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The effect of *ESCO*s on energy use

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Abstract

Energy saving can importantly help prevent greenhouse gas emissions and, thus, climate change. Energy service companies (*ESCO*s) provide a crucial instrument for delivering improved energy efficiency and potentially contributing to substantial energy savings in the public and private sectors. This paper investigates empirically the effect of *ESCO* activities on energy use. Based on a dynamic *IPAT* model, using a panel data of 94 countries over the period 1981 to 2007, we provide significant evidence that *ESCO*s reduce energy use. This finding proves robust to different dates of the first *ESCO*. The negative *ESCO* effect increases over time. The dynamic adjustment process produces small effects in the short run, but large effects in the long run. Moreover, the long-run *ESCO* effect differs across the stages of development. That is, for the high- and low-income countries, the short-run *ESCO* effect remains negative, but the long-run effects differ, remaining negative in high-income countries, but becoming positive in low-income countries. Finally, we discuss energy policy implications.

Keywords: Energy use, Energy service companies (*ESCO*s), Dynamic *IPAT* model

JEL Classification: O13, Q43, Q55

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1. Introduction

Many analysts argue that the increased greenhouse gas (GHG) emissions, largely from the excessive use of fossil fuels, explain much of recent and projected climate change. With the growing awareness of the serious consequences of climate change (IPCC, 2007; Tol, 2009), many countries enacted energy policies to reduce energy use. For example, the European Union (EU) *Energy Efficiency Plan 2011* (EEP), published in March 2011 by the European Commission as a follow-up to the *2006 Action Plan for Energy Efficiency: Realizing the Potential* (EEAP), proposes to save 20 percent of its primary energy consumption by 2020 compared to projections.[1] EU leaders know that the greatest energy saving potential lies in buildings, since nearly 40 percent of final consumption comes from houses, public and private offices, shops, and other buildings. Thus, to meet the energy reduction targets, the EEP considers instruments to trigger the renovation process in public and private buildings and to improve the energy performance of the components and appliances used in them.

The European Commission proposes the development of energy service companies (*ESCO*s) as catalysts for the renovation. Marino *et al*. (2010) update the *ESCO* market in the EU members and neighboring countries, exploiting energy saving potentials through *ESCO*s in addition to special barriers and policy interventions to increase energy efficiency investments. Since the early 1970s, high energy prices, greater energy demand, climate change, global warming, emerging carbon markets, environmental concerns, and international agreements created opportunities for the development of *ESCO* businesses (Goldman *et al.* 2005; Vine, 2005; Bertoldi *et al.*, 2006; Kiss *et al*., 2007; Urge-Vorsatz *et al.*, 2007; Ellis, 2010; and Sarkar and Singh, 2010). To what extent does the newly emerging *ESCO* industry improve energy use? Or, equivalently,

[1] The 20-percent objective translates into a saving of 368 million tons of oil equivalent (Mtoe) by 2020 compared to projected consumption in that year of 1842 Mtoe.

how effective are *ESCO* activities as a policy tool to cut energy use? Moreover, do the stages of economic development (low- and high-income countries) influence the effect of *ESCOs* on energy use differently? To answer these questions requires empirical analysis. In this present paper, we develop a dynamic panel model to evaluate the effect of *ESCO*s on energy use.

An *ESCO* offers energy-efficiency technologies, including development and design of energy efficiency and emission reduction projects, installation and maintenance of energy efficient equipment, monitoring and verification of the project's energy savings, and finally, a guarantee of the savings for clients in the public, industrial, commercial, or residential sectors (Vine, 2005; WEC, 2008; Ellis, 2010; Marino *et al*., 2011). The *ESCO*'s remuneration relies directly on the amount of energy saved through energy performance contracting (*EPC*). Two main models for *EPC* exist -- shared-saving and guaranteed-saving models (Bertoldi *et al*., 2006; and Okay *et al*., 2008). In the shared-saving model, the *ESCO* and the client share the cost saving at a pre-determined percentage for a fixed number of years. In the guaranteed-saving model, the *ESCO* guarantees a certain level of energy saving for the customer. Europeans seem to prefer, at the margin, guaranteed-saving schemes, since they use shared-saving contracts to a lesser extent (Marino *et al*., 2011). The investment's financing can come from the internal funds of the *ESCO*, from the customer's own funds, or from a third party funding source. In the latter case, a financial institution allows a credit either to the *ESCO* or directly to its client and, then, the loan receives a guarantee for the projected energy or cost savings given by the *ESCO*.

Today, the United States (US) owns the most mature *ESCO* market in the world. Energy-efficiency technologies represent a major share of industry activity, accounting for 75-percent of *ESCO* revenues in 2008 (Satchwell *et al*., 2010). The US market, however, possesses a short history. *ESCO*s emerged first in the 1970s after the oil crisis, which led to higher energy prices, and grew during the utility integrated resource planning and demand-side management (DSM) era of the late 1980s and early 1990s (Goldman *et al.*, 2005; Urge-Vorsatz *et al.*, 2007). The concept gradually spread to Europe and Japan (Vine *et al.*, 1998; Shito, 2003; Vine, 2005; Bertoldi *et al.*, 2006; Patlitzianas *et al.*, 2006; Rezessy *et al.*, 2006; Kiss *et al.*, 2007; Patlitzianas and Psarras, 2007; Marino *et al*., 2010; and Marino *et al*., 2011). For example, Italy initiated *ESCO* activity in the early 1980s (Vine, 2005), where now *ESCO*s account for 90 percent of the energy-efficiency actions (Linares and Perez-Arriaga, 2009). Despite the increased awareness of energy efficiency measures and favorable legislative framework, the *ESCO* market in Europe grew slowly in recent years, partly due to the 2008 financial crisis and the Great Recession. Germany, Italy, and France established a large number of *ESCO*s, while most countries only established a few (Marino *et al*., 2011). In the 1990s, the *ESCO*s spread to developing countries (Davies and Chan, 2001; Lee *et al.*, 2003; Okay *et al.*, 2008; and Ellis, 2010). By 2008, China established the largest *ESCO* industry in the developing world in terms of total investment (Taylor *et al.*, 2008). Recently, the *ESCO* industry received attention from international agencies as a new business model to promote energy efficiency in the world (Bleyl, 2009; Singh *et al.*, 2009; Sarkar and Singh, 2010; Ellis, 2010; and Limaye and Limaye, 2011). Some key international agencies involved in *ESCO* development include the World Bank, the Asian Development Bank, and the US Agency for International Development (ESMAP, 2006; ADB, 2009; and USAID, 2010). Currently, EU leaders plan to promote the development of *ESCO*s to reach their energy saving target (EEP, 2011).

