fedea

Fundación de Estudios de Economía Aplicada

Focus-Abengoa Forum

energy and climate change

http://www.energiaycambioclimatico.com

Greenhouse gases emissions, growth and the energy mix in Europe: A dynamic panel data approach *

by

Gustavo A. Marrero*

Documento de Trabajo 2009-16

Programa de Investigación Energía y Cambio Climático
Fedea – Focus Abengoa

April 2009

* Universidad de La Laguna, FEDEA and ICAE

ISSN:1696-750X

Jorge Juan, 46
28001 Madrid -España
Tel.: +34 914 359 020
Fax: +34 915 779 575
infpub@fedea.es

N.I.F. G-78044393

Greenhouse gases emissions, growth and the energy mix in Europe: a dynamic panel data approach

Gustavo A. Marrero[1]

Departamento de Análisis Económico (Universidad de La Laguna), FEDEA and ICAE

Abstract:

The 20/20/20 plan for Europe emphasizes the role of changing the energy model as a means to reach the objective of reducing emissions in 2020 by 20% with respect to 1990 levels. Most empirical emission models are found within the framework of the Environmental Kuznetz Curve (EKC), which focuses on the relationship between emissions and economic activity, ignoring energy aspects. However, the importance of energy on GHG emissions is reflected by the fact that 80% of said emissions in Europe are currently due to the use and production of energy. This paper includes energy variables in an EKC dynamic panel data (DPD) model and uses the one-step system GMM estimator of Blundell and Bond (1998), which should allow for endogeneity, measurement error and omitted variable problems. For a panel of 24 European countries between 1990 and 2006, results suggest the existence of conditional convergence in terms of GHG emissions, no evidence of the EKC hypothesis, a positive and lower than one emissions-energy elasticity and how merely shifting the energy mix toward renewable sources (and, to a lesser extent, nuclear) would yield significant reductions in per capita emissions.

JEL: Q43, Q42, Q53, C23

Key Worlds: GHG emissions, energy consumption, dynamic panel data models

[1] The author acknowledges the financial support of Focus-Abengoa through the Energy and Climate Change research program, and the Ministerio de Educación y Ciencia of Spain (SEJ2006-14354).

1. INTRODUCTION

The European Union is positioned as one of the most active economic areas in terms of measures for combating greenhouse gas (GHG) emissions. In addition to ratifying the Kyoto Protocol in 2002, another prominent agreement was signed in December of 2008 (20/20/20 plan), by which EU member countries committed to reduce emissions in 2020 by 20% with respect to 1990 levels. This agreement also emphasizes the role of the changing energy model as a means to reach this objective. As such, the framework for 2020 also establishes a reduction in primary energy consumption by 20% and an increase in the share of renewable energy as a part of overall energy consumption by 20%. The importance of energy on GHG emissions is reflected by the fact that 80% of said emissions in Europe are currently due to the use and production of energy. The Stern report (2007) emphasizes that, in the world as a whole, almost 65% of total GHG emissions are due to energy.

Most research on emissions is found within the framework of the Environmental Kuznetz Curve (EKC), which focuses on the relationship between emissions and economic activity, ignoring energy aspects.[2] Even from an empirical point of view, there are few exceptions that simultaneously study the relationship between emissions, growth and energy consumption.[3] This paper contributes to the existing literature and includes energy aspects in an EKC dynamic panel data (DPD) framework and uses the

---

[2] The studies by Selden and Song (1994), Grossman and Krueger (1995) and Schmalensee et al. (1998) are consistent with the EKC hypothesis, while other authors, such as Holtz-Eakin and Selden (1995), Shafik (1994) or, more recently, Huang et al. (2008), do not present evidence to support this hypothesis. See also Dinda and Coondoo (2006) and Coondoo and Dinda (2008) for studies of the relationship between income and emissions. Wagner (2008) points out that many studies of the EKC made with traditional methods can be spurious. Brock and Taylor (2005), Stern (2004), Dinda (2004), Verbeke and Clercq (2006), among others, offers excellent surveys of the EKC topic.

[3] An exception is Ang (2007), which examines the dynamic relationship between pollutant emissions, energy consumption and economic growth under an integrated framework.

one-step system GMM estimator of Blundell and Bond (1998), which should allow for endogeneity, measurement error and omitted variable problems. For a panel of 24 main European countries between 1990 and 2006, results suggest the existence of conditional convergence in terms of GHG emissions, no evidence of the EKC hypothesis, a positive and lower than one emissions-energy elasticity and how merely shifting the energy mix toward renewable sources (and, to a lesser extent, nuclear) would yield significant reductions in per capita emissions.

