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The effect of *ESCO*s on carbon dioxide emissions

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Abstract

Proponents of energy service companies (*ESCO*s) argue that these firms provide a crucial instrument for delivering improved energy efficiency in public and private sectors, thus contributing to carbon dioxide (CO_2) emissions reduction around the world. Do *ESCO*s reduce CO_2 emissions? To answer this question, we develop an estimating equation, which approximates the IPAT model, from a simple model of production. Based on the modified dynamic IPAT model, using the panel data of 129 countries over the period 1980 to 2007, we provide significant evidence to show that the *ESCO*s effectively reduce CO_2 emissions and this effect increases over time. These findings also prove robust to the inclusion of a set of control variables, different dates of the first *ESCO*, and the Kyoto Protocol. Finally, we discuss energy policy implications.

Keywords: Energy service companies (*ESCO*s), Carbon dioxide (CO_2) emissions, Dynamic IPAT model

JEL Classification: Q55, Q56

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1. Introduction

The 1992 international environmental treaty, United Nations Framework Convention on Climate Change (UNFCCC), aimed to stabilize greenhouse gas (GHG) concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. The 1997 Kyoto Protocol established legal obligations for most developed countries and some central European transition economies (defined as Annex B countries) to reduce their GHG emissions, on average, to 6 to 8 percent below 1990 levels between 2008 and 2012. Investment in energy-efficiency technologies provides a key component to achieve global commitments to reduce GHG emissions and global warming (Popp, 2004, 2010; Linares and Perez-Arriaga, 2009; Linares and Labandeira, 2010; Sarkar and Singh, 2010). One mechanism to promote investment in energy-efficiency technologies and, thus, to reduce GHG emissions engages energy performance contracting (EPC) undertaken by energy service companies (*ESCO*s). Since the early 1970s, high energy prices, greater energy demand, climate change, global warming, emerging carbon markets, environmental concerns, and international agreements, such as the Kyoto Protocol, created opportunities for the development of *ESCO* business (Goldman *et al*., 2005; Vine, 2005; Bertoldi *et al*., 2006; Kiss *et al*., 2007; Urge-Vorsatz *et al*., 2007; Ellis, 2010). This paper examines the effect of *ESCO* activities on global carbon dioxide (CO_2) emissions, which the Intergovernmental Panel on Climate Change (IPCC, 2007) identifies as the most important anthropogenic GHGs.

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 sector (Vine, 2005; WEC, 2008; Ellis, 2010). The *ESCO*'s revenue directly links to the amount of energy saved through the

EPC. Two main EPC models exist: the shared savings model and the guaranteed savings model (Bertoldi *et al*., 2006; Okay *et al*, 2008). In the first model, the *ESCO* and the client share the cost savings at a pre-determined percentage for a fixed number of years. In the guaranteed savings model, the *ESCO* guarantees a certain level of energy savings to the customer. Financing for the investment can either come from the internal funds of the *ESCO*, from the customer, or from a third-party funding source, where a financial institution allows a credit for the *ESCO* or directly to its client. A guarantee for the projected energy or cost savings given by the *ESCO* backs the loan.

*ESCO*s emerged in the US in the 1970s after the oil crisis, which led to increasing energy prices. They grew during the utility integrated resource planning and demand side management (DSM) era of the late 1980s and early 1990s. Now, the US possesses the most mature *ESCO* market in the world. Energy-efficiency technologies represent a major share of the industry activity, accounting for 75 percent of *ESCO* revenues in 2008 (Goldman *et al*., 2005; Urge-Vorsatz *et al*., 2007; Satchwell *et al*., 2010). The concept gradually spread to Europe and Japan (Vine *et al*., 1998; Shito, 2003; Vine, 2005; Bertoldi *et al*., 2006; Patlitzianas *et al*., 2006; Kiss *et al*., 2007; Patlitzianas and Psarras, 2007). For example, Italian *ESCO* activity began in the early 1980s (Vine, 2005), and now, *ESCO*s account for 90 percent of energy-efficiency activity (Linares and Perez-Arriaga, 2009). In the 1990s, the *ESCO*s emerged in developing countries (Davies and Chan, 2001; Lee *et al*., 2003; Okay *et al*., 2008; Ellis, 2010). By 2008, China housed the largest *ESCO* industry in the developing world by total investment (Taylor *et al*., 2008). Today, international agencies view the *ESCO* industry as the new business model to promote energy efficiency in the world (Bleyl, 2009; Limaye and Limaye, 2009; Singh *et al.*, 2009; Sarkar and Singh, 2010; Ellis, 2010). 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; USAID, 2010).

Vine (2005) and Goldman *et al.* (2005) analyze the results of a survey on *ESCO* activity in 38 countries outside of the US and the US, respectively. Vine (2005, Table 7) gives details on 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, 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 are some key mechanisms for promoting *ESCO* projects. Moreover, countries that remove subsidies, and privatize the energy industry and the power sector will lead 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. Recently, Sarkar and Singh (2010) provide ideas for scaling up energy-efficiency investments through EPCs. They propose an innovative public-private partnership business model (i.e., a Super *ESCO*) 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 relationships among 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). They find important dependences between *ESCO* activity indicators and country indicators such as the global innovation index. In their descriptive study, the positive slope (or correlation) of each of the *ESCO* indicators with respect to CO_2 emissions leads the authors to conclude the ineffectiveness of *ESCO*s in most of the countries.