Vine (2005), Goldman *et al.* (2005), and Kiss *et al.* (2007) analyze the results of a survey of *ESCO* activity in 38 countries outside the US, inside the US, and inside 40 pan-European countries, respectively. Marino *et al*. (2010) and Marino *et al*. (2011), based on the results of a large-scale survey carried out in 2009 and 2010 in 39 European countries, present a comprehensive view of the European *ESCO* industry and propose policy recommendations to further promote *ESCO* activities. Vine (2005) gives details on the most important barriers facing the *ESCO* industry in various countries such as customers and engineering companies unfamiliar with or uninterested in *ESCO*s and *EPC*; lack of financing; low energy prices; and lack of government support, commitment, and leadership by example; and so on. In some countries, *ESCO*-industry associations; financing, measurement, and verification protocols; and information and education programs provide key mechanisms for promoting *ESCO* activities. Vine (2005) concludes that countries putting emphasis on the removal of subsidies, and the privatization of energy industry and power sector will lead in the development of the *ESCO* industry. Goldman *et al.* (2005) find that *EPC* overcomes market barriers for energy-efficiency investments among large, institutional public-sector customers in the US. Kiss *et al.* (2007) review European national *ESCO* market indicators and find that the public sector provides the primary focus of *ESCO* activity. Marino *et al*. (2010) and Marino *et al*. (2011) point that as of 2010, the *ESCO* market in Europe still falls far below utilizing its full potential. The authors along with Sarkar and Singh (2010) and Limaye and Limaye (2011) promote ideas for scaling up energy-efficiency investments through *EPC*s. They propose an innovative public-private partnership (or Super *ESCO*) business model to bundle public facilities to lower transaction costs, bring in economies-of-scale, and attract large service providers into the markets.

Using the international survey data from Vine (2005), Okay and Akman (2010) plot the relationships amongst a set of *ESCO* indicators (age of *ESCO* market, number of *ESCO* companies, total value of *ESCO* projects, and sectors targeted by *ESCO*s) and country indicators (per capita GDP, energy consumptions, CO_2 emissions, and global innovation index). In their descriptive study, the positively correlated relationships between the *ESCO* indicators and energy consumption per capita lead them to conclude that the ineffectiveness of *ESCO*s or the lack of saturation of *ESCO* markets limit the reduction of energy use in most of the countries. Bivariate correlations, however, do not provide reliable results, since one does not control for other relevant factors.

In this paper, we use an empirical approach to examine the effects of *ESCO*s on energy use. To the best of our knowledge, we use the first econometric method to evaluate this issue. Our analytic framework uses a dynamic panel model derived from the *IPAT* identity (Commoner *et al.*, 1971; Ehrlich and Holdren, 1971; 1972; Holdren and Ehrlich, 1974). The sample consists of 94 countries over the period 1981 to 2007. We provide significant evidence that *ESCO*s effectively reduce energy use and this result remains robust to different dates of the first *ESCO*. Further examination shows that this negative *ESCO* effect increases over time. These findings illustrate the rationale and support for the EU's adoption of *ESCO*s as a policy tool to reduce energy use. Moreover, we find that the *ESCO* effect differs across the stages of development over time, keeping negative in high-income countries, becoming positive in low-income countries, however. With this finding and the literature reviewed, we propose policy recommendations to promote *ESCO* activities for developing countries or for those countries where *ESCO*s are still in their infancy.

The rest of the article flows as follows. Section 2 presents a brief review of the dynamic *IPAT* model and its properties. Section 3 describes the data, and reports and discusses the results. Section 4 analyzes the possible effects of time on the effectiveness of *ESCO*s. Section 5 examines *ESCO* effects across the stages of economic development. Section 6 concludes and provides policy recommendations.

2. A dynamic *IPAT* model

The well-known *IPAT* (or *I=PAT*) model identifies resource depletion or any environmental impact (I) of the product of three factors: population size (P), affluence of the economy (A) measured by per capita GDP, and the existing technology (T), measured by the environmental effect per unit of economic activity. Holdren (1991) uses this formula to show that population contributed at least 49 percent of the global growth in total energy use in the period 1850 to 1990. We expand this model to examine the effect of *ESCO* activity on energy use.

The *IPAT* is a mathematical identity [i.e., by definition, I = P (GDP/P) (I/GDP)]. Thus, it does not permit hypothesis testing for the driving forces of environmental effects. To overcome this limitation, Dietz and Rosa (1994, 1997) and York *et al.* (2003a) reformulate *IPAT* into a stochastic impacts by regression on population, affluence, and technology (*STIRPAT*) model as follows: $I_i = aP_i^b A_i^c T_i^d e_i$. With panel data, after taking natural logarithms (ln), the model becomes:

$$\ln I_{it} = a_i + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \eta_t + e_{it} \qquad (1)$$

where the subscript, *i*, denotes the country; *t* denotes the year; a_i is a country-specific fixed-effect; η_t is a year-specific effect; and e_{it} is the error term.

Many authors successfully use the *STIRPAT* to analyze the effects of driving forces on a variety of environmental impacts (Shi, 2003; York *et al.*, 2003a, 2003b; Cole and Neumayer, 2004; Martinez-Zarzoso *et al.*, 2007; York, 2007; Liddle and Lung, 2010; Poumanyvong and Kaneko, 2010; Liddle, 2011; and Martinez-Zarzoso and Maruotti, 2011). For example, considering the difference in energy intensity, Shi (2003) decomposes technology (T) into two parts, the share of the manufacturing and service sectors in GDP, to examine the effect of population on global carbon dioxide emissions. Considering countries whose GDP heavily derives from the industrial sector will exhibit energy-intensive production and higher energy use; whereas countries whose

GDP largely derives from services will exhibit less energy-intensive production and lower energy use. Poumanyvong and Kaneko (2010) include these two structural variables in their model to examine the effect of urbanization on energy use across different levels of income. Liddle and Lung (2010) argue that using the structural share of manufacturing or industry activity to explain aggregate carbon emissions or energy use mis-specifies the *STIRPAT* model because "the share of economic activity from manufacturing or industry has declined does not mean the level of such activity has fallen; and it is the level of activity that should influence the level of emissions (or energy use)" (p. 323). Excluding the two structural variables, Liddle and Lung (2010) as well as York (2007) find that urbanization in addition to population size, age structure, and per capita GDP contributes to changes in energy consumption in seventeen developed countries and fourteen EU countries, respectively.

The percentage of total population living in urban areas measures urbanization. The effect of urbanization on environment also produces a debate.[2] Some researchers show that urbanization or urban density improves the efficient use of public infrastructure and lower energy use (Ehrhardt-Martinez, 1998; Liddle, 2004; Chen *et al.*, 2008). Other scholars, however, find that urbanization increases energy demand and consumption (Jones, 1991; Parikh and Shukla, 1995; Foster, 1999; York *et al.*, 2003a; Cole and Neumayer, 2004; York, 2007; Liu, 2009; Liddle and Lung, 2010). Focusing on differences in income levels, Poumanyvong and Kaneko (2010) find that the effect of urbanization on energy use varies across the stages of development: urbanization decreases energy use in low-income countries, while it increases energy use in the middle- and high-income countries.

[2] Liddle and Lung (2010) provide a detailed discussion of this issue.

Another category of work, the environmental Kuznets curve (EKC), focuses on an inverted-U relationship between environmental effect and economic growth: the effect worsens in the early stages of growth, but eventually reaches a peak and declines as income passes a certain threshold level (Dasgupta *et al.*, 2002; Dinda, 2004; Stern, 2004; Caviglia-Harris *et al.*, 2009; Carson, 2010; and Kilima *et al.*, 2010). Empirical models testing for the EKC hypothesis typically regress the effect of per capita on real GDP per capita and squared real GDP per capita along with other explanatory variables. If the squared term exhibits a significantly negative coefficient and the estimated extreme point lies within the data range, an inverted-U relationship exists.[3] Richmond and Kaufmann (2006) and Luzzati and Orsisni (2009) investigate the energy-environmental Kuznets curve. They find that energy consumption and real GDP per capita follow a positive, monotonic relationship, revealing no evidence of EKC.

