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Modeling international trends in energy efficiency

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ARTICLE INFO

Article history:

Received 18 August 2010
Received in revised form 3 March 2012
Accepted 14 March 2012
Available online 23 March 2012

JEL classification:

O13
O33
O47
Q43
Q54
Q55
Q56

Keywords:

Energy
Efficiency
Carbon emissions
Technological change
Between estimator
Stochastic frontier

ABSTRACT

I use a stochastic production frontier to model energy efficiency trends in 85 countries over a 37-year period. Differences in energy efficiency across countries are modeled as a stochastic function of explanatory variables and I estimate the model using the cross-section of time-averaged data, so that no structure is imposed on technological change over time. Energy efficiency is measured using a new energy distance function approach. The country using the least energy per unit output, given its mix of outputs and inputs, defines the global production frontier. A country's relative energy efficiency is given by its distance from the frontier—the ratio of its actual energy use to the minimum required energy use, *ceteris paribus*. Energy efficiency is higher in countries with, *inter alia*, higher total factor productivity, undervalued currencies, and smaller fossil fuel reserves and it converges over time across countries. Globally, technological change was the most important factor counteracting the energy-use and carbon-emissions increasing effects of economic growth.

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1. Introduction

The empirical purpose of this paper is to estimate the levels of, and trends in, energy efficiency for most countries in the world over recent decades; to investigate the factors that are associated with variations in energy efficiency across countries; and to investigate the implications of trends in energy efficiency and other factors for global energy use and carbon emissions. Methodologically, the paper introduces a new energy distance function approach to defining and measuring energy efficiency and a new econometric approach to estimating such models.

Though energy intensity (energy/GDP) is often used as a measure of energy efficiency, it is a crude and inaccurate indicator of the true technical efficiency with which a country uses energy (Ang, 2006). For example, countries with cold winters or larger shares of output derived from mining will, *ceteris paribus*, use more energy per unit of output than those with mild winters or smaller mining sectors. But this does not mean that they are necessarily using energy in a less efficient way given their climate and economic structure. In the distance function framework developed in this paper, the country

using the least energy per unit output, given its mix of outputs and energy carriers and other inputs, defines the global production frontier. Countries' relative energy efficiencies are given by their distances from the frontier or, in other words, the ratio of their actual energy use to the minimum required energy use, *ceteris paribus*. Countries may converge towards, or diverge from, the best practice frontier over time, which itself will shift with technological change.

In previous research on sulfur emissions and energy efficiency, I used the Kalman filter to model individual technological change trends in each country in a panel data set (Stern, 2005, 2007). In this paper, I instead use an indirect method of estimating the trends in energy efficiency that further develops the between estimation approach I previously applied to estimating the environmental Kuznets curve (Stern, 2010b). I use the cross-section of time-averaged data to estimate the long-run parameters of a stochastic production frontier where the stochastic state of energy efficiency in the cross-section is modeled as a function of additional explanatory variables. Then I derive the level of energy efficiency over time in each country as the time series residual computed using these long-run parameters. This approach has several advantages. It is much less computationally intensive than the Kalman filter, imposes no structure on the time trends, and controls for potential correlation between the level of energy efficiency and the other explanatory variables.

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A few recent papers (Filippini and Hunt, 2011; Wang, 2011; Wei et al., 2009) pursue related but different approaches to modeling aggregate energy efficiency. Filippini and Hunt (2011) use a stochastic frontier approach to estimate the differences in energy efficiency across OECD countries. However, they assume that these differences are random rather than a systematic function of other variables and that there is a common trend in energy efficiency across the OECD. The current paper is global in scope, does not make these simplifying assumptions, and is based on the formal productivity literature rather than the energy demand modeling approach used by Filippini and Hunt. As Filippini and Hunt use a demand function framework, their measure of energy efficiency is contingent on energy prices in each country. Filippini and Hunt's definition of energy efficiency, therefore, measures how well consumers and producers respond to the economic environment with policy parameters such as fuel taxes taken as given. By contrast, in this paper, I try to uncover the deeper drivers of differences between countries' economic environments that will result in variations in both local energy prices and levels of energy efficiency.

Wei et al. (2009) compute energy efficiency using a distance function approach, but their energy efficiency index differs significantly from that proposed in this paper. They use data envelopment analysis rather than a stochastic frontier model to compute their energy efficiency index for a panel of 29 Chinese provinces over the 1997–2006 period. They then regress the estimated energy efficiency index on a variety of explanatory variables. The model in the current paper integrates both steps into a single stochastic frontier model rather than using a two-stage procedure. Wang (2011) uses index number decomposition to model changes in energy intensity for the Chinese provinces. In common with the decomposition in the current paper he attributes part of the change to changes in capital and labor intensity. But his approach does not explain the differences between provinces and requires very detailed data that is not available globally.

The following section of the paper develops the production frontier model and introduces the econometric methods. The third section of the paper reviews the relevant literature on the adoption of energy efficiency technology. The fourth section presents the econometric results and the convergence and decomposition analyses. The final section provides a discussion and conclusion.

2. Theory and methods

2.1. Energy distance function

In this section, I develop a model for estimating technical energy efficiency using a distance function approach, which is a generalization of the framework I introduced previously (Stern, 2005, 2007). A distance function is a specialized form of production frontier model used to measure technical inefficiency. Inefficiency is measured by the relative distance of the actual levels of outputs and inputs from the best practice levels given by the production frontier. Conventionally, distance from the frontier is measured in “input” or “output” directions. The output distance function measures by how much output could be increased if best practice was used, while the input distance function measures by how much all inputs could be reduced to produce the same level of output. But we can measure distance in any direction in the multi-dimensional production space.

