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Does energy price affect energy efficiency? Cross-country panel evidence

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Abstract

In this paper, we analyze the relationship between energy intensity and energy price in a panel of 120 countries over 34 years, from 1980 to 2013. We use information on energy intensity and real oil price, and merge it with macroeconomic data on the countries’ structural characteristics. We assess their direction of causality using fixed effects, dynamic panel data models and Granger causality tests. We identify a statistically significant, but weak negative effect of real oil price on energy intensity, which corresponds to a positive effect of energy price on energy efficiency. We also show significant, large regional differences in this relationship. We thus posit that a global policy aimed at increasing the price of oil would induce a limited increase in average energy efficiency through a more efficient use of energy, but this increase would differ considerably across regions around the world.

Keywords: energy price, energy efficiency, real oil price, panel data

JEL: Q41, Q43, Q55

1. Introduction

The intensity of energy production, or simply energy intensity, measures the average amount of energy used for the economic activities of a country, and is typically expressed as the ratio of total primary energy consumption per unit of GDP. It is a summary indicator of energy usage, often calculated when disaggregating the components of some energy-output relationship. It is used, for instance, in the Kaya identity (Kaya 1990) to disaggregate the determinants of CO_2 emission into carbon intensity (amount of CO_2 per unit of energy), energy intensity (energy consumption per unit of GDP), per capita GDP and population.

Throughout history, or since the Industrial Revolution at least, the aggregate energy intensity has been decreasing (Stern 2011, and references therein). Nakicenovic and Swart (2000) show that, since 1970, it has been declining at the worldwide aggregate level, while per capita GDP has risen, the population has grown, and carbon intensity has remained constant. Different pictures emerge, however, when we disaggregate by country, geographical region or level of economic wealth. For instance, International Energy Agency (IEA) statistics[1] show that there was a decline in energy intensity from 1990 to 2015 for OECD countries, a fairly stable trend for Latin America and Asia, and a U-shaped curve for countries in non-OECD Europe and Eurasia (including the former Soviet Union).

Energy intensity changes over time depend on a country's ecological, social and environmental context. To assess the determinants of change in energy intensity we should therefore consider several elements affecting energy efficiency (broadly defined as the amount of work enabled by a unit of energy), such as the country's economic structure, size, climate and currency exchange rate (IEA 2014). There is plenty of literature on the determinants of energy intensity. Energy is a key input in the production function. A rise in the price of energy should induce its more parsimonious use by raising energy efficiency (Birol and Keppler 2000). The *ceteris paribus* assumption of such a

[1] Source: http://www.iea.org/statistics/statisticssearch/

reasoning is crucial, however, because both country-specific and global effects can limit flexibility in the substitution of energy in the production functions. Some scholars have tackled the issue of estimating the determinants of energy efficiency econometrically at country level (or for limited groups of countries) by including energy prices in the explanatory variables (Gamtessa and Olani 2016; Adom 2015; Mulder and De Groot 2012; Wu 2012; Huntington 2010; Wing 2008; Hang and Tu 2007; Fisher-Vanden et al. 2004; Sanstad et al. 2006). Hardly any attempts have been made, however, to assess the relationship between energy intensity and energy price, both across countries and across time, in a sufficiently large longitudinal dataset. This is our research framework. We investigate to what extent a rise in the price of energy has influenced energy intensity across countries, controlling for a series of country-specific characteristics.

In producing output, countries can use several types of energy source and different carriers. In this work, we consider the cost of energy as a determinant of energy intensity by constructing a measure of a country's domestic oil price. More precisely, we calculate this oil price - for each country, and as a yearly average - taking Brent for reference and multiplying it by each country's (average yearly) currency exchange rate. We use Brent as a reference price for oil because it is the type of oil with the largest market share. Similarly, we consider the price of oil as a proxy for the price of energy, given its importance in the fuel vectors. We are well aware that oil is not the only relevant energy input in production, but it is still the most important primary energy source in the energy input-output relationship (35% of primary energy input, 40% of total final consumption worldwide)[2]. Oil prices are also coupled with those of natural gas, either at contractual level or because of longstanding economic relationships[3]. The price of oil can therefore also be taken as a

[2] Source: our elaborations from IEA (http://www.iea.org/Sankey) for 2015.

[3] There is increasing evidence of oil and natural gas prices becoming uncoupled in the US since the boom in shale gas production early in 2010 (Caporin and Fontini, 2017), while they remain coupled in many other parts of the world (see Zhang and Ji 2018, and references therein). While it may be that their prices are no longer coupled nowadays, this would be scarcely relevant for our dataset, which spans the years from 1980 to 2013.

proxy for the price of natural gas (and, together, oil and natural gas account for 56% of total fuel consumption)[4]. To take the different energy sources used in production into account, we control for the relative composition of countries' fuel vectors. As a proxy for this, we use the relative share of CO_2 emissions over total fuel emissions. This is an indirect, but fair measure of the relative importance of oil in a country's economy. Indeed, emissions can change over time if inputs are reduced, or due to a more efficient energy conversion. So, by using emissions rather than oil composition, we can control both for changes in the relative use of oil and for technological improvements in the fuel conversion rate.

Energy intensity can be influenced by other elements, such as global economic trends, a country's growth and changes in its GDP, demographics, and climate patterns. We consider these factors in our analysis. In particular, we adopt a methodological strategy that controls for them by building a panel of 120 countries observed over a period of 34 years (1980 to 2013), and including regional and time specific effects. The analysis is conducted on both a global and a regional level, separating the full panel into 19 geographical regions.