Both population and per capita real income generate environmental pressure in either total or per capita terms. We focus more on the total effect simply because it directly links to climate change and global warming. In the *IPAT* framework, the technology or policy variable proves critical in environmental improvement. We need to control global energy use by changes in technology or policy to offset, at least partly, the adverse effects of population growth and per capita real income growth. Doing so can achieve a sound process of sustainable world development. *ESCO*s can contribute by developing public and private projects designed to improve energy efficiency and reduce energy use.

To examine the effect of *ESCO*s on energy use, we develop a dynamic *IPAT* model that explicitly captures the dynamics of adjustment in the energy series. The idea is straightforward. It

[3] Empirical findings generally show that global pollutants (such as carbon dioxide) either increase monotonically with per capita income, start declining at income levels well beyond the observed range, or depend on different income levels and regions, while only local pollutants (such as air and water pollutants) emerge with a meaningful EKC (Grossman and Krueger, 1995; Holtz-Eakin and Eslden, 1995; Cole *et al.*, 1997; Lee *et al.*, 2009; Caviglia-Harris *et al.*, 2009; and Gassebner *et al.*, 2011).

takes time to achieve the energy reduction target such as the objective proposed by the EU commission. In the process of gradual adjustment toward the target, current and lagged energy uses correlate with each other. This dependency suggests using a dynamic model to capture the lagged effect as follows:

$$\ln I_{it} = a_i + b\ln I_{it-1} + c\ln P_{it} + d\ln A_{it} + e\ln A_{it}^2 + f\ln UB_{it} + \eta_t + e_{it} \tag{2}$$

where I_{it} (I_{it-1}) is the amount of energy use in kiloton (kt) in country i and year t ($t-1$). A_{it} (A_{it}^2) is the per capita real GDP (squared) in PPP (purchasing power parity at 2005 constant international dollars) to test for the EKC hypothesis. UB_{it} denotes urbanization.[4]

The country-specific effect (a_i), such as geography and demographics, may correlate with the explanatory variables. For estimation, we take the first differences of equation (2) to remove this effect. Then adding a variable to capture *ESCO* activity completes our estimation equation as follows:

$$\begin{aligned}\Delta\ln I_{it} = b\Delta\ln I_{it-1} + c\Delta\ln P_{it} + d\Delta\ln A_{it} + e\Delta\ln A_{it}^2 + f\Delta\ln UB_{it} \\ + \alpha\ ESCO + \Delta\eta_t + \Delta e_{it}\end{aligned} \tag{3}$$

where Δ is the first difference operator. Taking the first differences also typically converts the variables to stationary ones.[5] *ESCO* is a dummy variable, which equals one the year the country

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[4] The specification in equation (1) does not consider the dynamics of adjustment, since the dependent variable does not depend on its lagged value as it does in equation (2). That is, the data-generating process in equation (1) represents a static *IPAT* model.

[5] Researchers consider the stationarity of data used in model estimation. In the energy economics literature, variables, such as energy consumption, renewable energy consumption, GDP, urbanization, transport carbon emissions, residential electricity consumption, labor force, population, and so on, exhibit nonstationarity in levels and stationarity in first differences (see, e.g., Mishra *et al*., 2009; Apergis and Payne, 2010; Liddle, 2011). That is, the variables are integrated of order one, *I(1)*. OLS regressions with *I(1)* variables in levels are inefficient and possibly spurious. Mishra *et al*. (2009) and Apergis and Payne (2010) apply panel cointegration and error-correction modeling to test for Granger causality between energy consumption and GDP. Liddle (2011) uses a cointegrated-STIRPAT model to examine the effects of the population age structure on transport carbon emissions and residential electricity consumption. Martinez-Zarzoso *et al*. (2007), on the other hand, apply the generalize method of moments (GMM) method to the first-differenced series (Arellano and Bond, 1991) in the STIRPAT

started its *ESCO* business; zero otherwise. The *ESCO* represents the technology (*T*) that can reduce energy use. We find evidence supporting the adoption of *ESCO*s as a policy tool to reduce energy use if $\alpha < 0$.

We further modify this specification and interact the *ESCO* dummy variable with the number of years of *ESCO* activities and its squared term to examine the possible effects of time on the effectiveness of *ESCO* in affecting energy use. That is,

$$\begin{aligned} \Delta \ln I_{it} &= b\Delta \ln I_{it-1} + c\Delta \ln P_{it} + d\Delta \ln A_{it} + e\Delta \ln A_{it}^{2} + f\Delta \ln UB_{it} \\ &+ \alpha\ ESCO + \gamma(ESCO \cdot year) + \delta(ESCO \cdot year^{2}) + \Delta\eta_{t} + \Delta e_{it}, \end{aligned} \tag{3a}$$

where *year* and $year^2$ denotes the number of years since the *ESCO* adoption and its squared term, respectively.

Finally, to examine whether the *ESCO* effect on energy use differs across the stages of development, we also divide our panel data into two sections based on per capita GDP. That is, we separately estimate the sample divided into two income groups, low and high, based on a positional value, the median of the observations on per capita GDP (= US$7,270) in this study. Each of the low- and high-income groups thus consists of 47 countries with per capita GDP lower and higher than US$7,270, respectively.

In equations (3) and (3a), two potential econometric problems may arise. First, the lagged difference dependent variable, $\Delta \ln I_{it-1}$, probably correlates with the error term, Δe_{it}. Second, the explanatory variables probably are endogenous. Therefore, we require instrumental variables to calculate the difference estimators. Under the assumptions that the error term is not serially correlated and that the lagged levels of the explanatory variables are weakly exogenous, we use the generalized method of moments (GMM) system estimator, which is designed for dynamic panel

model to analyze the effect of population on carbon emissions. In this study, we combine difference GMM estimator with an estimator in levels to produce a more efficient system GMM estimator (Blundell and Bond, 1998) to estimate the effect of *ESCO*s on energy use.

analysis, proposed in Arellano and Bover (1995) and Blundell and Bond (1998) (see Roodman, 2009, for applications) to solve these problems. This method jointly estimates the equation in differences and levels, with the differences equation estimated with lags of the levels of regressors and dependent variables and the level equation estimated with the first difference of the regressors. The regression needs to pass two standard specification tests: the Sargan test for over-identification and second-order serial correlation test. The null hypothesis of the former is that the instruments used do not correlate with the residuals from the respective regression. The null hypothesis of the latter test is that the errors in the first-difference regression exhibit no second-order serial correlation (significant negative first-order serial correlation is allowed).