Fig. 1 presents a two input, single output example, where E is energy and K is capital. $L(Y_0)$ is the isoquant for the level Y_0 of output. Points to the left and below the isoquant are infeasible. Points to the right and above the isoquant are technically inefficient as less energy and capital could be used to produce the output Y_0 . Point A is inefficient as it uses more energy and capital than necessary, while C, which reduces both inputs along a ray from the origin, is efficient. The value of the input distance function for A, given output Y_0 , is the distance A_0 divided by C_0 . But B, which instead reduces

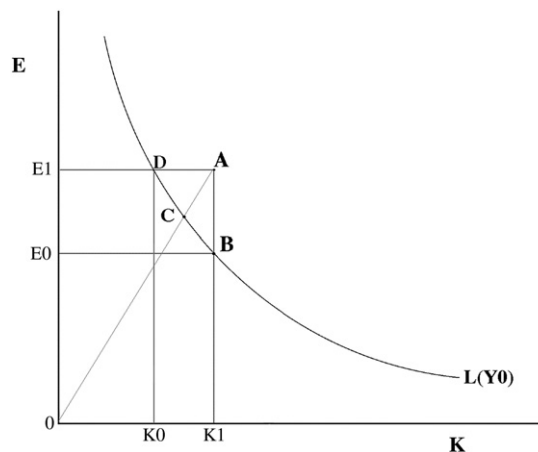


Fig. 1. Multi-input energy efficiency.

energy use alone, is also an efficient point. E_1/E_0 is the distance in this “energy direction”. This is simply the ratio of energy use to the minimum technically feasible energy input, *ceteris paribus*, and is the measure of relative energy efficiency used in this study.

In order to define the energy distance function formally in the general multiple output case, I define the input requirement set, F , following Färe and Primont (1995):

$$F_t(\mathbf{y}_{it}) = \{(\mathbf{E}_{it}, \mathbf{x}_{it}) : (\mathbf{E}_{it}, \mathbf{x}_{it}, \mathbf{y}_{it}) \in T_t\} \quad (1)$$

where T is the set of feasible production vectors under best practice, \mathbf{E} is a vector of energy inputs, \mathbf{y} a vector of outputs, and \mathbf{x} a vector of non-energy inputs. i indexes individuals—in this paper, countries—and t periods—in this paper, years. The best practice technology is common to all countries but may change over time. Then the energy distance function is defined as:

$$d_{it}^E(\mathbf{E}_{it}, \mathbf{x}_{it}, \mathbf{y}_{it}) = \sup_{\lambda} (\lambda > 0 : (\mathbf{E}_{it}/\lambda, \mathbf{x}_{it}) \in F_t(\mathbf{y}_{it})) \quad (2)$$

That is, the distance in the energy direction indicates the greatest factor by which all the energy inputs can be reduced on condition that the specified output remains feasible. For feasible input vectors $d_{it}^E \geq 1$. If $d_{it}^E = 1$, production is as energy efficient as possible given the global state of technology.

The energy distance function is homogenous of degree one in the energy vector. Increasing all energy inputs by 1% with no increase in output or change in the non-energy inputs results in a 1% increase in distance. But for a 1% increase in output the reduction in energy distance is greater than or equal to 1% for a constant or decreasing returns to scale technology. Fig. 2 illustrates this for the two input and a single output constant returns to scale case. The technology can be represented by a single isoquant, which is the boundary of the feasible input requirement set F . For point A, energy distance is e_3/e_0 . An increase in output, Y , is equivalent to a contraction in the levels of both E/Y and K/Y to say point B. At point B, energy distance is e_2/e_1 . If only energy use per unit output had decreased, energy distance would instead be $e_2/e_0 \geq e_2/e_1$. For increasing returns technologies, whether the effect of output has a more or less than one to one effect on energy distance will depend on the degree of returns to scale and the elasticity of substitution between energy and the other input.

2.2. Econometric model

If we want to distinguish between several different energy inputs and to disaggregate output it is not feasible to estimate a flexible

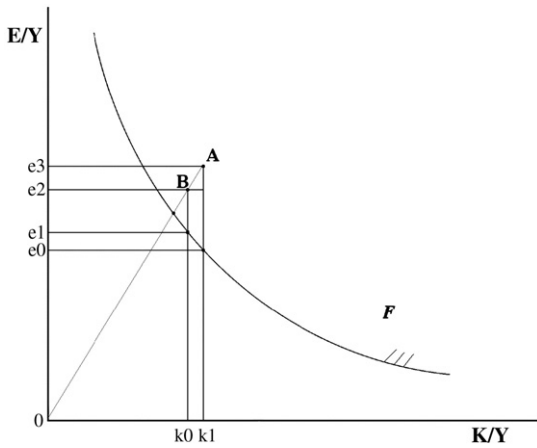


Fig. 2. Effect of output increase on energy distance.

functional form such as the translog or quadratic function (Färe et al., 2010) given the available data. Additionally, some variables such as natural gas use are zero in some countries in some years so that a Cobb–Douglas function for all the disaggregated inputs and outputs is also not feasible. The following model is a Cobb–Douglas function with somewhat ad hoc factors to adjust the constant term, α_0 , for the effects of input and output mix on energy distance, d^E :

$$\frac{\alpha_0 K_{it}^{\alpha_K} H_{it}^{\alpha_H} E_{it} \exp(\alpha_W W_{it}) \exp\left(\sum_{j=2}^5 \beta_j e_{jit}\right)}{Y_{it}^{\alpha_Y} \exp\left(\sum_{k=2}^4 \gamma_k y_{kit}\right) A_{it}^E} = d_{it}^E v_{it} \quad (3)$$

where E is aggregate energy use, Y is aggregate output, K is capital, H is human capital, and W is winter temperature. The e_j are the shares of the various fuels in total energy use and the y_k are the shares of the industries in total output. As these shares sum to unity, one type of energy and one type of output are treated as the defaults and dropped from the model. v is a probably serially correlated error term with mean zero that may reflect measurement and approximation errors as well as the dynamics of adjustment to long-run equilibrium. A_{it}^E represents the frontier—hence the f subscript—state of technology. Smaller values of A_{it}^E indicate more advanced and energy efficient technologies. Improvements in this global state of best practice technology increase the distance from the frontier in all countries, *ceteris paribus*. To identify the model, I assume that the mean over time of the frontier state of technology is unity, i.e. $\ln A_{it}^E = 0$, where the lack of a time subscript indicates a time-averaged mean.