We also take into account the influence of the degree of economic development on energy intensity. To do so, we include per capita GDP and check whether its relationship with energy intensity is nonlinear. In particular, the presence of a U-shaped relationship would support applying the Environmental Kuznets Curve hypothesis to the relationship between energy usage and economic growth (Deichmann et al. 2018; Luzzati and Orsini 2009; van Benthem and Romani 2009; van Benthem 2015). We also control for population density, for the adoption of a common currency, and for a country being a net oil exporter. The purpose of including this last variable is to see whether oil-exporting countries have lower opportunity costs of using oil as energy input, and whether this affects their energy efficiency.

[4] Source: our elaboration from IEA (http://www.iea.org/Sankey) for 2015.

Finally, there is a potential endogeneity issue when relating energy price to energy intensity. On the one hand, any unobserved country-specific attributes may affect energy intensity, regardless of energy price. On the other, reverse causality can occur if energy intensity and energy price are determined jointly. When considering energy as an input in the production function, its price should be considered as a determinant of energy intensity but, because energy inputs are traded in the market, changes in energy intensity could affect energy prices by prompting changes in energy demand. We address these issues using panel fixed effects, dynamic panel modeling techniques, and Granger causality tests.

The paper is arranged as follows: Section 2 presents the data and the variables used in the estimates; Section 3 illustrates the methodological approach; the results are presented and discussed in Section 4; and Section 5 concludes and suggests some policy implications. All the technical details are provided in the Appendix.

2. Data and variables

The energy intensity data considered here come from the World Energy Statistics and Balances dataset provided by the International Energy Agency (IEA). Our energy intensity (*EI*) indicator is computed as the ratio of total primary energy supply (TPES, in petajoule) to GDP: the higher this ratio, the greater the amount of energy required to generate a unit of GDP, and the lower the energy efficiency.

From the IEA data we also take the yearly amount of CO_2 emissions (*CO2E*) from oil combustion out of the total emissions from fuel combustion. This variable captures the relative importance of oil in a country's fuel mix. We include its (mean-centered) squared term as well, to detect possible non-linear effects.

We merge these data with information on oil prices[5]. Data concern yearly historical crude oil price (Brent), which we adjust for the US real consumer price index (taking the year 2010 for reference). The Brent price does not vary across countries, so we multiply it by a country's yearly average real exchange rate against the US dollar, obtaining an index (P_{OIL}) that reflects the real price that a country pays in dollars to purchase a barrel of crude oil. We mainly expect energy efficiency to increase as the price of oil rises because the latter induces countries to reduce their energy consumption and/or invest in new technologies to produce energy more efficiently.

Figure 1 shows how *EI* and P_{OIL} evolved. We can see that, over the course of more than three decades, an initial period of stagnation (during the 1980s and early 1990s) was followed by a sharp drop in energy intensity while the real price of oil rose rapidly, the sole exception coinciding with the years of the financial crisis, 2007-2009.

FIGURE 1

Looking at how *EI* and P_{OIL} evolved, we also investigate whether energy intensity predictions based on oil price are subject to a structural break, i.e. an unexpected shift in at least one of their time series that can lead to a forecasting error. The test identifies a structural break in 1997 (see Appendix, Table A2), so we run our regressions not only on the whole sample, but also on a subsample covering the years 1997-2013. This latter period is characterized by two significant events: (i) the consolidation of new countries, like those of the former USSR and former Yugoslavia; and (ii) a clear upward trend in real oil price, and a clear downward trend in energy intensity, as shown in Figure 1.

We also include data on real per capita GDP (*GDPPC*) and population density (*POPDEN*) from the World Development Indicators (WDI) provided by the World Bank. Again, to control for potential nonlinear effects we include their (mean-centered) squared terms too. Testing for a nonlinear

[5] Sources: International Energy Agency and Inflationdata.com.

relationship between energy efficiency and per capita GDP involves identifying the Environmental Kuznets Curve, if any: energy efficiency should decline as a country's level of economic development increases, but only up to a certain per capita income threshold, beyond which the relationship becomes positive (Deichmann et al. 2018). We should therefore expect a U-shaped relationship between real per capita GDP and energy intensity.

The WDI also reports yearly information on net energy imports, from which we compute a dummy (*NX*) that equals 1 if the country is a net exporter of oil and natural gas. Oil-exporting countries typically subsidize their internal energy consumption, either directly through oil subsidies, or indirectly by using the oil revenues to subsidize national welfare. A rise in the price of oil can stimulate domestic oil consumption, partly because of the subsidies and partly because of a positive income effect deriving from the country's foreign exchange account. We therefore expect a positive correlation between *NX* and *EI*.

Finally, we compute three additional dummies to check, for each year, whether a country is part of a common currency area. Our oil price indicator P_{OIL} differs across countries because of the real exchange rate, but countries that are part of a currency area are not exposed to this source of volatility. For instance, belonging to a currency area may enable a country to take advantage of lower interest rates, or a lower country risk, and this might reduce the internal energy cost. To account for this, we consider the three largest currency areas and group countries by their adoption of a common currency - dollar (*DOLLAR*), euro (*EURO*), or ruble (*ROUBLE*) - as their main currency. These dummies can vary over time because some countries joined a common currency area (as in the case of the Euro), and others left (like the countries belonging to the former USSR abandoning the rouble) during the period considered.

After merging all these data, we obtain a balanced panel of 120 countries (see Appendix, Table A1) and cover 34 years (from 1980 to 2013), for a total amount of 4,080 observations. Table 1 summarizes all the variables included in the regression analysis, with their descriptive statistics.

TABLE 1 HERE

The correlations among regressors are very weak, thus preventing any potential multicollinearity problems (the only strongly correlated variables are *GDPPC* and *POPDEN*, but transformed into natural logarithms the correlation drops to 0.11; see Appendix, Table A3).