Another econometric issue may arise if our panel data across countries exhibit dependence. For example, countries that develop *ESCO*s to reduce energy use will enter energy performance contracts (*EPC*s) to overcome market barriers and guarantee energy saving, which may imply dependence in energy consumption across countries. In panel data analysis, if observations are dependent across individuals, then estimators based on the assumption of cross-sectional independence may prove inefficient (Hsiao *et al*., 2012; Sarafidis and Wansbeek, 2012). We, therefore, need to test for cross-sectional dependence before embarking on estimation and inference. We employ the Sargan's difference test, proposed by Sarafidis *et al*. (2009) and Sarafidis and Wansbeek (2012), for detecting error cross-sectional dependence after estimating a linear dynamic panel data model with regressors using the system GMM estimator. Sarafidis *et al*. (2009) also suggest the inclusion of year dummy variables to remove possible time effects in dynamic panel models. We, thus, include such dummy variables in all specifications. The Sargan's difference test involves computing Sargan's statistic for over-identifying restrictions based on two different GMM estimators: one uses the full set of instruments available and the other uses only a subset of instruments. Under the null of hypothesis of cross-sectional independence, both GMM estimators are consistent, whereas under the alternative of error cross-sectional dependence, the latter estimator remains consistent but the former does not. A large difference between the two statistics implies that the moment conditions with respect to lags of the dependent variable are not valid -- a direct consequence of cross-sectional dependence. Under the null hypothesis, the Sargan's difference test statistic based on the system GMM estimator is distributed as chi-squared.[6]

Finally, we also use the t-bar statistic proposed by Im *et al*. (2003) to test the null hypothesis of a unit root in residuals. This stationary panel residual test suggests a well-specified regression.

3. Data, estimation results, and discussion

Data description

We use a balanced panel dataset of 94 countries from 1981 to 2007, yielding a total of 2,435 observations. *ESCO*s first appeared in the late 1970s and early 1980s in a few countries such as Canada, Sweden, the UK, and the US. Most *ESCO* activities began in the late 1980s and 1990s, and the number of *ESCO* countries continued to grow in the 2000s. In equation (3), we proxy for *ESCO* activity with the dummy variable, which equals one the year *ESCO* activity began in the country and thereafter; zero otherwise. In his international survey, Vine (2005) lists 38 countries (outside the US) that became involved in *ESCO* activities with the initial year or range of years when that activity began. Given the ranges, we use the mid-point as the starting year. For example, since Vine identifies the range for Argentina and Philippines as the 1990s, we adopt 1995 as the time of the first *ESCO*. Germany's range equals 1990 to 1995, meaning that we adopt 1993 as the

[6] We implement the test in Stata (see Roodman, 2009).

starting year. Italy's range equals the early 1980s, which we translate into 1983 as the starting year. And finally, Hungary's range of the late 1980s to the early 1990s leads to the adoption of 1990 as the starting year. In a pan-European survey of *ESCO*s, Kiss *et al.* (2007) provide some new European *ESCO* countries in addition to starting dates for *ESCO* activity that differ from those in Vine (2005) for some countries. We use these alternative dates as a robustness check on our results. Table 1 lists the *ESCO* countries and their starting years from Vine (2005) and Kiss *et al.* (2007). The US started its *ESCO*s in the 1970s (Urge-Vorsatz *et al*. 2007). To avoid confusion, we refer to the different dates as the Vine or Kiss starting years. In the model estimation, the Kiss starting years includes Kiss *et al.* (2007) pan-European data plus countries outside of Europe in Vine (2005) and the US.

The data on energy use, population, per capita GDP, and urbanization come from the World Development Indicators published by the World Bank.[7] Total energy use originally comes from the International Energy Agency (IEA). Table 2 reports a detailed description of the variables, preliminary statistics on the data, and simple correlation coefficients between the variables (in logarithmic form) in the model.

The high significant positive correlation (= 0.9997) between current (I) and the lagged energy use (I_{t-1}) suggests a dynamic model. Also, the correlations between current energy use and each of the other variables studied match closely to the correlations between the lagged energy use and the variables. All human activities positively correlate with energy use except for urbanization, which negatively correlates with energy use. Okay and Akman (2010), based on positive correlations between per capita energy consumption and three *ESCO* indicators – the age of the *ESCO* market, the number of *ESCO*s, and total value of *ESCO* projects -- conclude that *ESCO*s do

[7] Data come from the following source: http://data.worldbank.org/data-catalog.

not effectively reduce energy use. As we noted above, drawing conclusions based on bivariate correlations can lead to erroneous conclusions, as we will demonstrate. We use an aggregate *ESCO* measure (the dummy variable) and employ an empirical approach (the dynamic *IPAT* model) to examine the effect of *ESCO*s on energy use.

Estimation results

*ESCO*s offer technical services to implement energy efficiency projects and guarantee that the energy savings associated with the project will cover the costs of the project over a certain period of time. We first use the following simple dynamic panel model with the system GMM estimator to examine whether *ESCO*s improve energy efficiency (*EE*):[8]

$$\Delta \ln \mathrm{EE}_{it} = b\Delta \ln \mathrm{EE}_{it-1} + \alpha\ \mathrm{ESCO} + \eta_t + e_{it} \tag{4}$$

The estimation results are:

$$\begin{gathered} \Delta \ln EE_{it} = \underset{(0.002)}{0.9870}\Delta \ln EE_{it-1} + \underset{(0.001)}{0.0080}\, ESCO \end{gathered} \tag{5}$$

where *EE* equals real GDP divided by energy use and *ESCO* is the dummy variable based on Vine (2005). The *ESCO* estimate is significant at 1-percent level (p-values appear in parentheses) and the regression passes the Sargan, autocorrelation, and Sargan's difference tests.[9] The positive coefficient of *ESCO* (α>0) implies that *ESCO* activity improves energy efficiency (*EE*). As addressed by Oikonomou *et al*. (2009), Linares and Labandeira (2010), and Bertoldi *et al*. (2010), improving energy efficiency becomes interesting only when it produces net savings. We now focus on whether *ESCO*s generate energy savings.[10]

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[8] We implement all the GMM results by the Stata command xtabond2 (see Roodman, 2009).

[9] We omit the year dummy variables and their estimated coefficients. Results are available on request

[10] We can achieve energy saving by improving the energy efficiency of the service provided (technological aspects) and/or by changing the consumption pattern without necessarily making technological improvements (behavioral aspects, e.g., avoid overheating, prevent overcooling, or reduce driving). Energy efficiency provides an important

Table 3 reports the results from the system GMM estimator of equation (3). In Model 1, we regress energy use on the lagged energy use, total population, and real per capita GDP with p-values in parentheses, statistics for the Sargan, autocorrelation, Sargan's difference and panel unit-root tests for residuals. This baseline model incorporates only the basic elements from our dynamic *IPAT* framework.[11] The results indicate that all three explanatory variables are statistically significant at the 1-percent level and display the expected positive signs. The lagged dependent variable explains the largest part of current energy use, lending support to the dynamic specification. In the log-log specification, the coefficient estimates represent elasticities or the ratios of percent changes. A 1-percent increase in population associates with a 0.0722-percent increment in energy use, while a 1-percent increase in real per capita GDP associates with a 0.0459-percent increase in energy use. Note that in our dynamic *IPAT* model, the estimates report short-run elasticities. The long-run elasticities take the short-run parameters and divide them by 1 minus the coefficient on the lagged energy use variable. Thus, the long-run elasticities equal 1.0760 and 0.6941, respectively, for population and real per capita GDP. The regression passes the specification tests. The Sargan test for over-identification does not reject the null. The test for first-order serial correlation rejects the null of no first-order serial correlation, but it does not reject the null of no second-order serial correlation. The Sargan's difference test does not reject the null hypothesis of error cross-sectional independence.[12] The panel unit-root test indicates the residuals are stationary.

component of achieving energy saving, as it implies that the same goods and services are produced with reduced energy use. This is the focus of *ESCO*s.

[11] Note that we cannot include the energy efficiency variable in equation (3) because it is measured by GDP divided by energy use, containing part of the dependent variable.