I consider temperature to be an input, as a warmer climate contributes to economic activity and substitutes for energy use. The coefficient of temperature should be positive, as a country with higher winter temperatures would be less efficient and further from the frontier, *ceteris paribus*. The coefficients α_K and α_H are also expected to be positive. Fig. 1 illustrates this for α_K . Increasing capital while holding energy and output constant, for example moving from point D, which is technically efficient, to point A, which is technically inefficient, results in an increase in distance in the energy direction.

Oil is treated as the default fuel and is dropped from the function. Therefore, the coefficients of the fuel shares represent the partial derivatives of distance with respect to a reduction in the share of oil and an increase in the share of the fuel in question and reflect the qualities of the different fuels (Stern, 2010a). The coefficients of higher quality fuels should be positive as, countries with higher shares of more productive fuels are, *ceteris paribus*, more inefficient. The coefficients of the industry shares have a similar interpretation with manufacturing treated as the default. More energy intensive

industries will have positive coefficients, as a country that has a greater share of energy intensive industries will be more efficient, *ceteris paribus*, than one that has the advantage of a less energy intensive industry structure.

Imposing $\alpha_Y = 1 + \alpha_K + \alpha_H$, taking logarithms, and manipulating yields the following model for the log of energy intensity:

$$\ln \frac{E_{it}}{Y_{it}} = -\alpha_0 - \alpha_K \ln(K_{it}/Y_{it}) - \alpha_H \ln(H_{it}/Y_{it}) - \alpha_W W_{it} - \sum_{j=2}^5 \beta_j e_{jit} + \sum_{k=2}^4 \gamma_k y_{kit} + \ln u_{it} \quad (4)$$

$$\ln u_{it} = \ln A_{it}^E + \ln d_{it}^E + v_{it}$$

Therefore, the effects of the explanatory variables on energy intensity are the opposite of their effects on distance. More capital- and human capital-intensive economies should be less energy intensive as these inputs substitute for energy. Warmer countries should be less energy intensive and countries that use lower quality fuels or have an industry mix with a higher share of energy intensive industries should be more energy intensive.

2.3. Estimation

Panel data contain two dimensions of variation—the differences between countries—the “between variation” and the differences over time within countries—the “within variation”. Fixed effects estimation—also known as the “within estimator”—eliminates the average differences between countries prior to estimation so that the coefficient estimates primarily exploit the variation within the countries. The between estimator only exploits variation across countries and not within countries. In the absence of a variety of misspecification issues and time effects, both of these estimators as well as other panel estimators should converge on identical estimates in large samples (Pesaran and Smith, 1995). But empirically, the various estimators diverge due to misspecification error and differences in the treatment of time effects.

Given two standard assumptions of linear regression—that the regression slope coefficients are common to all countries (and implicitly time periods) and that there is no correlation between the regressors and the error term—the between estimator is a consistent estimator of the long-run relationship between the variables when the time series are stationary or stochastically trending and is super-consistent for cointegrating series (Pesaran and Smith, 1995). A further advantage of the between estimator is that it makes no assumptions about the nature of the time effects (Stern, 2010b).

The between estimator has been shunned by researchers due to the concern that omitted variables represented by the individual effects may be correlated with the included explanatory variables. As the individual effects are absorbed into the regression residual term, the error term and the regressors may be correlated leading to inconsistent estimates of the regression coefficients. The random effects estimator, which treats the individual effects as error components, suffers from a similar potential bias. Random effects and fixed effects estimates, which should both be consistent estimators in the absence of such a correlation (assuming that there are no other econometric issues) are commonly found to be significantly different in the environmental Kuznets curve literature (e.g. Stern and Common, 2001). However, this is only one of several potential misspecifications of panel data models. Hauk and Wacziarg (2009) show that the between estimator is the best performer among potential panel data estimators even when the orthogonality assumption is violated but measurement error is present. Additionally, fixed effects estimation of the slope coefficients tends to converge to short-run rather than long-run effects and it also tends to amplify the effects of measurement error and other noise, which the between estimator smoothes out (see Stern, 2010b).

However, when estimating a model such as Eq. (4), the issue of omitted variable bias is more clear-cut than usual. The unobserved local state of technology, $\ln A_{it}^E = \ln A_{it}^E + \ln d_{it}^E$, included in the residual is chosen by economic actors jointly with the levels of the inputs, and in particular capital (Eberhardt and Teal, 2011). There are four main approaches for addressing this omitted variables bias in the current context: instrumental variables, fixed effects, adding covariates or modeling the technology term as a function of auxiliary observable variables, and possibly by imposing identifying restrictions. These approaches can also be combined (Breusch et al., 2011), though I do not consider such estimators here.

Unfortunately, it is hard to think of credible instrumental variables in this macro-economic context. For example, initial values of the explanatory variables are likely to be correlated with the omitted state of technology. Fixed effects estimation eliminates the average effects of omitted variables in each country before estimating the model. However, we wish to explain the differences in technology between countries rather than eliminate them and, as discussed above, this “within estimator” has other problems. On the other hand, if a sufficient number of auxiliary variables that co-vary with the unobserved state of technology can be included in the model, the correlation between the remaining residual term and the regressors will be eliminated.