Do *ESCO*s reduce CO_2 emissions? To answer this question, we use an empirical approach to examine the effect of *ESCO*s on CO_2 emissions. To the best of our knowledge, we provide the first econometric analysis of this issue. Based on the IPAT formula (Ehrlich and Holdren, 1971; 1972; Commoner *et al.*, 1971), we derive an estimating equation from a simple production model of CO_2 emissions. We estimate a dynamic panel model for a sample of 129 countries from 1980 to 2007. We provide new evidence that *ESCO*s effectively reduce CO_2 emissions and this result proves robust to the inclusion of a set of control variables, different dates of the first *ESCO*, and the Kyoto Protocol. Moreover, the *ESCO* effect increases over time.

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, reports and discusses the results. Section 4 concludes.

2. A dynamic IPAT model

The well-known IPAT (or I=PAT) model tries to identify the 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 impact per unit of economic activity. The Kaya identity (Yamaji *et al.*, 1991; Raupach *et al.*, 2007) provides a specific application of the IPAT identity. It decomposes the global CO_2 emissions driving forces into four multiplicative factors: global population, global GDP per capita (i.e., GDP/Population), energy intensity of world GDP (i.e., Energy/GDP), and carbon intensity of energy (i.e., CO_2/Energy). In the same form, Waggoner and Ausubel (2002) developed the ImPACT model to predict total CO_2 emissions. While the ImPACT model identifies some factors that when reduced, can reduce CO_2 emissions, like the IPAT and the Kaya identities, the ImPACT model also is a definition and does not emerge from some underlying theoretical model. Rather, it is an ad hoc identity that does not permit hypothesis testing for the underlying driving forces of environmental change. These equations, however, may help assess the effect of *ESCO* activity as another indicator of the technological factor on environmental degradation.

To estimate the effects of population, affluence, and technology on CO_2 emissions, Dietz and Rosa (1994, 1997) and York *et al.* (2003) reformulate IPAT into a stochastic impacts by regression on population, affluence, and technology (STIRPAT) model as follows:

$$I_i = aP_i^b A_i^c T_i^d e_i \ , \qquad (1)$$

where the subscript *i* denotes the country; a, b, c and d are parameters to be estimated; e_i is the error term. After taking natural logarithms, the model becomes:

$$\ln I_i = \ln a + b \ln P_i + c \ln A_i + d \ln T_i + \varepsilon_i \ , \qquad (2)$$

where $\varepsilon_i = ln\ e_i$

We now propose a simple model of CO_2 that generates an estimating equation similar to that of equation (2). First, we formulate the problem as a production process for CO_2 emissions. Such emissions come from the use of energy resources. We propose a simple Cobb-Douglas production function for CO_2 emissions as follows:

$$I_i = a_i E_i^{\alpha} e^{\varepsilon_i} \ , \qquad (3)$$

where I = CO_2 emissions;

a = the technological, structural, and other effects;

E = energy use;

e = the Euler's number, and

ε = the error term.

Demographic and economic developments play a crucial role in determining CO_2 emissions. We can augment this equation by dividing both sides of this production function for CO_2 emissions by population and then real GDP as follows:

$$\left(\frac{I}{P}\right)_i = a_i \frac{E_i^{\alpha}}{P_i} e^{\varepsilon_i} = a_i \left(\frac{E}{P}\right)_i^{\alpha} \left(\frac{1}{P_i}\right)^{(1-\alpha)} e^{\varepsilon_i} = a_i \left(\frac{E}{Y}\right)_i^{\alpha} \left(\frac{Y}{P}\right)_i^{\alpha} \left(\frac{1}{P_i}\right)^{(1-\alpha)} e^{\varepsilon_i} \qquad (4)$$

where P = population; and

Y = real GDP.

Thus, taking natural logarithms gives us

$$\ln\left(\frac{I}{P}\right)_i = \ln a_i - (1-\alpha)\ln P_i + \alpha \ln\left(\frac{Y}{P}\right)_i + \alpha \ln\left(\frac{E}{Y}\right)_i + \varepsilon_i; \text{ or} \qquad (5)$$

$$\ln I_i = \ln a_i + \alpha \ln P_i + \alpha \ln\left(\frac{Y}{P}\right)_i + \alpha \ln\left(\frac{E}{Y}\right)_i + \varepsilon_i. \qquad (6)$$

Equation (6) matches equation (2), where $b = c = d = \alpha$. That is, we can characterize the literature's STIRPAT model as the simple production function (for CO_2 in this case), where the restrictions on the coefficients of population, real GDP per capita, and energy use per real GDP (i.e., energy intensity) are relaxed. Note that the translation of variables from our formulation to STIRPAT is as follows:

$$\mathrm{A}_i = \left(\frac{Y}{P}\right)_i \text{ and } T_i = \left(\frac{E}{Y}\right)_i \qquad (7)$$

Furthermore, one can think of additional control variables that can affect CO_2 emissions through the constant term as follows:

$$a_i = aX_i^g \text{ or } \ln a_i = \ln a + g \ln X_i \tag{8}$$

In the additive regression (6), we express all variables in natural logarithmic form to facilitate estimation and hypothesis testing, where a_i includes all variables other than population. real GDP per capita, and energy use per real GDP. Researchers use the STIRPAT model to analyze the effects of different driving forces on a variety of environmental effects (Shi, 2003; York *et al*., 2003; Cole and Neumayer, 2004; Martinez-Zarzoso *et al*., 2007; Grunewald and Martinez-Zarzoso, 2009; Iwata and Okada, 2010; Poumanyvong and Kaneko, 2010; Martinez-Zarzoso and Maruotti, 2011). For example, Shi (2003) argues that the difference in energy intensity, which is T in the IPAT equation, could depend on the differences in economic structures between countries. Countries whose GDP depends heavily on manufacturing will use more energy and will produce higher CO_2 emissions; whereas countries whose GDP depends largely on services will use less energy and will produce lower emissions. Shi (2003), thus, specifies two variables: the share of the industry and service sectors in GDP in the STIRPAT model to examine the effect of population on global CO_2 emissions. Poumanyvong and Kaneko (2010) employ the STIRPAT model and add urbanization as an additional variable to investigate its impact on CO_2 emissions.