[12] If we do not include the time (year) dummy variables, we can reject the null hypothesis of error cross-sectional independence.

Second, we estimate the dynamic *IPAT* model, where we include the dummy variable for *ESCO* activity in Model 2, but still exclude the other explanatory variables. The dummy equals one from the year of the first *ESCO* activity through the end of the sample; zero otherwise, based on Vine's (2005) *ESCO* country data in Table 1. The coefficient of the *ESCO* dummy proves significantly negative at the 5-percent level. All other estimates and the diagnostic statistics match those in the baseline model (Model 1). These results suggest that *ESCO*s reduce energy use. The antilog of the coefficient for the *ESCO* dummy variable shows the ratio of energy use with *ESCO* activity to that without such activity. For example, the antilog of the coefficient of -0.0366 equals 0.9641, indicating that *ESCO* countries produce about 96.41 percent of the energy use of non-*ESCO* countries, controlling for other factors. In other words, *ESCO* countries exhibit approximately 3.59-percent lower energy use. This reflects the short-run effect, however. The long-run effect is calculated as -0.4772 (= -0.0366/(1 – 0.9233)). Thus, the antilog of -0.4772 equals 0.6205, indicating that *ESCO* countries exhibit about 62.05 percent energy use of non-*ESCO* countries or 37.95 percent lower energy use.

Third, to examine the existence of an inverted-U-shaped EKC, Model 3 adds squared real per capita GDP to Model 2. The estimate of the squared term proves insignificantly positive. The positive coefficients for both real per capita GDP and its squared value indicate that energy use shows no evidence of the EKC hypothesis. The coefficient for *ESCO* dummy variable remains negative and significant at the 10-percent level.

Fourth, we estimate equation (3) where we include the urbanization variable, but still use the Vine dating of *ESCO* adoption (Model 4). The significant negative energy use-*ESCO* relationship still holds, if we accommodate the potential linkages between urbanization and energy use. Adding the urbanization variable to the model does not alter in any major way the coefficients for the lagged dependent variable, population, per capita GDP, squared per capita GDP, and *ESCO*. Urbanization reduces energy use. The negative energy use-*ESCO* relationship remains robust to inclusion of the control variable.

Fifth, to further check the robustness of the effect of *ESCO* activities on energy use, we ask whether the finding on the negative energy use-*ESCO* relationship continues to hold if we use the different dates of the first *ESCO* activity. That is, we use the dates from Kiss *et al.* (2007) for the pan-European *ESCO* countries data combined with the international data from outside Europe in Vine (2005), and the US date of the first *ESCO* activity in Urge-Vorsatz *et al.* (2007) to replace the Vine data. That is, Models 5, 6, and 7 report the estimation results that correspond to Models 2, 3, and 4, except with the new pattern of dates in the Kiss data. In each of the three models, the coefficient of the *ESCO* dummy confirms a negative association between energy use and *ESCO* activities at the 10-percent level or better. Thus, the model adjusting for different years of the first *ESCO* yields robust results with regard to the effect of *ESCO* activity on energy use.

Discussion

In the dynamic *IPAT* model, lagged energy use clearly and significantly predicts current energy use. In all seven models, the significant coefficient at the 1-percent level on lagged energy use lies consistently around 0.92 or 0.93. The models also consistently pass the two standard specification tests as well as the Sargan's difference test and a panel unit-root test, exhibit no correlation between the instruments used with the residuals from the respective regression, no second-order serial correlation in the errors of the first-differenced regression, no cross-sectional dependence, and stationarity of residuals, indicating the appropriate specification of the dynamic model. Model 4 fits the data well. All variables, except for the squared real per capita GDP, experience significant coefficients and adding other variables to simple models (Models 1, 2, and 3) or using different dates of the first *ESCO* activity (Models 5, 6 and 7) does not substantially alter the coefficients for population, affluence, and the *ESCO* dummy variable. We, therefore, primarily focus our discussion on Model 4.

This study focuses on the effect of *ESCO*s on energy use. The coefficient estimates prove negative and significant at least at 10-percent level in all models when we add the *ESCO* dummy variable as an explanatory variable, indicating that *ESCO* activities around the world effectively reduce energy use. In Model 4, the negative estimate (-0.0387) suggests that adoption of *ESCO* reduces energy use by around 3.80 percent in the short-run. The long-run *ESCO* effect equals 0.6034, suggesting 39.66 percent lower energy use, larger than the effect in Model 2 (= 37.95 percent) with no additional control variables.

Population generally associates with higher energy use. The population elasticity effect on energy use (0.0848) appears to fall below the estimate of 2.665 in York (2007) and 1.23 in Poumanyvong and Kaneko (2010). These studies use a static *STIRPAT* model such as equation (1), however. Since the authors did not include the lagged dependent variable in their models, the coefficient estimates reflect long-run elasticities. In our dynamic *IPAT* model, the short-run estimate implies a long-run population elasticity of 1.1070 (= 0.0848/(1-0.9234)), which then matches closely to the estimate of 1.038 in Liddle and Lung (2010) who include the one-period lagged dependent variable among the regressors to account for correlation between current and past levels of energy consumption. The nearly one long-run elasticity conforms to the unity assumption for the population elasticity embedded in the original *IPAT* formulation of Ehrlich and Holdren (1971).

The affluence coefficient exerts a positive and significant effect on energy use, while the insignificantly positive coefficient for the squared affluence term suggests no EKC effect. This conclusion supports studies such as York (2007), who employs a *STIRPAT* model, and in Luzzati and Orsisni (2009), who uses an EKC analysis.

Urbanization exhibits a significant negative effect on energy use, corresponding to the negative correlation between energy use and urbanization in Table 2. The negative relationship also appears in Liddle (2004), Chen *et al*. (2008), Pachauri and Jiang (2008), Mishra *et al*. (2009), and in Poumanyvong and Kaneko (2010) for low-income countries, while a positive relationship appears in Jones (1991), York (2007), Liu (2009), Liddle and Lung (2010), and in Poumanyvong and Kaneko (2010) for middle- and high-income countries. Different theoretical models, sample countries, sample periods, static or dynamic empirical models, as well as different estimators may lead to different results. Considering temporal dependency of energy use, we use a dynamic panel *IPAT* model with system GMM estimator, which differs from most previous studies.

4. The *ESCO* effect varies with time

Our analysis to this point considers the effects of the *ESCO* dummy variable on energy use. Our data on *ESCO* only identifies when *ESCO* operations started in each country. We do not know the size of these operations and/or how these activities changed over time after the initial adoption. This section includes additional test to examine the *ESCO* effect on energy use over time. Since we do know the number of years since the permitting of *ESCO* activities, we interact the *ESCO* dummy variable with the number of years of *ESCO* activities (*ESCO*year*). Without the interaction term (such as in Model 4), the *ESCO* effect on energy use assumes implicitly that the effect remains constant over time. Moreover, since non-linear effects may exist (e.g., diminishing returns over time), we also interact the *ESCO* dummy variable with the number of years since permitting *ESCO* activity squared ($ESCO*year^2$). See equation (3a) for this specification. At this stage, we take the most robust variables to estimate the model. That is, we exclude the squared term of real GDP per capita in the estimation because no evidence supports the inverted-U relationship between energy use and real per capita GDP in Table 3.