Rather than include the additional variables directly in the regression equation, I assume that the inefficiency term, $\ln d_{it}^E$, is a function of these auxiliary variables. I implement this using a stochastic frontier approach where the mean of the one-sided inefficiency terms is a function of auxiliary explanatory variables (Battese and Coelli, 1995; Kumbhakar and Lovell, 2003; Kumbhakar et al., 1991) and the stochastic frontier is estimated using the cross-section of time-averaged data for each country in the fashion of the linear between estimator. I discuss the choice of auxiliary variables in the following section of the paper. The estimated model is:

$$\begin{aligned} \ln \frac{E_i}{Y_i} &= -\alpha_0 - \alpha_K \ln(K/Y)_i - \alpha_H \ln(H/Y)_i - \alpha_W W_i - \sum_{j=2}^5 \beta_j e_{ji} + \sum_{k=2}^4 \gamma_k \mathcal{Y}_{ki} \\ &\quad + \ln d_{it}^E + \ln v_i \\ \ln d_{it}^E &\sim N^+ \left(\delta' \mathbf{w}_i, \sigma_d^2 \right) \\ \ln v_i &\sim N \left(0, \sigma_v^2 \right) \\ \ln u_i &= \ln d_{it}^E + \ln v_i \end{aligned} \tag{5}$$

where the year subscript, t , has been dropped to indicate that the variables are averaged over time. $\ln d_{it}^E$ has a truncated (at zero) normal distribution with mean $\delta' \mathbf{w}_i$ and standard deviation σ_d , where \mathbf{w}_i is the vector of auxiliary variables and δ a vector of parameters to be estimated. $\ln v_i$ is assumed to be normally distributed with mean zero and standard deviation σ_v . As the minimum of $\ln d_{it}^E$ is zero, $d_{it}^E \geq 1$ as required. $\ln v_i$ and $\ln d_{it}^E$ are assumed to be distributed independently of each other.

I estimate Eq. (5) by maximum likelihood (Battese and Coelli, 1993) using the RATS procedure MAXIMIZE with the options BHHH and ROBUSTERRORS. The values of d_{it}^E are estimated as the expected value conditional on the estimated value of the residual, $\ln \hat{u}_i$ (Kumbhakar and Lovell, 2003), where the hat indicates an estimate. The estimate of the error term, $\ln \hat{v}_i$, is then retrieved using $\ln \hat{v}_i = \ln \hat{u}_i - \ln \hat{d}_{it}^E$. The estimated time-varying technology and distance variables are retrieved as follows. First we calculate:

$$\begin{aligned} \ln \hat{v}_{it} &= \ln \frac{E_{it}}{Y_{it}} + \hat{\alpha}_0 + \hat{\alpha}_K \ln(K/Y)_{it} + \hat{\alpha}_H \ln(H/Y)_{it} + \hat{\alpha}_W W_i \\ &\quad + \sum_{j=2}^5 \hat{\beta}_j e_{jit} - \sum_{k=2}^4 \hat{\gamma}_k \mathcal{Y}_{kit} - \ln \hat{d}_{it}^E \end{aligned} \tag{6}$$

which is composed of the following components:

$$\ln \hat{v}_{it} = \ln \hat{A}_{it}^E + \ln \hat{d}_{it}^E + (\ln \hat{v}_{it} - \ln \hat{v}_i) \tag{7}$$

I assume that the final term in Eq. (7) is stationary with mean zero and that the estimated trend in technology in each country, $\ln \hat{A}_{it}^E = \ln \hat{A}_{it}^E + \ln \hat{d}_{it}^E$, is quite smooth (Rotemberg, 2003). I use the Hodrick–Prescott filter (Hodrick and Prescott, 1997) to smooth Eq. (7) using the default tuning parameter of 100 for annual data. Then:

$$\ln \hat{A}_{it}^E = \min_t \left(\ln \hat{A}_{it}^E \right) \tag{8}$$

and distance from the frontier can be retrieved as follows:

$$\ln \hat{d}_{it}^E = -\ln \hat{A}_{it}^E + \ln \hat{A}_{it}^E \tag{9}$$

3. Factors affecting the choice of energy efficiency technology

There are few studies that try to explain variations in energy efficiency across countries at the macro-economic level, so I first review the factors that have been found to affect technology diffusion more generally.

Recent theory and empirical results in development economics find that differences in income per capita between countries cannot be explained by differences in capital stocks, even including human capital, alone (Easterly, 2002; Parente and Prescott, 2000). Total factor productivity (TFP) varies across countries. Comin and Hobijn (2004) gather data on many key innovations over the last three centuries and examine their rate of adoption across what are now the developed economies. They find that adoption rates across countries have mostly converged over time, the rate of catch-up has increased, that there is a strong correlation between the level of GDP and the level of adoption of each technology, and that innovations mostly occur in the leading economy of the time and then trickle down to the other countries. Comin and Hobijn (2010) confirm the length of adoption lags and their dramatic reduction over time for a much larger sample of countries. Comin and Hobijn (2004) also find significant evidence of “technology locking”. It takes a long time for new technologies to dominate old ones and significant investment continues in non-frontier technologies. Their regression analysis shows that high adopters of predecessor technologies adopt successor technologies more rapidly too. They suggest that factor endowments, openness to trade, and political institutions are likely to be most important in explaining these differential adoption rates. Various theories predict a relation between factor endowments and technology adoption including q-complementarity between capital goods and existing factor endowments (such as between computers and skilled labor), the role of factor-saving technologies which will be differentially adopted where a factor is scarce, and the idea of “appropriate technology”—a particular technology can only be implemented successfully by countries with the appropriate portfolio of endowments. Countries that are more open to trade are likely to be faster adopters due to the greater importation of other high technology goods, the lower influence of vested monopoly interests in an open economy, and the resulting higher degree of competition in the domestic economy.

Comin and Hobijn's regression analysis indicates that higher GDP per capita—a proxy for capital and technology endowments—and human capital indicators are both positively correlated with the rate of adoption. Benhabib and Spiegel (2005) carry out an empirical analysis of the international diffusion of TFP finding a positive role for human capital in the catch-up process. I include a general total factor productivity variable in the model to reflect these human capital and technology factors as well as an indicator of openness to trade.

Policymakers are often assumed to maximize a representative individual's utility where utility is a function of per capita consumption and

shared environmental quality (Jones and Manuelli, 2001; Weitzman, 2009). Energy use is a rough proxy for total environmental impact (Common, 1995) so that environmental quality can be measured as energy use per unit area or energy density. In order to explain the choice of energy efficiency level, we need a proxy for what energy density would be in the absence of policies to improve energy efficiency. Assuming that energy and capital are poor substitutes, capital per unit area or capital density could be such a proxy and I include this variable in the model. The higher capital density is, the more stringent we would expect environmental policies to be.