The IPAT model views population coupled with growing affluence as the primary forces driving adverse environmental effects (Dietz and Rosa, 1997; Shi, 2003; York *et al*., 2003; Martinez-Zarzoso *et al*., 2007). Another category of work, the environmental Kuznets curve (EKC), focuses on an inverted-U relationship between environmental degradation and economic growth. That is, pollutants such as CO_2 emissions worsen in the early stages of growth, but eventually peak and start declining as income passes a certain threshold level (Grossman and Krueger, 1995; Dasgupta *et al*., 2002; Dinda, 2004; Stern, 2004; Brock and Taylor, 2010; Carson, 2010; Kijima *et* *al*., 2010). Empirical models, which test for the EKC hypothesis, typically regress CO_2 emissions per capita on per capita GDP and a squared term of per capita GDP along with other explanatory variables. If the coefficient of the squared term proves significantly negative and the estimated extreme point falls within the data range, it concludes that an inverted-U relationship exists. The existing findings generally show that CO_2 emissions increase monotonically with per capita income, start declining at income levels well beyond the observed range, or depend on different income levels and regions (Holtz-Eakin and Eslden, 1995; Cole *et al*., 1997; Lee *et al*., 2009; Caviglia-Harris *et al*., 2009; Gassebner *et al*., 2011). No unanimous evidence supports the inverted-U relationship yet.

Both population and per capita income lead to environmental pressure in either total or per capita CO_2 emissions. We focus on the total measure of the pollutant because it directly links to climate change and global warming. In the IPAT framework, the technology factor critically determines environmental improvement. Technological advance must control global CO_2 emissions to offset, at least partly, the adverse effect of population and per capita income growth to achieve a sound process of sustainable world development. *ESCO*s can contribute to the effort by developing public and private projects designed to improve energy efficiency.

Empirical implementations of the STIRPAT model employ panel data techniques to ameliorate a number of statistical problems with cross-country investigations (Shi, 2003; Cole and Neumayer, 2004; Martinez-Zarzoso *et al*., 2007; Iwata and Okada, 2010; Poumanyvong and Kaneko, 2010; Martinez-Zarzoso and Maruotti, 2011). To examine the effect of *ESCO*s on CO_2 emissions, we develop a dynamic, panel-data IPAT model that explicitly captures the dynamics of adjustment in the CO_2 series. The idea is straightforward. It takes time to reach any of the GHG emissions reductions targets such as the levels proposed by the Kyoto Protocol. The process of moving toward the target gradually implies that current and lagged CO_2 emissions are correlated. This dependency suggests using a dynamic model to capture the lagged effect. And finally, adding a variable to capture *ESCO* activity completes our estimation equation as follows:

$$\ln I_{it} = \mu_i + \eta_t + b \ln I_{it-1} + c \ln P_{it} + d \ln A_{it} + e \ln T_{it} \\ + f \; ESCO + g \ln X_{it} + \varepsilon_{it} \tag{9}$$

where the subscript *t* denotes the year. Note that with panel data, our constant *ln a* in equation (8) becomes a country-specific fixed-effect, μ_i, along with a year-specific fixed-effect, η_t, and the error term, ε_{it}.

In the dynamic panel-data model, I_{it} (I_{it-1}) equals CO_2 emissions in kilotons (kt) in country *i* at year *t* ($t-1$). P_{it} is total population. A_{it} is real per capita GDP in PPP (purchasing power parity 2005 constant international dollars). T_{it} is energy intensity defined as the amount of energy use per unit of real GDP in PPP (2005 constant international dollars). The *ESCO* dummy variable equals one beginning in the year the country started its *ESCO* business; zero otherwise. We also modify this specification and include the number of years of *ESCO* activities and its squared term to examine the *ESCO* effect over time. X_{it} is a set of control variables: per capita GDP squared to test for the EKC hypothesis (Caviglia-Harris *et al.,* 2009, Gassebner *et al.*, 2011), the percentage share of industry (including manufacturing) and service sectors value added in GDP to account for the effect of economic structure (Shi, 2003), the percentage of total population living in urban areas to measure the effect of urbanization (Poumanyvong and Kaneko, 2010; Martinez-Zarzoso and Maruotti, 2011), and the *Kyoto* dummy variable, which equals one beginning in the year of treat's adoption; zero otherwise, to evaluate the role of the Kyoto Protocol (Iwata and Okada, 2010; Almer and Winkler, 2011).

The inclusion of $\ln I_{it-1}$ as a regressor leads to biased and inefficient OLS estimates due to correlation between the lagged dependent variable and the error term. Moreover, two additional econometric problems may arise from estimating equation (9): the explanatory variables are probably endogenous and the country-specific effect may correlate with the explanatory variables. To solve these problems, we use the generalized method of moments (GMM) difference estimator proposed in Arellano and Bond (1991) (see Roodman, 2009, for applications). This method takes the first differences of equation (9) to remove the country-specific fixed-effect and permits the use of lags of the levels of regressors and the dependent variable as instrumental variables, and thereby provides more precise estimates of the relationship. The regression needs to pass two standard specification tests: Sargan and serial correlation. The null hypothesis of the former states that the instruments do not correlate with the residuals from the respective regression. The null hypothesis of the latter states that the errors in the first-difference regression exhibit no second-order serial correlation (significant negative first-order serial correlation is allowed). Evidence that supports the efficacy of *ESCO*s in reducing CO_2 emissions emerges when the coefficient of the *ESCO* dummy variables proves significantly negative (i.e., $f < 0$).

