0.03	-0.002
	(0.24)	(0.02)	(0.14)	(0.26)	(0.02)	(0.14)
Upper middle income	-1.87^{***}	-0.02	-0.12	-1.68^{***}	-0.05	-0.22
	(0.53)	(0.04)	(0.20)	(0.54)	(0.05)	(0.25)
Lower middle income	-1.47^{***}	0.05	-0.27	-1.32^{***}	-0.09	-0.0004
	(0.12)	(0.03)	(0.17)	(0.13)	(0.10)	(0.24)
Short run†						
High income	2.72	7.10^{**}	3.36	1.00	2.15	0.28
Upper middle income	0.79	3.91	0.37	1.51	4.79^{*}	0.04
Lower middle income	12.70^{***}	2.12	19.65^{***}	22.42^{***}	3.19	4.37

Note: ↓ denotes direction of Granger causality. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively. † The values represent the chi squared statistic for the test of Granger causality. Standard errors are reported in parentheses.

Appendix

Table A1: Linear interpolation for energy price

Country	Years
Austria	2001-2003; 2009-2011
Belgium	2001-2007
Cyprus	2007
Finland	2006
Greece	2006-2007
Luxembourg	1990-2007
Netherlands	2002-2006
Norway	1992 - 1999
Sweden	1998 - 2006
Macedonia	2000 - 2003
Romania	2006 - 2007
Mongolia	2000 - 2002