The results of this analysis appear in Table 4. Models 8 and 9 use the Vine (2005) dating of *ESCO* to re-estimate the specification with the interaction terms, whereas Models 10 and 11 correspond to Models 8 and 9, respectively, but use the modified dates on *ESCO* as reported by Kiss *et al.* (2007). Each of the models passes all diagnostic tests.

In Model 8, the *ESCO* estimate with significant *t*-statistic indicates a negative effect on energy use when the number of years since the permitting of *ESCO* activities equals zero (i.e., *year* = 0). To test for the null of no effect of *ESCO*s, we test if the estimates of *ESCO* and *ESCO*year* equal zero jointly using an F-test. The high F-statistic reported in Table 4 rejects the null, suggesting the *ESCO*-energy use relationship varies over time. Consider Model 8, for example. Adopting *ESCO* reduces energy use by -0.0103, ignoring the time effect. Each additional year since the adoption reduces energy use by -0.0018. According to the Vine's starting years in Table 1, the mean value of the number of years since *ESCO* adoption is 15 years. Thus, in our sample 15 years after adoption yields a reduction of energy use by -0.0373 [= -0.0103– 0.0018(15)] or by 3.66 percent, on average.[13] The long-run effect equals -0.5634 [= -0.0373/(1 – 0.9338)] or 43.08 percent. The long-run *ESCO* effect exceeds the effect identified above of a 39.66-percent reduction in energy use in Model 4 which assumes a constant *ESCO* effect. The *ESCO* effect increases over time.

Model 9 considers potential non-linear effects through the interaction of the *ESCO* dummy variable and the squared value of the number of years since adoption. Now, the initial effect is

[13] The interaction effect is defined as the cross-partial derivative of energy use with respect to *ESCOs*. In Model 4 the *ESCO* estimate of -0.0387 implicitly evaluates the effect at the mean value of the number of years since the permitting of *ESCO*s (i.e., *year*), which comes close to -0.0373. Thus, we can interpret the large change in the estimate to the *ESCO* term as reflecting the coefficient to *ESCO* as the marginal effect of *ESCO* when *year* equals zero.

-0.0619. Each additional year increases energy use by 0.0090, but at a decreasing rate of -0.0004**year*. The short-run marginal *ESCO* effect is -0.0169 [= -0.0619 + 0.0090(15) – 0.0004(15^2)] or 1.68 percent. Accordingly, the long-run effect equals -0.2511 (= -0.0169/(1 -0.9327)) or 22.21 percent.

Similar findings emerge when using the Kiss's starting years in Table 1. Now, the mean value of the number of years since *ESCO* adoption is 14 years. The calculated short-run marginal effect of *ESCO* is -0.0307 or 3.02 percent in Model 10 and -0.0179 or 1.77 percent in Model 11. The long-run effect equals -0.4411 (= -0.307/(1 – 0.9304)] or 35.67 percent in Model 10 and -0.2518 (= -0.0179/(1 – 0.9274)) or 22.26 percent in Model 11. Considering the *ESCO* effect on energy use over time, in either Model 9 or Model 11, the long-run *ESCO* effect reaches the EU's 20-percent energy reduction target. Thus, *ESCOs* provide an effective policy tool to reduce energy use.

5. The *ESCO* effect differs across the stages of development

Our analysis so far assumes implicitly a homogeneous *ESCO* effect on energy use for all countries. We do not consider the possible effect of differences in the stage of development or income on the effectiveness of *ESCO* in affecting energy use. Many characteristic differences, such as government energy policy, institutional framework, maturity of the energy efficiency market, knowledge of energy efficiency projects and the *EPC* concept, *ESCO* project financing and experience with successful *ESCO* projects, exist among countries of different levels of development. In their recent studies, Ellis (2010), Sarkar and Singh (2010) and Limaye and Limaye (2011) find that although countries established many programs and mechanisms to facilitate the growth of *ESCO*s, most developing countries only experienced moderate success (with the exception of China). Thus, we expect different effects of *ESCO*s on energy use in developed and developing countries. This section addresses this issue by splitting the full-sample into low- and high-income countries, based on the median observation (=US$7270)on per capita GDP in this study.

Table 5 reports the results. Models 12 and 13 use the Vine (2005) and Kiss *et al.* (2007) dating of *ESCO*, respectively, to estimate the specification with the interaction terms for low-income countries (corresponding to Models 9 and 11 in Table 4), whereas Models 14 and 15 correspond to Models 12 and 13, but for high-income countries. All regressions pass the Sargan, autocorrelation, cross-sectional dependence, and the panel unit-root tests.

All estimated coefficients in the models prove significant at least at the 10-percent level, except for the coefficients of urbanization in low-income countries, the interaction term of *ESCO* and the number of years squared, and the interaction term of *ESCO* and the number of years in high-income countries using the Vine (2005) data. The relationship between urbanization and energy use remains negative and significant in high-income countries. The insignificant estimate of the interaction term, $ESCO*year^2$, may reflect a weak *ESCO* effect on energy use over time. In recent studies, Ellis (2010), Sarkar and Singh (2010), and Limaye and Limaye (2011) find that *ESCO*s in most developing countries only experienced moderate success, while Marino *et al*. (2010) and Marino *et al*. (2011) find that European *ESCO* markets grew slowly in recent years, partly due to the 2008 financial crisis and Great Recession. The effect of *ESCO* on energy use emerges as evidenced by the significant F-statistics, testing jointly the estimates of *ESCO* and its interaction terms with time, in both the low- and high-income countries.

Now we compare Models 12 and 14. In Model 12, adopting *ESCO* reduces energy use by -0.0184 initially. Each additional year since the adoption increases energy use by 0.0051 at a decreasing rate of 0.0002**year*. The Vine's mean value of the number of years since *ESCO* adoption is 15 years. Thus, for low-income countries, the short-run *ESCO* effect equals 0.0131 [= -0.0184 + 0.0051(15) - 0.0002(15^2)]. The positive effect over time suggests 1.32 percent more energy use in *ESCO* countries than in non-*ESCO* countries. Accordingly, the long-run effect equals 0.1112 (= 0.0131/(1 - 0.8822)) or 11.76 percent more energy use. For high-income countries in Model 14, the initial *ESCO* effect is -0.0641. Each additional year increases energy use by 0.0076, at a decreasing rate of -0.0003**year*. The short-run marginal *ESCO* effect is -0.0176 [= -0.0641 + 0.0076(15) – 0.0003(15^2)] suggesting a 1.74 percent less energy use. The corresponding long-run effect equals -0.500 (= -0.0176/(1 - 0.9648)) or 39.35 percent less energy use. The F-statistic (= 3.47 with p-value 0.001) rejects the null hypothesis of equality of all the coefficients between Models 12 and 14. When we examine whether the three *ESCO* estimates (*ESCO*, *ESCO*year*, $ESCO*year^2$) are the same, the test (= 2.13 with p-value 0.075) also rejects the equality of the subset of coefficients between the two models. Thus *ESCO*s behave differently over time in low- and high-income countries: the former raise and the latter reduce energy use.

Similar findings emerge when using the Kiss's mean value of the number of *ESCO* adoption years of 14. For the low-income countries, the calculated short- and long-run effects of *ESCO* equal 0.0215 or 2.17 percent and 0.1960 or 21.65 percent more energy use, respectively, obtained from Model 13. In contrast, for the high-income countries, the short- and long-run effects of *ESCO* equal -0.0312 or 3.07 percent and -0.8000 or 55.07 percent less energy use, respectively, obtained from Model 15. The F-tests (= 3.41 with p-value 0.001 and 2.06 with p-value 0.084) reject, respectively, the hypothesis that all and the *ESCO* subset of the coefficients are the same in Models 13 and 15.