3. Data, estimation results and discussion

Data description

We use a panel dataset of 129 countries covering the period from 1980 to 2007. *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 (9), we proxy for *ESCO* activity with the dummy variable, which equals one the year *ESCO* activity began in the country; zero otherwise. In his international survey, Vine (2005) lists 38 countries (outside of 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, the range for Argentina and Philippines is the 1990s, then we adopt 1995 as the time of the first *ESCO*, Germany's range equals 1990 to 1995, meaning that we adopt 1993 as the 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 us to adopt 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 latter is eventually composed of Kiss *et al.* (2007) pan-European data plus countries outside of Europe in Vine (2005) and the US. Table 1 also lists 39 countries and the years they ratified the Kyoto Protocol.[1] These countries approved the quantified emission limitation or reduction commitments, which are legally binding.

The data on CO_2 emissions, population, per capita GDP, energy intensity, urbanization, the share of the industry and service sectors value added in GDP come from the World Development Indicators published by the World Bank.[2] The data on CO_2 emissions and total energy use originally come from the Carbon Dioxide Information Analysis Center of Oak Ridge National Laboratory and the International Energy Agency (IEA), respectively. Table 2 reports a detailed description of the variables, preliminary statistics of the data, and simple correlation coefficients between the variables in the model.

The highly significant positive correlation (= 0.9989) between current (*I*) and the lagged

[1] Data downloaded from http://unfccc.int.

[2] Data downloaded from http://data.worldbank.org/data-catalog.

(I_{t-1}) CO_2 suggests a dynamic model. The positive correlations between CO_2 emissions and each of the other variables studied accords with priors, since all human activities increase CO_2 emissions. Okay and Akman (2010), based on the positive correlations between per capita CO_2 emissions 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 contributed to the more CO_2 emissions. 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 CO_2 emissions. We have derived an estimating equation similar to the stochastic IPAT model based on a production model of CO_2 emissions.

Estimation results

Table 3 reports the results from the difference GMM estimator.[3] First, we estimate equation (9), where we regress CO_2 emissions (I_t) on lagged CO_2 emissions (I_{t-1}), population (P), real per capita GDP (A), and energy intensity (T) (Model 1) with standard errors in parentheses, statistics for the Sargan and autocorrelation tests, and p-values in brackets. This baseline model incorporates only the basic elements from our theoretically derived and modified IPAT framework. The results indicate that all four explanatory variables are statistically significant at the 1-percent level and display the expected signs. The lagged dependent variable explains the largest part of current CO_2 emissions, lending support to the dynamic specification. A 1-percent increase in population associates with a 0.3389-percent increment in CO_2 emissions. In the log-log specification, the coefficient estimates represent elasticities or the ratios of percent changes. The CO_2- real per capita GDP elasticity equals 0.6165, or a 1-percent increase in real per capita GDP associates with a

[3] We estimate the GMM results using the Stata command xtabond2 (see Roodman, 2009).

0.6165 percent increase in CO_2 emissions. Energy intensity exhibits an elasticity for CO_2 emission of 0.5060. 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 CO_2 variable. Thus, they are 1.2013, 2.1963 and 1.8026, respectively, for population, real per capita GDP, and energy intensity. The regression passes the standard specification tests: the two-step Sargan test for over-identification does not reject the null, and 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.

Second, we estimate the dynamic IPAT model by including the dummy variable for *ESCO* activity in Model 2, where we still exclude the other explanatory variables. The dummy equals one from the year of the first *ESCO* activity, zero otherwise, based on Vine's (2005) *ESCO* country data in Table 1. The coefficient of the *ESCO* dummy proves significantly negative at the 1-percent level. All other estimates and the diagnostic statistics match those in the baseline Model 1. These results suggest that *ESCO*s effectively reduce CO_2 emissions. York *et al.* (2003) interpret the coefficient of the dummy variable as follows. The negative sign indicates that CO_2 emissions decrease. The antilog of the coefficient for the *ESCO* dummy variable shows the ratio of CO_2 emissions with *ESCO* activity to that without such activity. For example, the antilog of the coefficient of -0.0615 equals 0.9404, indicating that *ESCO* countries produce about 94 percent of the CO_2 emissions of non-*ESCO* countries, controlling for other factors. In other words, *ESCO* countries exhibit approximately 6-percent lower CO_2 emissions.

Recent studies also debate the existence of an effect of the Kyoto Protocol on CO_2 emissions. Third, to examine this issue, Model 3 adds the dummy variable for the Protocol to Model 2. The coefficient of the *KYOTO* proves significantly negative at the 5-percent level, suggesting that the Kyoto Protocol does reduce CO_2 emissions. Moreover, the coefficient for *ESCO* dummy variable remains negative and significant at the 1-percent level. Note that the estimate of *ESCO* (= -0.0678) is much higher than the estimate of *KYOTO* (= -0.0123). The *ESCO* industry provides a more effective tool than the international agreement of the Kyoto Protocol to reduce global CO_2 emissions. The Kyoto Protocol reduces CO_2 emissions by approximately 1.12 percent.