Within the EU15 countries, Schmalenssen et al. (1998) called for research to explain why high-income countries, such as Germany, France, Sweden, Netherlands and the United Kingdom, have started to reduce per capita GHG emissions, while others in the same area, such as Spain, Portugal, Italy and Austria, have increased emissions over the same period. It is also worth noting how some Eastern European countries, such as the Czech Republic, Hungary, Poland and Slovakia, have reduced GHG emissions even more than the richest EU countries. Given these facts, the Environmental Kuznetz Curve (EKC) hypothesis is unable to explain the differences in emissions within EU27 countries because Eastern economies, despite having a smaller per capita GDP, have reduced emissions more than Western, richer countries. Thus, we might look at environmental policy or at changes in fundamental economic and energy forces to find the reasons for these differences. This statement is in keeping with the work by Tahvonen and Salo (2001). From a theoretical point of view, these authors developed a neoclassical growth model with nonrenewable and renewable energy to address the issue of why emissions have increased in some countries but have decreased in others. They conclude that the relationship observed between CO2 emissions and income levels may follow even without environmental policy, hence economic - and *energy* - fundamental forces must be playing an important role in their reductions. From an empirical point of view, we aim to characterize some of these fundamental forces which are generating the differences noted in GHG emissions within EU27 countries between 1990 and 2006.

Our empirical dynamic framework is along the lines of the estimating equations developed by Brock and Taylor (2004, 2005) and Álvarez et al. (2005). These authors adapt the neoclassical growth framework to a growth setting with emissions. As in Stokey (1998), they assume that emissions follow a by-product process. These authors derive an estimating dynamic panel data (DPD) equation for pollution directly from the theory, but they leave aside energy aspects. We extend these authors' model and include energy aspects in a dynamic EKC framework. Hence, in addition to including the level of activity (measured by real GDP) and its possible inverted U-shaped relationship (a real GDP quadratic term), we also consider three energy aspects in our model: i) an *aggregate energy effect*, measured as the difference in total primary energy consumption per inhabitant; ii) an *energy mix effect*, measured as the difference in the shares of alternative energy sources (solid fuels, oil and petroleum products, gas, nuclear and renewables) with respect to primary energy consumption; iii) an *energy sector effect*, measured as the difference in the distribution of final energy consumption (industry, transport, households or services).

In order to implement effective energy measures to abate GHG emissions, it is crucial to correctly estimate the relationship between emissions, energy and economic activity. However, traditional procedures for estimating panel data models (i.e., fixed or random effect methods) are well known to be unsuitable for estimating a DPD model. In this paper we use the one-step system GMM estimator [Arellano and Bover (1995) and Blundell and Bond (1998)], which should allow for endogeneity, measurement error and omitted variable problems. In order to discuss the importance of considering this appropriate estimation method, we follow Blundell et al. (2000) to compare the one-step system GMM estimates with respect to alternative, more traditional methods, and we find important differences that may even change policy recommendations. There are few exceptions in the energy and emissions literature that seriously consider the weakness of traditional methods in estimating DPD models. For example, Halkos (2003) and Metcalf (2008) address the endogeneity problem, but use a first difference GMM estimator, which does not consider the *weak* instruments problem of this procedure when time series are persistent [Blundell and Bond (1998)], which is the case for aggregate emissions and energy time series. Huang et al. (2008), which revisits the causal relationship between energy consumption and GDP, is an exception that properly addresses both the endogeneity and the weak instruments problems and considers a system GMM approach.[4] This paper also contributes methodologically to properly estimating dynamic pollution-energy models.

The rest of the paper is organized as follows. The next section describes the data taken into account in the model analyzed. Section 3 presents the DPD model and describes the system GMM methodology. Section 4 shows the estimation results and some robustness analysis. The last section provides the main conclusions.

2. EMISSIONS, ENERGY AND ECONOMICS IN THE EU27: AN OVERVIEW

The goal of this paper is to characterize the effects of economic and energy variables on GHG emissions within the EU27 countries, with a special focus on energy mix variables. Data on GHG emissions are obtained from the European Environment

[4] In the growth literature, Forbes (2000), Shioji (2001), Levine et al. (2000) and Bond et al. (2001), among others, use the system GMM estimator that we consider in this paper.