3. Method

We start by estimating the following baseline model:

[1] $lnEI_{it} = \beta_0 + \beta_1 lnPOIL_{it} + \boldsymbol{X'}_{it}\boldsymbol{\beta_2} + u_{it}$

where i is the country, t is the year, and $\boldsymbol{X}$ is a vector including *GDPPC*, *POPDEN*, *CO2E* (all transformed into natural logarithms), *NX, DOLLAR, EURO* and *ROUBLE.* To account for geographical fixed effects, we also include 19 geographical dummies according to the sub-region of the world to which the single countries belong[6]. We choose two model specifications, with and without the squared terms of the independent variables, to take possible nonlinear effects into account. The term θ_t is a year-specific effect, and u_{it} is the stochastic error component that is assumed to be independent of the other regressors.

The analysis is conducted in steps. First, we estimate equation 1 using pooled OLS. To check for any multicollinearity, we provide the mean variance inflation factor (VIF) statistics. As argued in Section 1, we expect β_1 to be negative and statistically significant, meaning that a higher real oil price is related to a lower energy intensity, and therefore to a greater energy efficiency.

[6] These supra-national regions are identified in the United Nation geoscheme, which adopts the M49 standard for area codes. They include: Northern America, Central America, South America, Caribbean, Northern Africa, West Africa, East Africa, Middle Africa, Southern Africa, Central Asia, Eastern Asia, Southern Asia, South-Eastern Asia, Western Asia, Northern Europe, Western Europe, Eastern Europe, Southern Europe, Australia and New Zealand.

There might be heterogeneity going unnoticed in the relationship between *EI* and P_{OIL}, however, due to unobserved features that can affect both energy intensity and some of the explanatory variables, making the latter correlate with the error term and biasing the OLS estimates. Examples of such unobserved characteristics include climatic conditions, transport infrastructure efficiency, and the quantity and quality of oil sources. In a second step, we use country fixed effects (which include country-specific characteristics that do not vary over time) to account for this, and we estimate the following equation:

[2] $lnEI_{it} = \beta_1 lnPOIL_{it} + \boldsymbol{X}'_{it}\beta_2 + \rho_i + \theta_t + \epsilon_{it}$,

where ρ_i is the country-specific time-invariant error component (fixed effect), and ϵ_{it} is the stochastic error.

Then we account for the fact that the energy intensity at time *t* might be determined by its past values, and that both energy intensity and oil price can be determined simultaneously. To account for both persistence and simultaneity, we estimate a linear dynamic panel data model using a system GMM estimator proposed by Arellano and Bover (1995), and Blundell and Bond (1998). The relation that we estimate is as follows:

[3] $lnEI_{it} = \beta_0 lnEI_{it-1} + \beta_1 lnPOIL_{it} + \boldsymbol{X}'_{it}\beta_2 + \rho_i + \theta_t + \epsilon_{it}$,

where $lnEI_{it-1}$ correlates, by construction, with μ_i, making standard OLS estimates inconsistent.

In this kind of model, a system of two equations is estimated, one in first differences and one in levels, the latter including area and time fixed effects. Then instruments are used to establish the moment conditions. We estimate equation 3 following Roodman (2009), keeping the number of instruments as low as possible by decreasing the number of time lags allowed to compute them, or by reducing the number of covariates. In the equation in levels, we thus instrument oil price by the corresponding first difference at time *t*-1, which is assumed not to correlate with $\Delta\varepsilon_{it}$. In the equation in first differences, on the other hand, the instrument we use is the one year lagged value of the oil price. We apply Windmeijer's correction to the variance-covariance matrix as well in order to have heteroscedasticity-robust standard errors. To estimate the system GMM model there needs to be a first-order serial correlation in the first-order residuals, but no second-order serial correlation. We check for this using the Arellano-Bond test for serial correlation in the first-differenced residuals, and we use the Sargan test to check for over-identifying restrictions.

In a fourth step, we run an additional test on the causality in the relationship between energy intensity and real oil price to make the three previous steps more robust. To do so, we use a Granger causality test (Granger, 1969). In this setting, the energy price is expected to Granger-cause a country's energy intensity if, after controlling for its past values, the lagged values of its energy price provide statistically significant information on the future values of its energy intensity. The inference from the standard Granger causality test is unreliable, however, when series are integrated to the first order (Rodriguez-Caballero and Ventosa-Santaulària, 2014). In the presence of a unit root, Toda and Yamamoto (1995) suggest an alternative approach based on an augmented VAR modeling that requires no preliminary cointegration test, and it can be applied regardless of the order of integration of the series. The method works as follows. First, we identify the highest order of cointegration of the two time series (*p*). Then, we identify the optimal number of lags (*m*) using standard information criteria, like the Akaike (AIC), or the Schwartz (SBIC). Third, we estimate an augmented VAR model using as many lags as we identified in the previous step, and we test for the absence of serial autocorrelation using a Lagrange Multiplier (LR) test. If the LR test does not reject the null hypothesis of no autocorrelation of order 1, we increase the number of lags until we find the new optimal number (m') such that the LR test rejects the null hypothesis of no serial autocorrelation. Finally, we estimate two VAR models of order $m'+p$, as follows:

[4a] $lnEI_t = \mu + \sum_{k=1}^{m'+p} \alpha_k lnEI_{t-k} + \sum_{k=1}^{m'+p} \beta_k lnPOIL_{t-k} + \epsilon_t,$

[4b] $lnPOIL_t = \mu + \sum_{k=1}^{m'+p} \gamma_k lnPOIL_{t-k} + \sum_{k=1}^{m'+p} \delta_k lnEI_{t-k} + u_{it}.$

We use a standard Wald test to see whether the estimated coefficients of the first m' lagged values of ln*POIL* in equation 4a (and the first m' lagged values of ln*EI* in equation 4b) are jointly zero, H_0: $\sum_{k=1}^{m'} \beta_k = 0$ (equation 4a), and $\sum_{k=1}^{m'} \delta_k = 0$ (equation 4b).