Fourth, we estimate equation (9) where we include all the other variables, but still use the Vine dating of *ESCO* adoption. Does the significant negative CO_2-*ESCO* relationship still hold, if we accommodate the potential linkages between squared per capita GDP, urbanization, industry share, service share, and CO_2 emissions. We address this concern with Model 4.[4] The estimates indicate that the other factors do produce significant effects on CO_2 emissions, except for the population living in urban areas. Also, the *KYOTO* dummy variable now becomes insignificant. Adding other factors to the model does not alter in any major way the coefficients for the lagged dependent variable, population, technology, and *ESCO*. The positive coefficient for real per capita GDP suggests that CO_2 emissions initially rise with per capita GDP, and then eventually fall, given the negative coefficient on the squared real per capita GDP term, tending to support the EKC hypothesis. The effect of the industrial sector exceeds the effect of service sector, not a surprise. The negative CO_2-*ESCO* relationship remains robust to the inclusion of the Kyoto Protocol and the set of other control variables.

Fifth, to further check the robustness of the effect of *ESCO* activities on CO_2 emissions, we ask whether the finding on the negative CO_2-*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

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[4] This model resembles the specification that Poumanyvong and Kaneko (2010) use in their study, except ours adopts a dynamic specification.

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 from Urge-Vorsatz *et al.* (2007) to replace the Vine data used in Models 2, 3, and 4. 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 variable confirms a significant negative association between CO_2 emissions and *ESCO*s at the 1-percent level. Thus, the model adjusting for different years of the first *ESCO* yields robust results with regard to the effect of *ESCO* activities on CO_2 emissions.

Finally, we use the number of years since the permitting of *ESCO* activities (*year*) and its squared term ($year^2$) to examine the *ESCO* effect over time.[5] At this stage, we take the most robust variables and estimate the final model. That is, we exclude the squared term of real GDP per capita and urbanization in the final model. Model 4 suggests a potential EKC. The estimated turning point occurs at a high level of per capita GDP ($ln\ A$ = 14.53), which far exceeds the income range ($ln\ A \in [5.49,\ 11.47]$) in our sample. The negatively estimated coefficient on the squared affluence term proves insignificant in Model 7, where we only use different data set for the years of the first *ESCO* activity. Thus, no robust evidence supports the inverted-U relationship between CO_2 emissions and real per capita GDP. Although urbanization positively influences CO_2 emissions, the coefficient is insignificant in Models 4 and 7, however.

Table 4 reports the results. Models 8 and 11 re-estimate the specification with the *ESCO* dummy variable without the squared value of real GDP per capita and the urbanization variable.[6]

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[5] Our data on *ESCO*s only identifies when *ESCO* operations initiated in each country. We do not know exactly the size of these operations and/or how these activities changed over time after the initial adoption. Thus, we interact the *ESCO* dummy variable, since the initial permitting of *ESCO* activities, to examine the *ESCO* effect over time.

[6] Models 8, 9, and 10 use the Vine (2005) dating of *ESCO* whereas Models 11, 12, and 13 correspond to Models 8, 9, and 10, respectively, but use the modified dates on *ESCO* as reported by Kiss *et al.* (2007).

Removing these two factors does not substantively alter the size and significance of the coefficients for *ESCO*. Furthermore, adding other factors to the basic model (Model 1) does not dramatically change the coefficients for population, affluence and technology. The models with interaction terms fit the data well. All variables exhibit significant coefficients. To test for the null of no effect of *ESCO*s, we test if the estimates of *ESCO* and *ESCO*year* (*ESCO*, *ESCO*year,* and *ESCO*year*^{2}) equal zero jointly in Models 9 and 12 (10 and 13) using a χ^2-test. The high χ^2-statistic rejects the null, suggesting the interaction effects of *ESCO*s in each of the four models. We, therefore, primarily focus our discussion on the final models.

Discussion

In the theoretically derived and modified dynamic IPAT model, lagged CO_2 clearly and significantly predicts current CO_2 emissions. In the six final models, the significant coefficient on lagged CO_2 lies consistently around 0.67 at the 1-percent level. The models also consistently pass the two standard specification tests: no correlation between the instruments used with the residuals from the respective regression and no second-order serial correlation in the errors of the first-differenced regression, indicating that we achieve the appropriate specification of the dynamic model.

Population generally associates with higher CO_2 emissions. The population elasticity of effect for CO_2 emissions (0.3755 in Model 10, for example) appears to fall below the estimate of 1.123 in Dietz and Rosa (1997), 1.416 in Shi (2003), 0.976 in York *et al*. (2003), 1.103 in Cole and Neumayer (2004), and, more recently, 1.125 in Poumanyvong and Kaneko (2010). These studies all use a static STIRPAT model with different estimators, 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 in Model 10 implies a long-run population elasticity of 1.1417 (= 0.3755/(1-0.6711)), which then matches closely to these studies. Additionally, the population estimate proves consistent with the coefficients estimated between 0.198 to 0.319 in Martinez-Zarzoso and Maruotti (2011), who do adopt a dynamic model, but with different estimators.[7]

The affluence coefficient exerts the most positive effect among all factors across models, meaning that growing affluence proves a major determinant of deteriorating CO_2 emissions. The long-run affluence elasticity equals 1.8693 in Model 10, implying that a cleaner CO_2 environment is a luxury good. The evidence on the robustness of the squared affluence term is weak. Hence, at least within the sample, the relationship between CO_2 emissions and real GDP per capita approximates a concave curve rather than an inverted U-shape. This conclusion supports many studies such as Shi (2003), York *et al*. (2003), Caviglia-Harris *et al*. (2009), Gassebner *et al*, (2011) and Martinez-Zarzoso and Maruotti (2011).