Agency (EEA) and are measured in thouthands of tons of CO2 equivalent. These data exclude land use and forestry. Energy consumption data are obtained from Eurostat, the official site for EU countries. Annual Energy and GHG emissions data cover from 1990 to 2006. We take all EU27 members except Luxemburg, Cyprus and Malta. Series on real GDP and population are obtained from *The Conference Board and Groningen Growth and Development Centre (2008).* GDP series are expressed in market prices and in 1990 US dollars converted at "Geary-Khamis" purchasing power parities (PPPs). Population series represents midyear population (in thousands of persons), which are mostly derived from the International Data Base of the U.S. Census Bureau.

Tables A1-A3 in the Appendix summarize data used in this work. They show 2006 levels and annual growth rates from 1990 to 2006 for each variable and country considered in the sample. Table A1 shows GHG emissions, real GDP and primary consumption data expresed in per capita terms; Table A2 shows energy mix ratios of alternative energy sources, which are expressed as a percentage of primary energy consumption; Table A3 summarizes sectoral energy ratios, which are meassured as a percentage of final energy consumption.

Between 1990 and 2006, per capita GHG emissions fell by 0.75% per year in the EU27 (see Table A1). Note the heterogeneity present among different groups of countries. Based on 1990 per capita GDP levels, we denote the ten richest countries as EU10,[5] all of them with a per capita GDP in excess of 16,000 $ US (1990 base), those countries which in 1990 had a per capita GDP of around 10,000$ US as EU4,[6] and as EU EAST

[5] This group of countries includes Belgium, Denmark, Germany, France, Italy, Austria, Netherlands, Finland, Sweden and the United Kingdom.

[6] These countries are Spain, Greece, Portugal and Ireland. Note that the case of Ireland is unique since in 1990 it was among those countries with an intermediate GDP, but had become one of the richest in the EU27 by 2006.

those countries of Eastern Europe, whose per capita GDP was approximately 6,000$ US.[7] Figure 1 shows the relationship between GHG emissions and real GDP for these three groups of countries between 1990 and 2006.

According to Table A1, in the EU10, with the exception of Italy, Finland and Austria, all reduced their per capita emissions. Of particular note are the United Kingdom and Germany, whose emissions dropped more than 1% per year. Emissions in the EU4 countries, on the other hand, increased by as much as 1.8% per year in the cases of Spain and Portugal. Except for a few cases, the link that has existed until now between income and per capita emissions is in keeping with the EKC hypothesis, in which the relationship between income and emissions is given by an inverted-U (see the lines associated with the EU10 and EU4 in Graph 1). This relationship disappears, however, when we add the countries of Eastern Europe to the sample. In fact, if we only consider the year 1990, we see a 'V' relationship, and if we focus on 2006 it is essentially linear. Except for Slovakia, every country in the East reduced its per capita emissions to a greater extent even than those of the EU10, despite their per capita GDP levels being the lowest in the EU27. Emissions in Estonia, Latvia and Lithuania, for example, fell by almost 4% per year. The inaccuracy of the EKC hypothesis reveals the existence of other factors - energy or technological, for example - that might help to explain the change in emissions between 1990 and 2006 in Europe.

FIGURE 1 ABOUT HERE

In an attempt to reconcile the shortcomings of the EKC hypothesis in explaining the link between emissions and development, the literature on growth and convergence [i.e.,

[7] These countries are Bulgaria, the Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia and Slovakia. Cyprus and Malta are not included.

see Barro and Sala-i-Martín (1992)] has recently been applied to the topic of emissions.[8] Based on the fact that pollution is a by-product process [i.e., see Stokey (1998)] and using a neoclassical growth model extended to include pollution, these authors derive a dynamic equation that relates emissions growth to lagged emission levels, among other factors. Figure 2 represents the basic relationship of this model. It shows the scatter plot between emissions growth and emission levels in 1990. Its negative relationship suggests that countries with initial higher levels of emissions tend to reduce (increase) emissions more (less) than countries with lower initial levels. This finding gives some evidence in favor of absolute convergence within EU countries in terms of GHG emissions between 1990 and 2006.[9] This theory also provides a partial explanation for the situation in some countries, such as Estonia or the Czech Republic, which had very high emission levels in 1990, and may explain a part of the substantial drop in their emissions despite having a small per capita GDP.