If the null hypothesis is rejected, we can conclude that the real energy price Granger-causes the energy intensity in equation 4a. If, on the other hand, the null hypothesis is rejected for equation 4b, we conclude that the energy intensity Granger-causes the real energy price.

4. Results

Tables 2, 3, 4, 5 and 6 show the results of our empirical analysis. Table 2 shows the pooled OLS estimates of equation 1 for the whole sample (1980-2013), and for the subsample (1997-2013), based on the structural break test in the Appendix, Table A1.

TABLE 2 HERE

Columns 1 and 3 show the estimates when only the linear terms of the regressors are included, while Columns 2 and 4 include their (mean-centered) linear and squared terms. As expected, in Column 1 the estimated coefficient of ln*POIL* is negative, and statistically highly significant: *ceteris paribus*, a 10% increase in real oil price relates to an average 0.14% decrease in energy intensity. Bearing in mind that the real oil price increased by almost 3000% between 1980 and 2013 (the two extremes of our panel), this coefficient indicates that the corresponding average increase in worldwide energy intensity is 42%.

As for the control variables, we find that per capita GDP correlates negatively with energy intensity: the greater a country's economic wealth, the higher its energy efficiency level (i.e. the lower the *EI*). The results in Column 2 reveal a nonlinear relationship between per capita GDP and energy intensity, however[7]. Since the estimated coefficient of ln*GDPPC* is negative and significant, and the coefficient of ln$GDPPC^2$ is positive and significant, we might expect the relationship between energy intensity and economic development to be U-shaped. But when we compute the minimum of the parabola, the resulting value belongs to the 99th percentile of the per capita GDP distribution. This means that we are still observing the left-hand side of the curve, not a clear U-shaped relationship between ln*EI* and ln*GDPPC*. This confirms the findings of a published study concerning a similar dataset (see Deichmann et al. 2018). Our estimates also show that energy intensity decreases nonlinearly with population density. As regards ln*CO2E*, from Column 1 we can see that, as the proportion of oil in the fuel mix increases, so does energy efficiency. Column 2 confirms this result and shows that this relationship is nonlinear too. Finally, it is worth noting that, on average, energy intensity is 15-16% higher for net oil exporters than for the other countries. This confirms our assumption that the opportunity costs of oil usage in oil-exporting countries are lowert. The low mean value of the VIF statistics also shows that multicollinearity is not an issue.

Column 3 confirms the previous results for the years 1997-2013, with the estimated coefficient of ln*POIL* slightly lower than in Columns 1 and 2. Surprisingly, the coefficient of ln*POIL* is not statistically significant in Column 4, when the (mean-centered) linear and squared terms of the other regressors are included. This might be due to a nonlinearity in the relationship between real oil price and energy intensity. To test this hypothesis, we estimate equation 1 again, including the (mean-centered) linear and squared terms of ln*POIL* as well. The results in Column 5 confirm our hypothesis. We also note that, unlike the case of Column 2, the coefficient of ln$CO2E^2$ is now positive and statistically significant. However, when we compute the maximum of the parabola, we find a value belonging to the 1st percentile of the corresponding distribution, meaning that we are seeing the right-hand side of a concave curve.

[7] We also included the squared value of ln*POIL*, but it was not statistically significant.

Table 3 replicates the pooled OLS estimates of Table 2 by geographical area[8]. To save space, we only report the estimated coefficients for ln*POIL*.

TABLE 3 HERE

Between 1980 and 2013, we find that the negative relationship between energy intensity and oil price holds for most regions in the world, the exceptions being Central and Southern America, Northern and Southern Europe, Western Africa, and Central and Southern Asia. There is an important difference in the coefficients estimated across regions, however. The negative relationship between oil price and energy intensity is strongest in Western European countries, where a 10% change in real oil price corresponds to an average 8.75% reduction in energy intensity. The relationship is strong in North America and the Caribbean, and in Eastern Asia too, which include the world's largest economies, Germany, the United States, China and Japan. Conversely, there is a weak, but significant positive relationship in Northern Europe: a 10% increase in real oil price is related to a mere 0.8% increase in energy intensity. Similar positive, but small relationships are found in Southern Europe, Southern America, Southern Asia and Western Africa as well. The estimated coefficients of ln*POIL* are negative, but not statistically significant, for Australia and New Zealand, and for Southern Africa, and for all the other regions they are negative, but relatively small, ranging from 0.01 to 0.11.

The sign and statistical significance of the estimated coefficients of energy price remain the same in the subsample (1997-2013). The relationship with energy intensity is no longer significant in Eastern Europe, Western Africa and Eastern Asia, while it becomes significant, but negative in

[8] Since some areas include a very limited number of countries, we could not replicate the estimates in Table 4 for all the areas using a fixed effect estimator.

Southern Europe. Eastern Asia is an interesting case because it includes China, which underwent major changes both in its economic structure and in its energy usage and production throughout the period considered. In Central America, Australia and New Zealand, and in Southern Africa, the estimated coefficients are all positive and statistically significant. For the remaining regions, the coefficients remain pretty much in line with those obtained for the whole sample. Interestingly, the strength of the negative relationship in Western Europe is even higher: between 1997 and 2013, we still find a 0.9 elasticity in energy intensity to oil price, the highest value across all world regions. Southern and Eastern Europe are the only two regions where elasticity level and its significance change when equation 1 is estimated for the years 1997-2013. We surmise that this reflects the impact of some unobserved systematic event affecting these European areas, such as the different composition of the European Union, and the fact that some EU countries benefited from relevant amounts of structural funding in the period considered. We leave the investigation of these aspects to future research.