Energy intensity, the inverse of energy efficiency, exhibits significant coefficient estimates that fall within a narrow range in the final models from 0.4974 to 0.5367. Both coefficients of economic structure are significantly positive. The coefficient for industry value added as a percent of GDP always exceeds the coefficient for services value added as a percent of GDP. While different sample countries and sample periods, static or dynamic models, as well as different estimators may lead to different estimation results, our estimated coefficients for energy intensity and economic structure fall close to those in Martinez-Zarzoso *et al*. (2007) and Martinez-Zarzoso and Maruotti (2011), where the authors use a dynamic model specification and the GMM estimator.

The effect of *ESCO*s on CO_2 emissions is the focus of our study. The coefficient estimate is

[7] The insignificant estimate in Model 7 also appears in Martinez-Zarzoso *et al*. (2007) and Martinez-Zarzoso and Maruotti (2011) when they use the difference GMM estimator for European countries and developing countries, respectively.

negative and significant in all the models when we add the *ESCO* dummy variable as an explanatory variable, indicating *ESCO* activities around the world effectively reduce CO_2 emissions. The estimates suggest that adoption of *ESCO* reduces CO_2 emissions by around 5.0 percent in Model 8 (a 3.8 percent reduction in Model 11), assuming implicitly the effect is constant. The *ESCO*-CO_2 relationship varies over time as evidenced by the interaction terms. Consider Model 9, for example. Adopting *ESCO* reduces CO_2 emissions, on average, by 2.2 percent, ignoring the time effect. Each additional year since the adoption reduces CO_2 emissions by 0.3 percent. 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 CO_2 emissions by 6.7 percent, on average. Model 10 considers potential non-linear effects (e.g., diminishing returns over time) through the interaction of the *ESCO* dummy variable and the squared value of the number of years since adoption. Now, the initial effect is 2.70 percent. Each additional year reduces CO_2 emissions by 0.4 percent, but at a decreasing rate of 0.01 percent. After 15 years, the total reduction effect is 6.45 percent. This finding comes close to the effect identified above of a 6-percent reduction in CO_2 emissions when we use only the *ESCO* dummy variable in Model 2.

The Kyoto Protocol receives criticism because the target reductions are too small to prevent global warming. In addition, the US has not ratified the Protocol. Recently, Grunewald and Martinez-Zarzoso (2009) and Iwata and Okada (2010) find a significantly negative effect of the commitments to the Kyoto Protocol on CO_2 emissions. Almer and Winkler (2011) investigate whether committing to a specific GHG emissions target can affect the actual CO_2 emissions of Australia, Canada, France, Germany, Great Britain, Italy, and Japan. They find no effect on actual emissions for the seven developed countries, except for Great Britain. We find negative coefficient estimate on the *KYOTO* dummy variable. The coefficient, however, proves sensitive to model settings with varying significance levels from insignificant to the 10-, 5-, to 1-percent levels. Model 8 suggests a reduction in CO_2 emissions of around 1.4 percent. When we add the Kyoto Protocol dummy variable (*KYOTO*) as another predictor, no substantial change occurs in the *ESCO* estimates across the models. And the *ESCO* dummy variable always exhibits a much bigger effect than the *KYOTO* dummy variable on CO_2 emissions.

In sum, the significant negative *ESCO* effect on CO_2 emissions is robust to the inclusion of a set of control variables, the different dates of the first *ESCO*, and the commitments to the Kyoto Protocol. Moreover, the *ESCO* effect improves over time.

4. Conclusion

This paper empirically investigates the effect of energy service companies (*ESCO*s) on CO_2 emissions, using theoretically derived and modified dynamic IPAT model with a panel dataset of 129 countries over 1980 to 2007. The results indicate that *ESCO*s significantly reduce CO_2 emissions. The magnitude of those decreases proves important, although not large relative to the effects of population, economic development, and energy use per unit of GDP. This finding supports the development of the *ESCO* industry worldwide as an instrument to reduce carbon dioxide emissions of energy use, particularly with regard to global warming.

We also find that *ESCO*s contribute more to the reduction in CO_2 emissions than the Kyoto Protocol. Moreover, the effect of the *ESCO* on reducing CO_2 emissions proves more stable and consistently significant than the Kyoto Protocol. Therefore, investment in the emerging energy-efficiency industry such as *ESCO*s proves more effective than the international agreement such as the Kyoto Protocol in reducing CO_2 emissions.

The findings of this study not only contribute to the existing literature, but also deserve special attention from policy makers from both developed and developing countries. The international environmental policy developed in the Kyoto Protocol allows developed countries to bear most of the burden of cutting emissions, while developing countries remain relatively free to pollute. Global warming effects emerge irrespective of the country where emissions occur: one unit of pollutant equally contributes to the greenhouse effect wherever it is emitted. The issue of the earth's sustainability needs attention at all levels of development to achieve an effective solution to global environmental problems. All countries must formulate appropriate energy policies to promote energy efficiency and accelerate the switch to low carbon energy, decoupling environmental effects from economic growth. The newly emerging *ESCO* industry studied in this paper provides a good example.