In sum, the effect of *ESCO*s on energy use differs across the stages of development. The positive and negative *ESCO* effects, respectively, in low- and high-income countries indicate that

*ESCO*s raise energy use in low-income countries and reduce energy use in high--income countries. This finding may reflect the general view that energy efficiency potential in most developing countries remains largely untapped such as addressed in Ellis (2010), Sarkar and Singh (2010), and Limaye and Limaye (2011).

6. Conclusion and policy recommendation

Reducing greenhouse gas (GHG) emissions that cause climate change involves using less energy. Improving energy efficiency provides one of the most cost effective ways to reduce energy use. One mechanism to promote investment in energy efficiency technologies and, thus, to reduce energy use engages energy performance contracting (*EPC*) undertaken by energy service companies (*ESCO*s), which deliver improved energy efficiency in the public and private sectors. *ESCO*s appeared in the US in the early 1970s. They spread to Europe and Asia in the 1980s and 1990s, and continued to grow in developing countries in the 2000s. Today *ESCO*s attract attention worldwide. For example, the EU supports the uptake of *ESCO*s as catalysts for renovation in public and private buildings.

The development of *ESCO*s marks forty-years of experience. The professional literature on the *ESCO* market is small, but informative. Most papers are descriptive studies, however. This paper contributes to the literature by investigating empirically the effect of *ESCO*s on energy use using a dynamic *IPAT* model and a balanced panel dataset of 94 countries over the period 1981 to 2007.

We use the data on years when the first *ESCO* appeared in 38 countries in Vine (2005), 40 pan-European countries in Kiss *et al*. (2007), and the US in Urge-Vorsatz *et al*. (2007) as indicators for international *ESCO* activities. We use this data to examine the effect of *ESCO* activity on energy use. Our system GMM estimation results indicate that *ESCO*s significantly reduce energy use and that this effect remains robust to different dates of the first *ESCO*. The *ESCO* reduction effect increases over time with the long-run effect exceeding 20 percent. The magnitude of this reduction proves sufficient to reach some current targets of energy savings, such as the EU's proposal for saving 20 percent by 2020. Moreover, the *ESCO* effect differs across the stages of development over time. *ESCO*s effectively reduce energy use in high-income countries but raise energy use in low-income countries.

The findings of this study that *ESCO* activities prove an effective policy tool to reduce energy use and more effective in high- relative to low-income countries deserve special attention from energy policy makers, particularly in developing countries or those countries where the establishment of *ESCO*s still remains in its early stages or even does not yet exist. Thus, based on the literature reviewed, we offer several policy recommendations to initiate or enlarge the *ESCO* market. First, if adopted, this policy tool will provide a strong signal from the public sector about its intention to reduce energy use. In countries such as the US and European countries, the public sector comprised the most important *ESCO* client, which eventually triggered the development of the national *ESCO* industry through projects in public buildings as well as through favorable legislation and financial support (Vine, 2005; Kiss *et al*., 2007; Urge-Vorsatz *et al*., 2007; EEP, 2011; Marino *et al*., 2011). Second, the EU Commission proposes binding measures for public authorities to refurbish from at least 3 percent of their buildings each year up to a total of 10 percent through *ESCO*s. Successful *ESCO*s in the public sector can lead by example and attract large suppliers and service providers into the markets (EEP, 2011). Third, the public sector infrastructure, such as hospitals, schools, municipalities, government buildings, and other public facilities, often represents the largest single energy user in a country. Public sector buildings and other facilities exhibit relatively homogeneous consumption patterns and common ownership and, thus, offer huge potential for implementing energy efficiency projects by combining projects in different buildings into one bundle. The bundling can lower transaction costs, deliver large-scale energy savings, and enlarge market activities (Singh *et al*., 2009; Sarkar and Singh, 2010; Limaye and Limaye, 2011; Marino *et al*., 2011). Fourth, informational, technical, financial, institutional, and behavioral barriers exist for *ESCO* investment in the public sector, however, particularly in developing countries. An innovative Super *ESCO* or public-private partnership (PPP) business model that functions as an *ESCO* for the public sector market recently evolved as a mechanism for overcoming some of the limitations and barriers hindering the large-scale implementation of energy efficiency projects (ADB, 2009; Singh *et al*., 2009; Ellis, 2010; Sarkar and Singh, 2010; USAID, 2010; Limaye and Limaye, 2011; Marino *et al*., 2011), while the European PPP expertise centre (EPEC) provides a useful information source and exchange.[14] In the business model, the Super *ESCO* established by the government supports capacity and project development activities of private sector *ESCOs*, which actually play the major role in the development and diffusion of energy-efficiency technologies. A closer collaboration between government and the *ESCO* industry can further stimulate the development and deployment of a broad portfolio of low-carbon technologies, including renewable and cleaner energy technologies, and reduce energy use.

[14] See http://www.eib.org/epec/.

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Table 1 *ESCO* countries and starting years

Country	Vine[a]	Kiss [b]
Argentina	1995	
Australia	1990	
Austria	1995	1998
Belarus		2005
Belgium	1990	1990
Brazil	1992	
Bulgaria	1995	1995
Canada	1982	
Chile	1996	
China	1995	
Columbia	1997	
Côte d'Ivoire	2000	
Croatia		2003
Czech Republic	1993	1993
Denmark		
Egypt	1996	
Estonia	1986	1986
Finland	2000	2000
France		1950
Germany	1993	1993
Greece		
Ghana	1996	
Hungary	1990	1991
Iceland		
India	1994	
Ireland		2006
Italy	1983	1983
Japan	1997	
Jordan	1994	
Kenya	1997	
Korea	1992	
Latvia		2001
Liechtenstein		
Lithuania	1998	1998
Luxembourg		
Macedonia		2007
Mexico	1998	
Monaco		
Morocco	1990	
Nepal	2002	
Netherlands		2000
New Zealand		
Norway		
Philippines	1995	
Poland	1995	1995
Portugal		
Romania		
Russian Federation		1996
Slovak Republic	1995	1994
Slovenia		2001
South Africa	1998	
Spain		1987
Sweden	1978	1978
Switzerland	1995	
Thailand	2000	
Tunisia	2000	
Turkey		
Ukraine	1996	1999
United Kingdom	1980	1984
United States	1975	1975

[a] Vine (2005) gives some entries as ranges. We use the mid-point of the given range as the year of the first *ESCO*.
[b] Kiss *et al*. (2007) also give some entries as ranges. We, thus, use the mid-point of the given range as the year of the first *ESCO*.
[c] US *ESCO*s started in the 1970s in Urge-Vorsatz *et al.* (2007). We, then, use 1975 as the year of the first *ESCO*.

Table 2 Description of the variables

Variable	Definition
Energy use (*I*)	Use of primary energy before transformation to other end-use fuels in kiloton of oil equivalent.
Population (*P*)	Midyear population (million persons).
per capita GDP (*A*)	Gross domestic product divided by midyear population in PPP (constant 2005 international dollars).
Urbanization (*UB*)	The percentage of the urban population in the total population.
Energy service company (*ESCO*)	The year of the first *ESCO* started in the country.