Table 4 shows the fixed effects estimates of equation 2, which confirm the negative relationship between real oil price and energy intensity.

TABLE 4 HERE

The estimated coefficient of ln*POIL* in Columns 1 and 2 is slightly lower than in the pooled OLS estimates: a 10% increase in real oil price is related to an average 0.10% decrease in energy intensity. This also means that a 3000% increase in real oil price between 1980 and 2013 corresponds to an average 30% increase in worldwide energy efficiency. Columns 3 and 4 show instead that, between 1997 and 2013, the coefficient is twice as large, ranging between -0.022 and -0.026. In this case, an approximately 1067% increase in energy price between 1997 and 2013 corresponds to an average 28% increase in worldwide energy efficiency.

The results in Column 1 confirm the negative relationship between *EI* and *GDPPC*, and between *EI* and *CO2E*, while the estimated coefficient of *POPDEN* is positive. Column 2 shows the results of the estimation when the (mean-centered) linear and squared terms of the regressors are included. In this case, we find the relationship between energy intensity and a country's per capita GDP negative but linear, while the relationship with population density is positive and linear. Only the relationship between energy intensity and CO_2 emissions remains negative and (weakly) nonlinear.

Table 5 shows the results of the system-GMM estimates of equation 3. Columns 1-3 refer to the estimates on the whole sample (1980-2013), and Columns 4-6 to the estimates on the subsample (1997-2013).

TABLE 5 HERE

For computational reasons[9], we are unable to run the two-step system GMM estimates for the full model, using the whole sample or the subsample. We therefore provide the corresponding one-step system GMM estimates. To show that the results are robust to the number of covariates and instruments, we also provide the two-step and one-step system GMM estimates for the model with real oil price as the only explanatory variable. Columns 1 and 2 confirm that, even controlling for past energy intensity values, the relationship with real energy price is negative and statistically highly significant. The estimated coefficient remains stable in Column 3, where we add all the other covariates, and we increase the number of instruments. We find that a 10% increase in real oil price corresponds to an average 0.7% decrease in energy intensity. Again, if we consider the dynamics of energy price and efficiency between 1980 and 2013, we find that the 3000% increase in real oil

[9] When the two-step regression is run with the full set of covariates, the variance-covariance matrix of the two-step estimator is not full rank and the two-step estimator is not available.

price corresponds to an average 21% increase in worldwide energy efficiency, which is half the effect seen in the pooled OLS estimates. Since the Sargan test tends to over-reject the null hypothesis of no over-identification in the one-step model, we rely on the Arellano-Bond test, which confirms that there is no serial autocorrelation in first-differenced errors.

Columns 4 to 6 confirm the previous results in the subsample. We note that the estimated coefficient of real oil price is lower than in the pooled OLS and fixed effects regressions, but it remains stable across specifications. In this case, the 1067% increase in real oil price between 1997 and 2013 corresponds to an average 9% (Column 6) increase in worldwide energy efficiency.

Finally, Table 6 shows the results of the Toda and Yamamoto test on the causality between energy price and energy intensity. Following the approach described on Section 3, we first identify the maximum order of co-integration of our two series, using the Dickey-Fuller test. Table A4 in the Appendix shows that the order of co-integration (p) of $\ln EI$ and $\ln POIL$ is 1. Then, we find that the optimal number of lags that minimizes the AIC and the SBIC statistics (m) is 1 (see Appendix, Table A5). But when we estimate our VAR model of order m, the LR test does not reject the null hypothesis concerning the presence of a serial autocorrelation. We therefore increase the number of lags until the test rejects the null hypothesis, finding a new optimal number of lags (m'), which is 6 (see Table A6). We estimate a VAR model of order $m'+p=7$ for equations 4a and 4b, and we test that the estimated coefficients of the first $m'=6$ lagged values of $\ln POIL$ in equation 4a, and the first $m'=6$ lagged values of $\ln EI$ in equation 4b are jointly zero, using a standard Wald test.

TABLE 6 HERE

Table 6 shows that, in both cases, the null hypothesis is rejected, so we find that energy price and energy intensity influence one another. This reinforces the idea that the lower estimated coefficient of ln*POIL* in the system-GMM estimates may be due to the presence of simultaneity.

5. Conclusions and policy implications

This paper provides cross-country empirical evidence of the relationship between energy price and energy intensity. This linkage had hitherto been investigated mainly for single countries and limited periods. Instead, we consider a panel of 120 countries and a time frame spanning the years between 1980 and 2013. We merge information on energy intensity, real oil price - used as a proxy for real energy price - and other macroeconomic variables from different data sources. We account for endogeneity using fixed effects and dynamic panel data models. Our results show that, after controlling for per capita GDP, population density, and the importance of oil in the energy mix, a higher real oil price induces a significant, but small, decrease in energy intensity, which raises the average energy efficiency. The Toda and Yamamoto test for Granger causality also confirms that energy price and energy intensity influence one another. In addition, we find that these results vary across regions of the world, and can explain the significant increase in energy efficiency worldwide between 1980 and 2013.

Form a policy point of view, our findings can be interpreted in two ways. Several countries have adopted policies to favor a transition towards a hydrocarbon-free energy future, and replacing oil has a crucial role in such policies. On the one hand, our work shows that - on a global level - policies that increase the internal cost of oil have a rather limited impact on energy intensity. Policies such as the introduction of a carbon tax can hardly be effective in fostering energy efficiency. Leaving aside any substitution or rebound effect (that we cannot capture in our static framework), we show that a 10% increase in real oil price induces an average reduction in energy use on a global level that ranges between 0.07 and 0.14% (depending on the period and the econometric method used). The picture changes when we consider the regional impact of such a policy: it has a 0.9 elasticity for Western European countries (i.e. a 10% increase in oil induces a 9% reduction in energy intensity), a negative impact in Australia and New Zealand (0.5 elasticity), and in Southern African countries (0.4 elasticity), a more limited negative impact in North America (0.2 elasticity), and little or no effect elsewhere, in China and Eastern Asian countries, for instance. In other words, regional differences in the energy cost-intensity relationship matter, and should be taken into account when devising policies that aim to affect energy efficiency. Our findings can contribute to the assessment of these effects.