The paper provides only preliminary results derived from two different surveys. *ESCO* development still remains in its early stages and must receive significant government support to succeed, as argued by Sarkar and Singh (2010). They list a series of barriers to energy-efficiency investments and state "To help remove implementation barriers to meet concrete energy-efficiency improvement targets on a global scale…, collective efforts of various institutions have to be mobilized and their convening force amongst the member countries needs to be utilized effectively to push the energy-efficiency acceleration agenda further." (p.5569)

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Table 1: *ESCO* and the Kyoto Protocol countries and starting years

Country	Vine's[a]	Kiss's[b]	the Kyoto Protocol[d]
Argentina	1995		
Australia	1990		2007
Austria	1995	1998	2002
Belarus			2005
Belgium	1990	1990	2002
Brazil	1992		
Bulgaria	1995	1995	2002
Canada	1982		2002
Chile	1996		
China	1995		
Columbia	1997		
Côte d'Ivoire	2000		
Croatia		2003	2007
Czech Republic	1993	1993	2001
Denmark			2002
Egypt	1996		
Estonia	1986	1986	2002
Finland	2000	2000	2002
France		1993	2002
Germany	1993	1993	2002
Greece			2002
Ghana	1996		
Hungary	1990	1991	2002
Iceland			2002
India	1994		
Ireland		2006	2002
Italy	1983	1983	2002
Japan	1997		2002
Jordan	1994		
Kenya	1997		
Korea	1992		
Latvia		2001	2002
Liechtenstein			2004
Lithuania	1998	1998	2003
Luxembourg			2002
Mexico	1998		
Monaco			2006
Morocco	1990		
Nepal	2002		
Netherlands		2000	2002
New Zealand			2002
Norway			2002
Philippines	1995		
Poland	1995	1995	2002
Portugal			2002
Romania			2001
Russian Federation			2004
Slovak Republic	1995	1994	2002
Slovenia		2001	2002
South Africa	1998		
Spain		1987	2002
Sweden	1978	1978	2002
Switzerland	1995		2003
Thailand	2000		
Tunisia	2000		
Turkey			2009
Ukraine	1996		2004
United Kingdom	1980	1984	2002
United States[c]	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*.
[d]Starting years of the Kyoto Protocol are the years the 39 Annex B parties ratified the Protocol, European Union is excluded, however.(visited online at http://unfccc.int).

Table 2: Description of the Variables

Variable	Definition
Total carbon dioxide CO2 (*I*)	CO2 emissions stem from fuel combustion and the manufacture of cement in kiloton.
Population (*P*)	Mid year population.
per capita GDP (*A*)	Gross domestic product divided by midyear population in PPP (constant 2005 international dollars).
Energy Intensity (*T*)	Total energy use (kg of oil equivalent) per $1000 PPP GDP (constant 2005 international dollar).
Urbanization (*UB*)	The percentage of the urban population in the total population.
Industry Share (*IN*)	The percentage of industrial sector value added in GDP.
Service Share (*SV*)	The percentage of service sector value added in GDP.
Energy Service Company (*ESCO*)	The year of the first *ESCO* started in the country.
The Kyoto Protocol (*KYOTO*)	The year of the Annex B country ratified the Kyoto Protocol.

Descriptive statistics

	Mean	Median	Std. Deviation	Maximum	Minimum
I	170353.8	27549.62	589368.5	6533019	7.33
P	40.8446	9.55	133.4319	1317.89	0.19
A	11688.84	6897.669	12323	95434.18	241.8058
T	253.5537	187.9	199.6211	1725.39	51.24
UB	57.07929	57.95	22.08313	6.1	100
IN	33.30464	31.2	11.71397	6.47	84.82
SV	52.33365	52.86	13.17385	10.26	92.26
ESCO	0.1536545	0	0.3606672	1	0
KYOTO	0.0550941	0	0.2281955	1	0

Correlation coefficients

	I	I_{t-1}	*P*	*A*	*T*	*UB*	*IN*	*SV*	*ESCO*
I_{t-1}	0.9989								
	[0.0000]								
P	0.6036	0.5932							
	[0.0000]	[0.0000]							
A	0.1634	0.1694	-0.1047						
	[0.0000]	[0.0000]	[0.0000]						
T	0.0366	0.0328	0.1159	-0.2873					
	[0.0389]	[0.0000]	[0.0000]	[0.0000]					
UB	0.0761	0.0781	-0.1630	0.6344	-0.3412				
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]				
IN	0.0270	0.0243	0.0248	0.2033	-0.0530	0.2454			
	[0.1407]	[0.1930]	[0.1695]	[0.0000]	[0.0000]	[0.0000]			
SV	0.1124	0.1177	-0.1094	0.4443	-0.4272	0.4805	-0.4878		
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]		
ESCO	0.1328	0.1325	0.1602	0.1332	-0.0816	0.2043	-0.0754	0.2770	
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	
KYOTO	0.0210	0.0226	-0.0301	0.3028	-0.0961	0.1616	-0.0889	0.2922	0.2538
	[0.2262]	[0.2029]	[0.0707]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: Numbers in brackets are p-values.