FIGURE 2 ABOUT HERE

This theory, however, falls well short of being complete, as evidenced by the fact that the countries are not perfectly aligned along the regression line. In fact, the dispersion is quite high - R^2 is only 0.26 - and we see how countries with very different characteristics, such as the United Kingdom and Poland, are very close to each other, while other seemingly more similar countries, like Sweden and Finland, are far apart. It does not help us understand, for example, the cases of Latvia, Lithuania or Romania, whose drops in emissions are much greater than those associated with their 1990 levels. Nor does it help us understand the cases of Spain, Greece or Ireland, whose emission

[8] See Brock and Taylor (2004, 2005) and Álvarez et al. (2005).

[9] Moreover, the estimate of -0.027 for the slope of the regression line indicates that the convergence speed is 2.7% a year, which is very close to the usual 2% convergence value for real GDP estimated by Barro and Sala-i-Matín (1992) and some other authors.

outputs are clearly above those associated with their 1990 levels. The poor economic growth experienced in Latvia, Lithuania and Romania on the one hand, and the high growth of Spain, Greece and Ireland on the other hand (Table A1), could explain these differences. Given this mixed evidence, there is a clear need to combine the convergence with the EKC theory.

However, there are cases which cannot be explained even by combining these two theories. For example, let us compare the United Kingdom with Finland (see Figure 2). Both economies were at similar emission levels in 1990 and had comparable annual growth between 1990 and 2006 (Table A1). And yet the United Kingdom lowered its emissions to a much greater extent than Finland. The key to the differences between these two countries could lie in their energy use. While the economy of the United Kingdom grew at an annual rate of 2.1% while increasing its annual energy consumption by just 0.2%, Finland's economy grew by 2% per year at the expense of a 1.4% annual growth in energy consumption (see third group of columns in Table A1). The case of Spain is also noteworthy in this comparison, since its 2.2% annual growth was accompanied by a similar expansion in its energy usage, which has resulted in Spain being one of the most polluting countries in recent years.

Our intention with these simple examples is to illustrate the pressing need to simultaneously consider economic, technological and energy aspects in emissions models. That is the main contribution of this paper, since most empirical research found in the literature relates emissions with GDP and technological variables.

Changes in energy usage can also be explained by variations in the type of energy used or by changes in final energy consumers. So as to account for these two important aspects, in addition to that of aggregate energy use, we will also consider energy consumption by type of primary energy source (solid fuels, oil and petroleum products, gas, nuclear and total renewables) and by type of end consumer (industry, transport, households, agriculture, services and others).

As concerns the change in the primary energy mix (Table A2), the overriding trend in the EU27 has been for a reduction in the amount of energy derived from solid fuels and, to a lesser extent, petroleum products. These drops have been offset by a notable increase in the importance of gas, renewable energies and, on a smaller scale, nuclear. For the EU27 as a whole, coal usage has fallen by 0.6 percentage points (p.p.) a year, that of petroleum products by just 0.1 p.p., that of gas has grown by 0.4 p.p., of nuclear by 0.1 p.p. and of renewable energy sources by 0.2 p.p. Despite these changes, renewable sources still account for the smallest share, at 7.1% in 2006, versus 14% for nuclear, 24% for gas, 37% for petroleum and 18% for solid fuels.

As concerns the distribution by type of end users, industry, transport and households account for almost 85% of final energy consumption in the EU27. The first two represent almost 30% each, while the third amounts to around 25%. The change in these ratios has been fairly stable among EU15 countries, though significant changes have taken place among the countries in the East. With the exception of Ireland, industry's share of energy consumption has decreased at an annual rate of 0.4% for the EU27. These drops have been particularly significant for the countries of the East, where industry has undergone a considerable renovation. Transportation has also played an increasing role in most economies. In the EU27, its energy consumption quota has increased by slightly over 0.3 p.p. a year. These changes have been driven by the countries of the East, although their 1990 levels were clearly below those of the most advanced European countries. Household energy usage has grown by almost 0.1 p.p. a year in the EU27. While no clear pattern exists for this ratio in the EU15, it has grown in most Eastern countries.

In the next section we present a Dynamic Panel Data model that relates GHG emissions with economic and energy aspects.