However, policy makers do not necessarily act optimally to maximize welfare. Parente and Prescott (2000) argue that the level of technology adopted in a country depends on policy barriers raised against the adoption of foreign technology. In the case of environmental technology, the lack of correction of environmental market failure due to either an ineffective or corrupted political process could raise an additional barrier against technology adoption. Fredriksson et al. (2004) investigate the effect of corruption and industry sector size on energy policy outcomes. The main predictions of their theory are that: (i) greater corruptibility of policy makers reduces energy policy stringency; (ii) greater lobby group coordination costs (increased industry sector size) results in more stringent energy policy; and (iii) workers' and capital owners' lobbying efforts on energy policy are negatively related. They test these predictions empirically for a number of OECD countries using Transparency International's corruption perception index and find that they hold up well. I include corruption and inequality variables as auxiliary variables. Comin and Hobijn (2004) find that military regimes, effective legislatures, and heads of government who do not hold official roles, all deter the rapid adoption of new technologies. Though it is not clear whether more democratic regimes will have better or worse environmental policy (Jones and Manuelli, 2001; Comin and Hobijn (2004), I include a democracy variable in the model.

Firms and households may also make systematically inefficient choices given the policy environment due to market failures, market barriers, and behavioral failures (Gillingham et al., 2009). In addition to environmental externalities and failures of innovation markets, market barriers to increased energy efficiency may include information problems and liquidity constraints in capital markets (Gillingham et al., 2009). These will raise the implicit costs of energy efficient capital, though Allcott and Greenstone (2012) argue that the absolute increased energy use due to these is small. It is not clear what variables that might vary across countries are correlated with differences in information problems. One option to model liquidity constraints is including a capital market and/or banking "depth" variable such as the private credit variable developed by Beck et al. (2000). But this data is only available for a subset of countries, which does not include China. Behavioral failures are harder to account for and anyway there is no evidence that they differ significantly across countries or across time.

There are a small number of empirical studies that do examine the factors affecting the level of energy efficiency technology and policy adoption. Matisoff (2008) carried out an empirical analysis of the factors affecting the adoption of energy efficiency programs across U.S. states. He finds that the most significant variable is citizen ideology. A broad band of states from Florida to Idaho has not adopted any energy efficiency policies. A potential source of data on ideology at the global level is the World Values Survey (Inglehart and Welzel, 2005), but using this data directly would mean dropping about half the countries in the sample. Matisoff (2008) also found that the initial level of criteria air pollutants was significant in regressions for the number of programs adopted and in probit models for the adoption of a renewable portfolio standard. This variable is proxied in my framework by capital density. He also found that the CO₂ intensity of the state's economy had a significant negative sign in some regressions. Gas and coal production per capita, income, and the policies of neighboring states did not, however, have significant effects. Wei

et al. (2009) find that energy efficiency is negatively associated with the secondary industry share in GDP, the share of output from state-owned firms in GDP, and the government expenditure share in GDP, and is positively associated with the level of general technology and the non-coal share in energy consumption. I include a fossil fuel reserves variable in the model, as this variable is more exogenous than consumption.

Stern (2005) estimated trends in sulfur abating technology finding that countries converged into clubs. These clubs appear to be related to legal origin (La Porta et al., 2008) as Japan and the Germanic language countries adopted the most stringent and English-speaking countries the least stringent technology, with Mediterranean countries adopting a middle level. Davis and Lacroix (2011) also find that the environmental Kuznets curve for French legal origin countries lies below that for English legal origin countries. Blanchard (2004) presents data on the stringency of product and labor market regulation. This data shows that countries of English legal origin have the lowest levels and countries of French legal origin the highest levels of regulation with German and Scandinavian legal origin countries occupying the intermediate position. Dummies for legal origin and for former and current Communist countries are included as auxiliary variables.

An alternative approach would be to use average energy prices in each country to proxy the level of technology, as higher real energy prices would be expected to result in greater energy efficiency. While the IEA maintains a database of energy prices in the OECD there is no easily available database for developing countries. Apart from taxes, the main factor that will affect the effective price of imported energy across countries is the deviation of each country's exchange rate from purchasing power parity (PPP). The lower a currency is below the purchasing power parity exchange rate the more costly imported energy is relative to domestic goods and services. Therefore, I include the ratio of a country's prices to PPP as an auxiliary variable.

4. Data and results

4.1. Data

I compiled a database for the years 1971–2007 for 85 countries as described in the Appendix. The extent of the time period is determined by the availability of energy data for the non-OECD countries. Countries were eliminated from the sample if they did not have reasonably complete series for the national accounting data. Unfortunately, this eliminated most former Soviet Bloc countries. I also dropped all oil producers with a larger share of GDP generated in the mining and utilities section than Norway has (19%). Several such oil producers had apparent TFP's much greater than that of the US due to the contribution of oil resources to the economy. Fig. 3 shows the average values of energy intensity for each of the countries in the sample as a function of GDP per capita. In contrast to the usual

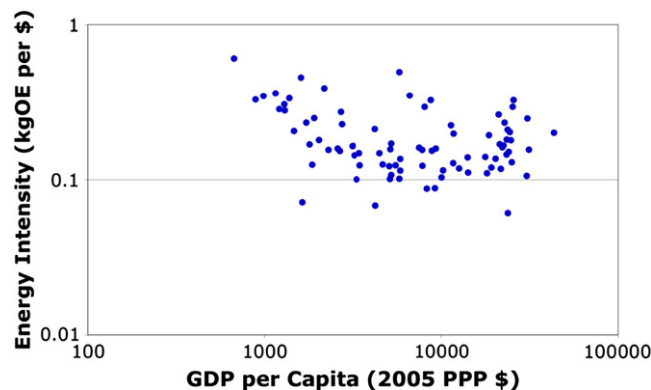


Fig. 3. Energy intensity and GDP per capita.

Table 1
Econometric estimates.