Table 3: Estimation results, 1980-2007

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lnI_{t-1}	0.7193***	0.7110***	0.7136***	0.6779***	0.7124***	0.7125***	0.6881***
	(0.0044)	(0.0066)	(0.0080)	(0.0072)	(0.0053)	(0.0055)	(0.0070)
ln*P*	0.3389***	0.3084***	0.2971***	0.2668**	0.3049***	0.2531***	0.1059
	(0.0320)	(0.0433)	(0.0544)	(0.1065)	(0.0489)	(0.0461)	(0.1321)
ln*A*	0.6165***	0.6136***	0.6138***	1.4182***	0.6048***	0.6156***	0.8016***
	(0.0156)	(0.0180)	(0.0216)	(0.3021)	(0.0145)	(0.0179)	(0.2080)
ln*T*	0.5060***	0.5223***	0.5173***	0.5291***	0.5029***	0.5086***	0.5191***
	(0.0132)	(0.0172)	(0.0188)	(0.0210)	(0.0123)	(0.0131)	(0.0205)
lnA^2				-0.0488***			-0.0125
				(0.0175)			(0.0121)
ln*UB*				0.0396			0.2482
				(0.1167)			(0.1682)
ln*IN*				0.0393***			0.0448***
				(0.0123)			(0.0122)
ln*SV*				0.0213*			0.0221**
				(0.0111)			(0.0103)
ESCO		-0.0615***	-0.0678***	-0.0565***	-0.0573***	-0.0580***	-0.0414***
		(0.0090)	(0.0079)	(0.0105)	(0.0061)	(0.0051)	(0.0069)
KYOTO			-0.0123**	-0.0057		-0.0153***	-0.0083*
			(0.0051)	(0.0049)		(0.0050)	(0.0044)
No. of observations	2936	2936	2936	2725	2936	2936	2725
No. of countries	129	129	129	126	129	129	126
Sargan test	105.5465	108.1156	112.5979	99.2111	110.2041	109.0372	97.8071
(p-value)	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]
AR(1)	-3.9155	-3.8580	-3.9067	-3.4149	-3.8919	-3.8895	-3.5168
(p-value)	[0.0001]	[0.0001]	[0.0001]	[0.0006]	[0.0001]	[0.0001]	[0.0004]
AR(2)	-0.8428	-0.8659	-0.8635	-1.4172	-0.8560	-0.8599	-1.3942
(p-value)	[0.3993]	[0.3865]	[0.3878]	[0.1564]	[0.3920]	[0.3898]	[0.1632]

Note: *ln* denotes natural logarithms, *P* denotes total population, *A* denotes per capita GDP, *T* denotes energy intensity, *UB* denotes urbanization, *IN* and *SV* denote percent GDP from industry and services, respectively, *ESCO* is the dummy variable for *ESCO*s, and *KYOTO* is the dummy variable for the Kyoto Protocol. The Sargan tests for over-identification. AR(1) and AR(2) test for the first- and second-order autocorrelation respectively. Numbers in parentheses are standard errors and in brackets are p-values.

* denotes 10-percent level.

** denotes 5-percent level.

*** denotes 1-percent level.

Table 4: Final Models, 1980-2007

Variables	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
lnI_{t-1}	0.6676***	0.6647***	0.6711***	0.6808***	0.6795***	0.6884***
	(0.0083)	(0.0083)	(0.0074)	(0.0105)	(0.0145)	(0.0092)
ln$P$	0.4333***	0.2853***	0.3755***	0.3895***	0.3103***	0.2485***
	(0.0592)	(0.0599)	(0.0653)	(0.0546)	(0.0609)	(0.0655)
ln$A$	0.6240***	0.6273***	0.6148***	0.6374***	0.6055***	0.6068***
	(0.0231)	(0.0190)	(0.0184)	(0.0225)	(0.0203)	(0.0380)
ln$T$	0.4974***	0.5367***	0.5025***	0.5127***	0.5019***	0.5113***
	(0.0250)	(0.0222)	(0.0225)	(0.0229)	(0.0220)	(0.0265)
lnIN	0.0692***	0.0694***	0.0684***	0.0550***	0.0713***	0.0677***
	(0.0135)	(0.0142)	(0.0106)	(0.0126)	(0.0108)	(0.0131)
lnSV	0.0579***	0.0524***	0.0485***	0.0397***	0.0488***	0.0469***
	(0.0101)	(0.0105)	(0.0102)	(0.0103)	(0.0104)	(0.0109)
ESCO	-0.0517***	-0.0223**	-0.0274***	-0.0386***	-0.0180***	-0.0111**
	(0.0095)	(0.0092)	(0.0093)	(0.0056)	(0.0050)	(0.0048)
*ESCO*year*		-0.0031***	-0.0041***		-0.0032***	-0.0053***
		(0.0008)	(0.0014)		(0.0007)	(0.0011)
*ESCO**$year^2$			0.0001			0.0001*
			(0.0001)			(0.0000)
KYOTO	-0.0144***	-0.0112**	-0.0099*	-0.0183***	-0.0092**	-0.0113***
	(0.0051)	(0.0051)	(0.0053)	(0.0050)	(0.0037)	(0.0038)
χ^2-*statistic*		27.25	30.42		28.75	33.81
		[0.0000]	[0.0000]		[0.0000]	[0.0000]
No. of observations	2725	2725	2725	2725	2725	2725
No. of countries	126	126	126	126	126	126
Sargan test	98.1205	92.255	98.5787	99.2918	102.5421	98.7149
(p-value)	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]
AR(1)	-3.3846	-3.3340	-3.3630	-3.4344	-3.4329	-3.4605
(p-value)	[0.0007]	[0.0009]	[0.0008]	[0.0006]	[0.0006]	[0.0005]
AR(2)	-1.3983	-1.3934	-1.3903	-1.3795	-1.3857	-1.3796
(p-value)	[0.1620]	[0.1635]	[0.1644]	[0.1677]	[0.1658]	[0.1677]

Note: See Table 3. *year* and $year^2$ denotes the number of years since the *ESCO* adoption and is squared term, respectively. χ^2–statistic tests if the estimates of *ESCO* and *ESCO*year* (*ESCO*, *ESCO*year* and *ESCO**$year^2$) equal zero jointly in Models 9 or 12 (10 or 13). Numbers in parentheses are standard errors and in brackets are p-values.

* denotes 10-percent level.
** denotes 5-percent level.
*** denotes 1-percent level.