Descriptive statistics

	Mean	Median	Std. Deviation	Maximum	Minimum
I	10.6902	10.3839	2.2433	15.6073	5.7430
P	17.3115	17.1828	2.1857	22.4280	12.2016
A	8.8232	8.8915	1.2711	11.4129	5.4881
UB	3.1600	3.1800	0.6010	4.6229	0.9223
ESCO	0.1749	0.0000	0.3800	1.0000	0.0000

Correlation coefficients

	I	I_{t-1}	*P*	*A*	*UB*
I_{t-1}	0.9997				
	(0.000)				
P	0.8842	0.8833			
	(0.000)	(0.000)			
A	0.1687	0.1701	-0.2783		
	(0.000)	(0.000)	(0.000)		
UB	-0.5101	-0.5109	-0.4858	0.0327	
	(0.000)	(0.000)	(0.000)	(0.106)	
ESCO	0.1267	0.1283	0.0374	0.1692	-0.2538
	(0.000)	(0.000)	(0.064)	(0.000)	(0.000)

Note: Numbers in parentheses equal p-values.

Table 3 Estimation results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$\Delta \ln I_{t-1}$	0.9329	0.9233	0.9240	0.9234	0.9265	0.9292	0.9330
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta \ln P$	0.0722	0.0864	0.0853	0.0848	0.0807	0.0781	0.0681
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.044)
$\Delta \ln A$	0.0459	0.0573	0.0187	0.0304	0.0585	0.0430	0.0538
	(0.000)	(0.002)	(0.086)	(0.037)	(0.002)	(0.069)	(0.032)
$\Delta \ln A^2$			0.0022	0.0017		0.0010	0.0061
			(0.721)	(0.704)		(0.891)	(0.169)
$\Delta \ln UB$				-0.0125			-0.0125
				(0.007)			(0.018)
ESCO		-0.0366	-0.0339	-0.0387	-0.0312	-0.0294	-0.0341
		(0.044)	(0.071)	(0.052)	(0.054)	(0.091)	(0.020)
Sargan test	90.463	88.982	93.632	88.650	89.644	89.784	89.902
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
AR(1)	-3.474	-3.437	-3.474	-3.441	-3.467	-3.464	-3.452
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
AR(2)	0.619	0.611	0.615	0.613	0.623	0.619	0.623
	(0.536)	(0.541)	(0.532)	(0.541)	(0.535)	(0.535)	(0.534)
Sargan	92.531	91.349	92.462	88.256	89.177	89.936	88.839
difference test	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
Unit-root test	-13.290	-13.884	-13.572	-11.915	-13.927	-13.951	-11.294
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: The dependent variables is $\Delta \ln I_{t,}$ where Δ is the first-difference operator and *ln* denotes natural logarithms, *I* denotes energy use, *P* denotes total population, *A* denotes per capita GDP, *UB* denotes urbanization, and *ESCO* is the dummy variable for *ESCO*s. Year dummies are included in all specifications, but coefficient estimates are omitted from the Tables. Results are avaialbe on request. The Sargan test examines over-identification. AR(1) and AR(2) test for the first- and second-order autocorrelation, respectively. The Sargan difference test detects error cross-sectional dependence. The unit-root test proposed by Im *et al*. (2003) considers the null hypothesis of a panel unit root in residuals. Numbers in parentheses equal p-values.

Table 4 Estimation results

Variables	Model 8	Model 9	Model 10	Model 11
$\Delta\ln I_{t-1}$	0.9338	0.9327	0.9304	0.9289
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta\ln P$	0.0671	0.0679	0.0706	0.0719
	(0.001)	(0.000)	(0.003)	(0.003)
$\Delta\ln A$	0.0513	0.0522	0.0543	0.0552
	(0.001)	(0.001)	(0.005)	(0.004)
$\Delta lnUB$	-0.0122	-0.0136	-0.0125	-0.0118
	(0.061)	(0.037)	(0.010)	(0.102)
ESCO	-0.0103	-0.0619	-0.0027	-0.0403
	(0.059)	(0.043)	(0.070)	(0.062)
ESCO year*	-0.0018	0.0090	-0.0020	0.0072
	(0.025)	(0.090)	(0.026)	(0.098)
ESCO year2*		-0.0004		-0.0004
		(0.065)		(0.082)
Joint test	7,086	7.499	7.382	7.389
	(0.000)	(0.000)	(0.000)	(0.000)
Sargan test	93.547	91.742	91.064	86.195
	(1.000)	(1.000)	(1.000)	(1.000)
AR(1)	-3.484	-3.455	-3.457	-3.485
	(0.001)	(0.001)	(0.001)	(0.000)
AR(2)	0.618	0.595	0.623	0.668
	(0.532)	(0.546)	(0.533)	(0.503)
Sargan difference test	93.272	91.759	89.650	83.534
	(1.000)	(1.000)	(1.000)	(1.000)
Unit-root test	-12.194	-12.194	-12.533	-12.565
	(0.000)	(0.000)	(0.000)	(0.000)

Note: See Table 3. The *year* and $year^2$ variables denote the number of years since the *ESCO* adoption and its squared term, respectively. The joint test examines if the estimates of *ESCO* and *ESCO*year* (*ESCO*, *ESCO*year*, and $ESCO*year^2$) equal zero jointly in Models 8 or 10 (9 or 11). Numbers in parentheses equal p-values.

Table 5 Estimation results for low- and high- income countries

Variables	Low-income countries		High-income countries	
	Model 12	Model 13	Model 14	Model 15
$\Delta \ln I_{t-1}$	0.8822	0.8903	0.9648	0.9610
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta \ln P$	0.1236	0.1147	0.0339	0.0378
	(0.004)	(0.030)	(0.018)	(0.021)
$\Delta \ln A$	0.0616	0.0607	0.0293	0.0323
	(0.003)	(0.033)	(0.026)	(0.028)
$\Delta lnUB$	-0.0111	-0.0120	-0.0072	-0.0067
	(0.201)	(0.241)	(0.050)	(0.057)
ESCO	-0.0184	-0.0149	-0.0641	-0.0508
	(0.043)	(0.047)	(0.010)	(0.014)
ESCO year*	0.0051	0.0026	0.0076	0.0056
	(0.055)	(0.038)	(0.108)	(0.031)
ESCO year2*	-0.0002	0.0000	-0.0003	-0.0003
	(0.770)	(0.958)	(0.268)	(0.223)
Joint test	6.658	6.801	7.454	7.038
	(0.000)	(0.055)	(0.000)	(0.000)
Sargan test	46.884	48.976	52.096	53.063
	(1.000)	(1.000)	(1.000)	(1.000)
AR(1)	-4.120	-4.134	-2.460	-2.460
	(0.000)	(0.000)	(0.014)	(0.014)
AR(2)	-1.013	-0.938	0.813	0.820
	(0.312)	(0.349)	(0.419)	(0.413)
Sargan difference test	50.121	47.922	52.085	53.060
	(1.000)	(1.000)	(1.000)	(1.000)
Unit-root test	-7.459	-4.029	-8.392	-4.444
	(0.000)	(0.000)	(0.000)	(0.000)

Note: See Table 4. The joint test examines if the estimates of *ESCO*, *ESCO*year* and *ESCO*year*^{2} equal zero jointly. Numbers in parentheses are p-values.