Variable	Between estimator	Fixed effects (within estimator)	Stochastic frontier: auxiliary variables
<i>Distance function parameters</i>			
Constant	−4.006 (−1.71)		11.454 (1.16)
Capital	−0.153 (−1.50)	−0.261 (−15.96)	0.292 (1.15)
Human capital	−0.422 (−2.80)	−0.514 (−36.56)	0.589 (1.05)
Winter	0.015 (1.50)		0.011 (1.32)
Coal	−0.998 (−3.00)	−0.706 (−14.06)	−0.485 (−1.28)
Natural gas	−0.653 (−1.21)	−0.828 (−14.61)	−0.416 (−0.87)
Primary elec.	−0.897 (−1.90)	0.001 (0.02)	−0.732 (−1.50)
Biomass	−0.543 (−1.53)	−0.206 (−3.79)	−0.867 (−3.48)
Agriculture	0.270 (0.27)	−0.550 (−5.64)	−0.225 (−0.21)
Mining	1.796 (1.33)	−1.051 (−8.77)	0.144 (0.13)
Other	1.038 (1.11)	−1.046 (−13.10)	−0.850 (−0.96)
<i>Technical inefficiency model and error variances</i>			
Constant			9.278 (1.59)
ln TFP			−1.296 (−1.63)
ln Capital density			−0.012 (−0.32)
ln PPP			0.884 (5.79)
ln Openness			0.113 (1.38)
Corruption			−0.050 (−1.47)
Inequality			0.000 (0.00)
Democracy			0.000 (0.00)
Fossil res.			0.008 (1.42)
Ger/Scand L.O.			−0.251 (−1.22)
French L.O.			−0.107 (−1.23)
Former comm.			0.538 (2.17)
σ_u			0.011 (0.01)
σ_v	0.352	0.134	0.220 (3.04)
Log likelihood	−26.059	1933.58	8.555
Model vs. OLS			69.228 (0.000)

t-statistics are in parentheses for parameters, p-values for LR tests.

patterns seen in the literature (e.g. Lescaroux, 2010; Medlock and Soligo, 2001), there is neither an inverted-U shape curve nor much of a monotonically declining relationship in this data. This is because I use GDP adjusted for purchasing power parity and include traditional biomass in the energy use variable.

4.2. Econometric results

Table 1 presents the econometric results. In addition to the stochastic frontier model, I estimated between and within models. The between estimate has an R-squared of 0.43. For the between estimator, higher winter temperatures are associated with significantly greater distance from the frontier, *ceteris paribus*, as expected. All

the fuels are found to be of lower quality than oil as their coefficients are negative. This is somewhat surprising, as primary electricity and perhaps natural gas are usually thought to be higher quality energy carriers than oil (Cleveland et al., 2000). Coal has the most negative coefficient showing it to be the lowest quality fuel. All three industrial sectors have positive coefficients showing them to be more energy intensive than manufacturing, which with the exception of mining is also surprising. However, these parameters are either insignificantly different from zero or only slightly significant. Most importantly, the coefficients of the capital and human capital variables are negative, which is theoretically inconsistent with the distance function model.

The skewness of the between residuals is 0.414 ($p=0.126$) and kurtosis is 1.451 ($p=0.009$). The Jarque–Bera test of normality yields a statistic of 9.886 ($p=0.007$). Therefore, we can reject the null hypothesis that the residuals are normally distributed. I also estimated half-normal and truncated-normal stochastic frontier models without any auxiliary variables but these estimates were not significantly different from the between estimates.

However, when we include the auxiliary explanatory variables the results are quite different. The standard deviation of the residuals, σ_v , is just under 2/3 of its simple between estimates value showing the explanatory power of the model is larger. These residuals are normally distributed. The tests of skewness and excess kurtosis have significance levels of 0.54 and 0.19 respectively. The likelihood ratio statistic for restricting the model to the between model is 69.23, which is distributed as approximately chi-squared with 13 degrees of freedom and is highly significant.

The estimates of the distance function parameters are in many cases quite different to their between estimator counterparts. Most importantly, the coefficients of capital and human capital are now positive, which is consistent with theory. With the exception of biomass, the coefficients of the fuels are smaller in absolute value and the coefficients of the industrial sectors are all lower with agriculture and other industries and services having negative coefficients though none of these are significant. Natural gas is now the highest quality of the four fuels but still lower quality than oil.

Among the auxiliary variables, the capital density, inequality, and democracy variables have zero or completely insignificant coefficients. The remaining variables all have t-statistics greater than unity in absolute value. Higher TFP is associated with greater efficiency, as we would expect. The elasticity is large—a 1% increase in general TFP results in a 1.3% improvement in energy efficiency. A higher exchange rate relative to the PPP level results in less energy efficiency. In contrast to the usual assumption that opening to trade will allow the adoption of more energy efficient technologies, we find that the more open an economy is, the less energy efficient it is. Possibly, more open economies have more of their economic activity in energy intensive sub-industries within the mining and manufacturing sectors.

Higher transparency is associated with higher energy efficiency as expected. Countries with greater fossil fuel reserves relative to the size of their economies are less energy efficient. Countries of German and Scandinavian legal origin (Scandinavia, Germany, Austria, Bulgaria, China, Hungary, Japan, Korea, Poland, and Switzerland) are more energy efficient than countries with English origin legal systems, *ceteris paribus*, and countries with French origin legal systems occupy an intermediate position as Stern (2005) found for sulfur abatement technology. Former communist countries are significantly less energy efficient than English legal origin countries, *ceteris paribus*.

The fixed effects results are also inconsistent with theory. In particular, capital and labor have negative coefficients and mining has a very negative coefficient. There is no constant or coefficient for winter temperatures in these results due to the fixed effects.