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TABLES AND FIGURES

Table 1. Variables

Name	Description	Source	Mean	Std. dev	Min	Max
EI	Total primary energy supply/GDP	IEA	8.813	6.844	0.456	67.07
P_{OIL}	Inflation-adjusted Brent price x average nominal exchange rate w.r.t. USD	IEA Inflationdata.com	24139.5	152180.8	2.22e-09	2696380
GDPPC	Real per capita GDP	WDI	20.624	80.60	0.256	1983.49
POPDEN	Population per km^2	WDI	0.0002	0.0007	1.76e-08	0.0076
CO2E	CO2 emissions from oil combustion/total emissions from fuel combustion	IEA	0.610	0.297	0.0017	1
NX	Dummy net energy exporter	WDI	0.347	0.476	0	1
DOLLAR	Dummy for adoption of dollar		0.018	0.132	0	1
EURO	Dummy for adoption of euro		0.049	0.215	0	1
ROUBLE	Dummy for adoption of ruble		0.034	0.182	0	1

Table 2. The relationship between energy intensity and oil price: pooled OLS estimates

	1980-2013		1997-2013		
	(1)	(2)	(3)	(4)	(5)
lnPOIL	-0.014***	-0.011***	-0.007**	-0.002	-0.013**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)
$lnPOIL^2$					0.002**
					(0.000)
lnGDPPC	-0.182***	-0.096***	-0.135***	-0.083***	-0.083***
	(0.010)	(0.006)	(0.013)	(0.008)	(0.008)
lnPOPDEN	-0.027**	-0.034***	-0.060***	-0.074***	-0.076***
	(0.009)	(0.009)	(0.012)	(0.011)	(0.011)
lnCO2E	-0.202***	-0.273***	-0.253***	-0.170***	-0.173***
	(0.014)	(0.021)	(0.021)	(0.025)	(0.025)
$lnGDPPC^2$		0.014***		0.021***	0.020***
		(0.002)		(0.002)	(0.003)
$lnPOPDEN^2$		-0.006**		0.000	0.001
		(0.002)		(0.003)	(0.003)
$lnCO2E^2$		-0.038***		0.211***	0.208***
		(0.005)		(0.030)	(0.029)
NX	0.157***	0.146***	0.195***	0.226***	0.214***
	(0.016)	(0.018)	(0.022)	(0.022)	(0.030)
ROUBLE	-0.065	0.317***			
	(0.062)	(0.042)			
DOLLAR	-0.039*	-0.092**	-0.056*	-0.122***	-0.156***
	(0.023)	(0.031)	(0.031)	(0.037)	(0.041)
EURO	-0.041*	-0.057**	0.001	0.064*	0.056
	(0.025)	(0.025)	(0.034)	(0.034)	(0.034)
Year dummies	Yes	Yes	Yes	Yes	Yes
Geographical dummies	Yes	Yes	Yes	Yes	Yes
N	4080	4080	2040	2040	2040
R^2 (within)	0.577	0.548	0.555	0.568	0.569
Mean VIF	1.97	2.16	1.98	2.02	2.14

Robust standard errors in brackets. All estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. The relationship between energy intensity and energy price by geographic area: pooled OLS

	1980-2013		1997-2013	
Area	Num. obs.	β_1	Num. obs.	β_1
Southern America	340	0.014***	170	0.011
		(0.002)		(0.007)
Central America	238	0.000	119	0.024***
		(0.002)		(0.008)
Northern America	68	-0.190***	34	-0.192***
		(0.038)		(0.056)
Caribbean	136	-0.207***	68	-0.435***
		(0.063)		(0.114)
Western Europe	238	-0.875***	119	-0.909***
		(0.072)		(0.196)
Northern Europe	340	0.080***	170	0.089***
		(0.012)		(0.016)
Eastern Europe	306	-0.021***	153	0.006
		(0.004)		(0.005)
Southern Europe	170	0.122***	85	-0.183**
		(0.029)		(0.084)
Northern Africa	204	-0.089***	102	-0.120***
		(0.006)		(0.016)
Western Africa	204	0.010***	102	0.006
		(0.004)		(0.007)
Middle Africa	136	-0.025***	68	-0.075***
		(0.002)		(0.020)
Eastern Africa	204	-0.047***	102	-0.060***
		(0.003)		(0.002)
Southern Africa	68	-0.106	34	-0.390***
		(0.181)		(0.114)
Western Asia	578	-0.024***	289	-0.038***
		(0.005)		(0.006)
Southern Asia	204	0.115***	102	0.054**
		(0.014)		(0.030)
South-Eastern Asia	272	-0.078***	136	-0.045***
		(0.007)		(0.006)
Central Asia	170	0.145***	85	0.070***
		(0.012)		(0.018)
Eastern Asia	136	-0.132***	68	-0.012
		(0.018)		(0.010)
Australia and New Zealand	68	-0.086	36	0.502***
		(0.143)		(0.140)

Notes: estimates also include the following regressors: lnGDPPC, lnPOPDEN, lnCO2E, NX, ROUBLE, DOLLAR, EURO and a series of time dummies. Robust standard errors in brackets. All estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. The relationship between energy intensity and energy price: fixed effects estimates