Fig. 4 shows the estimated time series of energy efficiency, \hat{A}_{it}^E , for all countries in all time periods. To interpret the figure, remember that energy efficiency is measured relative to the country on the

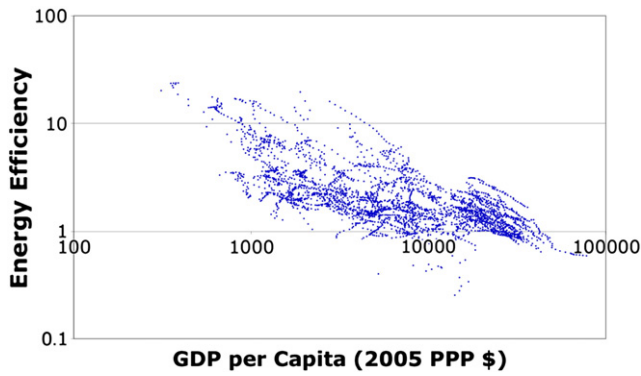


Fig. 4. Underlying energy efficiency and GDP per capita.

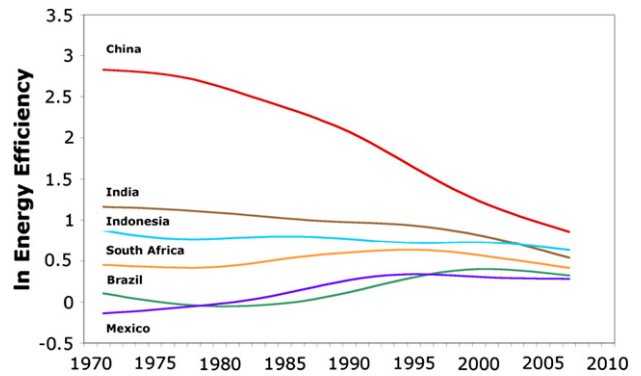


Fig. 6. Energy efficiency: major developing economies.

frontier at the time-averaged mean, which has an efficiency, \hat{A}_f^E , of unity. A country with an energy efficiency of 2 uses twice the energy of that frontier country, *ceteris paribus*, and is half as efficient. Away from the sample mean, some countries are more efficient than the most efficient country at the sample mean and have distances of less than one. The residual data points below the main grouping of data are for Lebanon, which had very erratic income from year to year.

There is a much stronger global relationship between income per capita and this measure of energy efficiency than there is between the former variable and energy intensity. Energy efficiency has improved over time among most high-income countries and among many poorer countries that started the period with very low levels of efficiency. But energy efficiency was flat over time or declining in many developing economies.

Fig. 5 shows the development of energy efficiency over time in Australia and the major economies of China, India, Germany, Japan, and the United States, which show convergence. Japan starts the period as the most energy efficient country but it sees less improvement over time (and none after 1990) than the other developed economies. China converges towards the other economies and its rate of improvement slows. According to Zhou et al. (2010), China's rapid progress in the 1980s and 1990s was the result of explicit energy efficiency policies, while its low initial energy efficiency is typical of the post-communist states.

Fig. 6 shows the time paths of energy efficiency for six major developing economies: China and India, which also appear in Fig. 5, and Brazil, Indonesia, Mexico, and South Africa. With the exception of China and to a lesser degree India, energy efficiency has been more or less flat or decreasing in these developing economies over this period.

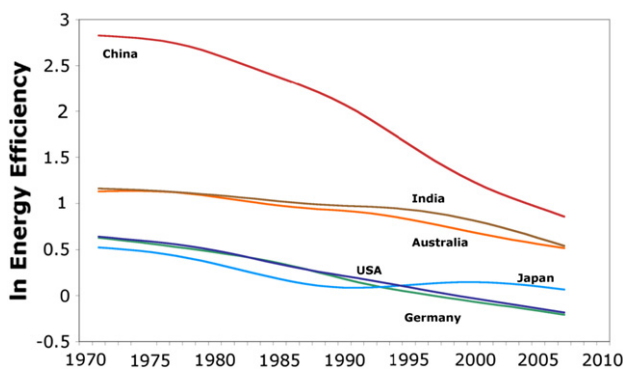


Fig. 5. Energy efficiency: Australia and major economies.

4.3. Convergence analysis

In the current context, β -convergence tests whether there is a negative correlation between the initial level of energy efficiency and its growth rate so that efficiency increases faster in initially less efficient countries resulting in those countries converging to the best practice frontier (Quah, 1996). σ -convergence investigates changes in the cross-sectional variance of energy efficiency over time. I test for β -convergence using the following regression:

$$\ln \hat{A}_{i2007}^E - \ln \hat{A}_{i1971}^E = \mu_0 + \mu_1 \ln \hat{A}_{i1971}^E + \varepsilon_i^E \quad (10)$$

The results are presented in Table 2. The hypothesis of non-convergence is strongly rejected. The slope is -0.65 with a t-statistic of -5.75 . But the constant term is 0.271 ($t=2.23$), so that countries that started the period with a high level of energy efficiency tended to become less energy efficient over time as we see in Fig. 6.

The standard deviation of $\ln \hat{A}_{it}^E$ declines from 0.697 in 1971 to 0.595 in 1982 but then increases to 0.759 in 2007. So there appears to be σ -convergence in the 1970s and divergence from the early 1980s onwards. Fig. 7 demonstrates these patterns quite clearly. There is σ -convergence in the 1970s and early 1980s, more stability of the distribution in the 1990s and some divergence in the 2000s. The countries with lowest energy efficiency in 2007 are: Zimbabwe, Congo (Kinshasa), Togo, Zambia, and Tanzania, Nicaragua, and Ghana. These appear to be responsible for much of the divergence. The standard deviation in 2007 without these countries was 0.500 .

Previous research, discussed by Le Pen and Sévi (2010), mostly found convergence of energy intensity among developed economies but no convergence in samples that included both developed and developing countries. Le Pen and Sévi (2010) applied a pairwise cointegration test to convergence of energy intensities in 97 countries rejecting the global convergence hypothesis. The current study shows that divergence in energy efficiency is mostly associated with economies that are lacking in economic progress.

4.4. Decompositions of energy use and carbon emissions

The decompositions of energy use and carbon emissions are based on the method developed by Stern (2002). I add the log of output to

Table 2
Beta convergence regression.

	Coefficient	Standard Error
Constant	0.271	0.122
Initial energy efficiency	-0.650	0.113
R-squared	0.285	

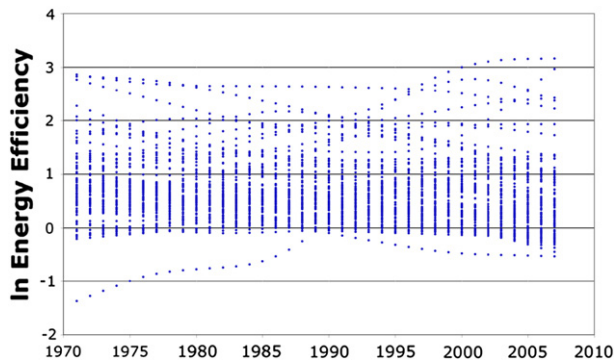


Fig. 7. Distribution of energy efficiency over time.

both sides of Eq. (5) to derive an equation to predict energy use. Then, to assess, for example, the contribution of economic structure to global energy use, we hold all other explanatory variables to their levels in the previous period while allowing economic structure to change as it actually did and observing the resulting predicted counterfactual energy use in each country in each year. The logarithmic difference contribution of factor k globally in year t is then:

$$\Delta \ln E_{kt} = \sum_i S_{it} \Delta \ln E_{kit} \quad (11)$$

where $\Delta \ln E_{kit}$ is the change in the logarithm of energy use in country i in year t under the scenario where only factor k changes and S_{it} is the share of country i in global energy use in year t . The percentage contribution of factor k over the period 1971–2007, r_k , as shown in Table 3 is:

$$r_k = \exp\left(\sum_t \Delta \ln E_{kt}\right) - 1 \quad (12)$$

These contributions aggregate to the total global change in energy use multiplicatively:

$$\frac{E_{2007} - E_{1971}}{\sum_t E_t} = -1 + \prod_k (1 + r_k) \quad (13)$$

The carbon decomposition analysis is carried out using the same approach but replacing predicted energy use with predicted emissions and the shares of energy use by shares of carbon emissions in Eqs. (11) to (13).

Global energy use increased by 121% from 1971 to 2007. As global GDP rose by 269%, global energy intensity fell by 40% over the period. Because more economic growth occurred in less energy efficient countries such as China the contribution of growth in each country

Table 3
Decomposition.

	Energy 1971–2007	Carbon 1971–2006
Capital/GDP ratio	−7.04%	−6.85%
Human capital/GDP ratio	44.79%	45.54%
Fuel mix	3.93%	1.82%
Economic structure	−9.29%	−9.58%
Technology	−55.45%	−56.88%
Scale	294.84%	282.53%
Total	123.20%	105.86%
Residual	−2.38%	−3.17%
Change in energy and emissions	120.81%	102.70%

to global energy use is greater than 269%. Changes in fuel mix raised energy use by 4% while shifts in economic structure reduced energy use by 9%. Capital deepening reduced energy intensity by 7% as capital substituted for energy. Capital accumulation also made a relatively small contribution to reduced energy intensity in China in contrast to Wang's (2011) finding that capital accumulation was the main driver of reduced energy intensity in China. The relatively slow global increase in human capital resulted in substitution of energy for human capital and a 45% increase in energy intensity globally, *ceteris paribus*. The most important mitigating factor though was technological change, which lowered energy use by 55%. The relatively high level of aggregation of industrial structure probably results in an overestimation of the contribution of technological change to the reduction in energy intensity. More disaggregated studies attribute a greater role to structural change and a smaller role to technological change (Stern, 2011).

The results for carbon are very similar. Data were only available up till 2006. The global carbon intensity of energy use fell from 2.54 t of CO2 per ton of oil equivalent in 1971 to 2.40 in 2006. As a result, fuel mix has a smaller effect on carbon emissions than on energy use. In both the case of energy use and carbon emissions, the actual increase over the period is less than half the increase that would have occurred due to the scale effect alone.

5. Discussion and conclusions

This paper introduces new approaches to measuring and estimating the level of and trends in energy efficiency and investigating the factors associated with the varying levels of energy efficiency across countries. The model is applied to a panel data set for 85 countries over the 1971–2007 period.

We found that between and fixed effects models result in theoretically inconsistent values for the parameters of the capital and human capital inputs. These estimates are presumably biased due to omitted variables. When auxiliary variables are included in the model for the error term the coefficients take more plausible values suggesting that the bias has been removed. Assuming that the auxiliary explanatory variables have removed the correlation between the stochastic component of the technology term and the regular regressors in the model, this approach should lead to consistent estimates of the long-run parameters. The estimates of the trends in energy efficiency are not constrained by any particular assumptions about the time series model generating those trends. The results mostly make intuitive and theoretical sense, though the time-averaged estimators have wide standard errors for many of the regression coefficients.

We find that the most important variables affecting the state of energy efficiency are TFP and the ratio of the exchange rate to the PPP exchange rate. More technologically advanced economies have higher energy efficiency, *ceteris paribus*. But countries with more undervalued currencies also tend to be more energy efficient. The extracted trends show that energy efficiency has improved over time in most developed countries. Some less energy efficient developing countries such as China and India also saw rapid progress. But other developing countries that were relatively efficient at the beginning of the period experienced flat or declining energy efficiency. Overall, there was convergence in energy efficiency across countries over time except for some African countries that have experienced economic troubles and declining energy efficiency in recent years.

The global decompositions of energy use and carbon emissions have similar results. The two most important factors affecting energy and emissions intensity are technological change and substitution of energy for human capital. The latter factor increases energy and emissions intensity, while technological change tends to reduce emissions and energy intensity over time.

Acknowledgements

This project was funded by the Australian Commonwealth Department of Environment, Water, Heritage and the Arts through the Commonwealth Environmental Research Facility Environmental Economics Research Hub. I thank Paul Burke and Sambit Bhattacharya for helping me locate data and Frank Jotzo, Ross Lambie, Tom Kompas, Hom Pant, seminar and conference participants, and two anonymous referees for helpful comments.

Appendix A. Supplementary data

Supplementary data to this article can be found online at doi:10.1016/j.eneco.2012.03.009.

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