	1980-2013		1997-2013	
	(1)	(2)	(3)	(4)
lnPOIL	-0.010**	-0.011**	-0.022**	-0.026***
	(0.005)	(0.005)	(0.011)	(0.009)
lnGDPPC	-0.582***	-0.582***	-0.695***	-0.694***
	(0.079)	(0.085)	(0.091)	(0.083)
lnPOPDEN	0.285**	0.884***	-0.038	0.724***
	(0.115)	(0.119)	(0.105)	(0.131)
lnCO2E	-0.138***	-0.243***	-0.162**	-0.150*
	(0.024)	(0.073)	(0.077)	(0.082)
$lnGDPPC.^2$		0.005		0.021**
		(0.007)		(0.010)
$lnPOPDEN^2$		-0.019		-0.083**
		(0.025)		(0.032)
$lnCO2E^2$		-0.025*		0.015
		(0.014)		(0.085)
NX	-0.004	0.004	0.056	0.066
	(0.044)	(0.039)	(0.055)	(0.048)
ROUBLE	-0.030	-0.004		
	(0.084)	(0.078)		
DOLLAR	0.090*	0.102*	0.034	0.052
	(0.051)	(0.057)	(0.045)	(0.039)
EURO	0.013	0.030	-0.054**	-0.041*
	(0.045)	(0.042)	(0.022)	(0.023)
Year dummies	Yes	Yes	Yes	Yes
Geographical dummies	No	No	No	No
N	4080	4080	2040	2040
R^2 (within)	0.539	0.547	0.579	0.606

Robust standard errors in brackets. All estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. The relationship between energy intensity and energy price: SYS-GMM estimates

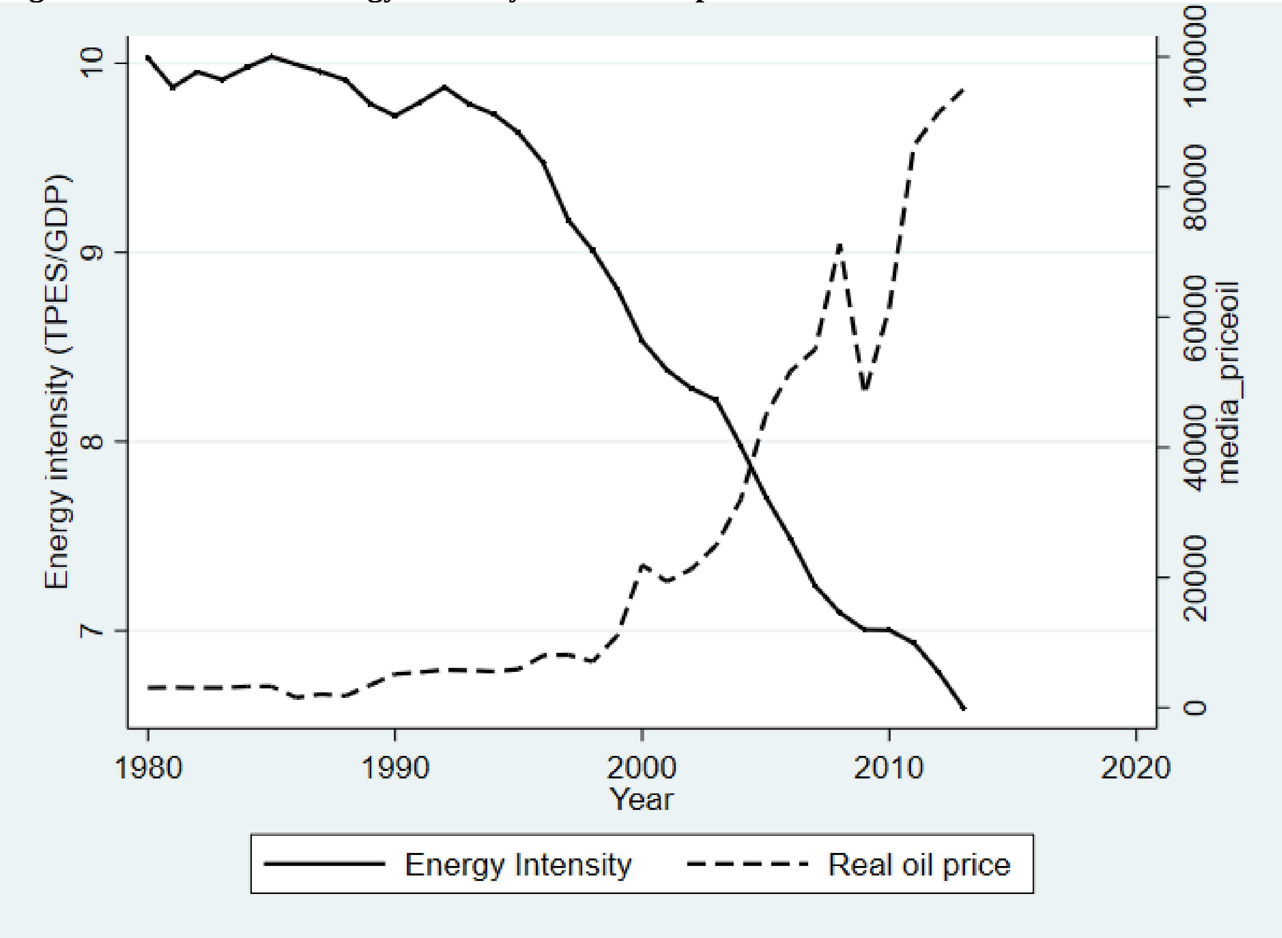
	1980-2013			1997-2013		
	(1)	(2)	(3)	(4)	(5)	(6)
$lnEI_{t-1}$	0.980***	0.979***	0.961***	0.945***	0.941***	0.955***
	(0.001)	(0.016)	(0.024)	(0.021)	(0.022)	(0.039)
lnPOIL	-0.007***	-0.007***	-0.007**	-0.007**	-0.007**	-0.009*
	(0.000)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
lnGDPPC			0.006			-0.015
			(0.018)			(0.025)
lnPOPDEN			0.013			-0.017
			(0.014)			(0.021)
lnCO2E			-0.019			-0.016
			(0.015)			(0.038)
NX			0.001			0.032
			(0.018)			(0.029)
ROUBLE			-0.027			
			(0.063)			
DOLLAR			-0.053			-0.067
			(0.041)			(0.055)
EURO			0.047			0.005
			(0.031)			(0.021)
Year dummies	No	No	Yes	No	No	Yes
Area dummies	No	No	Yes	No	No	Yes
N	3960	3960	3960	2040	2040	2040
N. instruments	129	129	360	69	75	191
Method	Two-step	One-step	One-step	Two-step	One-step	One-step
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.546	0.545	0.511	0.436	0.436	0.473
Sargan test (p-value)	0.683	0.000	0.000	0.094	0.000	0.000

Robust standard errors in brackets. All estimates include a constant term. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Toda and Yamamoto causality test

Equation	$\chi^2(6)$	p-value
[4a] ln*POIL*→ ln*EI*		
$\sum_{i=1}^{6} \gamma_i = 0$	4.00	0.045
[4b] ln*EI* → ln*POIL*		
$\sum_{i=1}^{6} \beta_i = 0$	18.51	0.000

Figure 1. Evolution of energy intensity and real oil price



Appendix

Table A1. List of countries

Algeria
Angola
Argentina
Armenia
Australia
Austria
Azerbaijan
Bahrain
Bangladesh
Belarus
Belgium
Benin
Bolivia
Botswana
Brazil
Brunei
Bulgaria
Cameroon
Canada
Chile
China
Colombia
Costa Rica
Cote d'Ivoire
Cyprus
Czech Republic
Democratic Republic of Congo
Denmark
Dominican Republic
Ecuador
Egypt
El Salvador
Estonia
Ethiopia
Finland
France
Gabon
Georgia
Germany
Ghana
Greece
Guatemala
Haiti
Honduras
Hong Kong
Hungary
Iceland
India
Indonesia
Iran
Iraq
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kazakhstan
Kenya
Kuwait
Kyrgyz Republic
Latvia
Lebanon
Libya
Lithuania
Luxembourg
Malaysia
Malta
Mauritius
Mexico
Moldova
Morocco
Mozambique
Myanmar
Nepal
Netherlands
New Zealand
Nicaragua
Nigeria
Norway
Oman
Pakistan
Panama
Paraguay
Peru
Philippines
Poland
Portugal
Qatar
Russian Federation
Saudi Arabia
Senegal
Singapore
Slovak Republic
South Africa
South Korea
Spain
Sri Lanka
Sudan
Sweden
Switzerland
Syria
Tajikistan
Tanzania
Thailand
Togo
Trinidad and Tobago
Tunisia
Turkey
Turkmenistan
Ukraine
United Arab Emirates
United Kingdom
United States
Uruguay
Uzbekistan
Venezuela
Vietnam
Yemen
Zambia

Table A2.

Table A2. Wald and likelihood ratio tests for the presence of a structural break

Wald statistics	156.47
p-value	0.000
LR statistics	46.660
p-value	0.000
Number of observations	34
Whole sample	1980-2013
Subsample	1996-2008
Estimated break	1997

Table A3. Correlation matrix

	P_{OIL}	GDPPC	POPDEN	CO2E	NX	DOLLAR	EURO	ROUBLE
P_{OIL}	1							
GDPPC	-0.03	1						
POPDEN	-0.02	0.61	1					
CO2E	0.02	-0.14	-0.04	1				
NX	0.17	-0.01	-0.13	-0.06	1			
DOLLAR	0.25	-0.02	-0.02	0.13	-0.00	1		
EURO	-0.04	0.03	-0.00	-0.06	-0.16	-0.03	1	
ROUBLE	-0.02	-0.03	-0.04	-0.37	-0.14	-0.03	-0.04	1

Table A4. Augmented Dickey-Fuller unit root test

ln*EI*	Test statistics
Z(t) #lags=1	-1.849
MacKinnon p-value	0.6809
Z(t) #lags=2	-1.251
MacKinnon p-value	0.8994
Z(t) #lags=3	-1.969
MacKinnon p-value	0.6179
ln*POIL*	Test statistics
Z(t) #lags=1	-3.032
MacKinnon p-value	0.1233
Z(t) #lags=2	-2.751
MacKinnon p-value	0.2157
Z(t) #lags=3	-2.714
MacKinnon p-value	0.2303

Table A5. Identifying the optimal number of lags in the Toda and Yamamoto (1995) approach

Lag	LL	LR	AIC	SBIC
0	22.548		-1.644	-1.546
1	**91.020**	**136.9**	**-6.802**	**-6.509**
2	92.923	3.806	-6.634	-6.146
3	97.895	9.942	-6.712	-6.029
4	99.884	3.980	-6.551	-5.673
5	104.36	8.957	-6.589	-5.516
6	105.58	2.443	-6.367	-5.099
7	114.22	17.26	-6.737	-5.275
8	118.62	8.816	-6.770	-5.112
9	122.32	7.394	-6.746	-4.893

Table A6. LR test of serial autocorrelation in the Toda and Yamamoto (1995) approach

Lag	χ^2	p-value
1	2.414	0.660
2	6.039	0.196
3	7.736	0.102
4	3.973	0.410
5	0.860	0.930
6	**12.59**	**0.013**

Notes: We only report the LR statistics of the test of serial autocorrelation of order 1.