3. A DYNAMIC PANEL DATA MODEL OF POLLUTION EMISSIONS

In this section, we present a dynamic panel data (DPD) model for pollution emissions for estimation by system GMM. Brock and Taylor (2004, 2005) and Álvarez et al. (2005) derive an estimating dynamic equation directly from an extended neoclassical growth model with pollution. They estimate a model that relates current emissions growth with lagged emissions levels and economic factors. We build on their equations so as to propose the following DPD model that relates pollution, growth and including also energy variables:

$$p_{it} = \alpha_i + \xi_t + \beta p_{it-1} + \lambda_1 y_{it} + \lambda_2 y_{it}^2 + \theta e_{it} + \sum_{j=1}^{J} \delta_j m_{jit} + \sum_{k=1}^{K} \varphi_k s_{kit} + \varepsilon_{it} \qquad \textbf{(1)}$$
$$t = 1990, 1991, ..., 2006; i = 1, 2, ..., 24.$$

The p_{it} variable is the log of per capita GHG emissions; its lagged level controls for short-term dynamics and conditional convergence;[10] y_{it} is the *log* of per capita real GDP and its quadratic term controls for its possible inverted U-shaped relationship with emissions (the EKC hypothesis). Remained variables capture alternative energy factors. The e_{it} term is the log of per capita primary energy consumption, which meassures an

[10] In the case of GHG emissions, testing the conditional convergence hypothesis within EU countries is of special interest because these countries share common environmental policies and targets.

aggregate energy use effect. The m_{jit} variables show the ratios with respect to primary energy consumption of oil and petroleum products, total gas, nuclear energy and total renewable energy, respectively, which capture differences in the *energy mix*. The ommited energy source is the solid fuel, thus remaining energy mix coefficients are referred to the solid fuel ratio. The s_{kit} variables show the shares of final energy consumption of main consumers (the industry sector, the transport sector and the households), which capture an *energy composition effect*. The ommited sectors are the agriculture and the services, which represent less than 15% of total final energy consumption. Thus, the industry, transport and households coefficients are referred to the coefficients of these less energy intensive sectors.

Since all these economic and energy variables may affect emissions contemporaneously, it makes sense that they enter in equation (1) dated at period *t*. Hence, regressors are endogenous, which must be taken into account in order to determine the set of valid instruments in the system GMM approach. We follow Blundell et al. (2000) to handle this issue.[11] Equation (1) can be rewritten more compactly as

$$p_{it} = \alpha_i + \xi_t + \beta p_{it-1} + X_{it}^{'}\Omega_t + \varepsilon_{it}, \qquad \textbf{(1)'}$$

where *X* groups all endogenous regressors and Ω is a vector of their associated parameters.

The country-specific terms α_i capture all fixed factors inherent to each country, which are either not considered in the model, such as geographical, social and local policy country aspects, or not directly observer, such as the initial pollution technology. From

[11] See the technical appendix for more details about this point.

a theoretical point of view, most of these fixed factors are expected to be heterogeneous within countries and correlated with, at least, each country's initial level of emissions. Hence, from an empirical point of view, to assume away those fixed differences would lead to biased estimates.[12] ξ_t is a period-specific constant, which captures productivity, regulatory or economic changes that are common to all countries. Finally, $\varepsilon_{i,t}$ encompasses effects of a random nature and not considered in the model, which are assumed to have the standard error component structure in DPD models [Arellano and Bond (1991), Arellano and Bover (1995) and Bundell and Bond (1998)],

A1) $E\left[\varepsilon_{it}\right]=0;\ E\left[\alpha_i\varepsilon_{it}\right]=0; E\left[\varepsilon_{it}\varepsilon_{is}\right]=0,\ i=1,...,N; t=1,...,N \ and \ s\neq t$ **.**

A2) $E\left[y_{i1}\varepsilon_{it}\right]=0,\ for \ \ i=1,...,N \ and \ t=2,...,T$ **.**

The interpretation of equation (1) and (1)' depend on the level of β. A β smaller than one is consistent with conditional convergence, which means that countries relatively close to their steady-state per capita emissions levels will experience a slowndown in their emissions growth. In this case, α_i and all explanatory variables affect to the steady-state the emissions of country i is converging to. On the other hand, if β is greater than one, there is no convergence effect and α_i and all regressors would meassure differences in steady-state emissions growth rates. Estimated β will be lower that one in all cases, hence we will focus on the conditional convergence interpretation.

Traditional procedures for estimating a panel data model like (1) (i.e., fixed or random effects methods) are known to be unsuitable [Anderson and Hsiao (1982); Hsiao (1986)]. Holtz-Eakin et al. (1988) and Arellano and Bond (1991) propose an alternative

[12] Fixed effects would be omitted in a standard OLS pool regression, resulting in bias estimates. In this situation, it is well known that OLS β estimates is downward bias. See Anderson and Hsiao (1992) and Hsiao (1986) for more details about this point.

approach, where first differences in the regression equation are taken to remove unobserved time-invariant country specific effects and then particular moment conditions for lagged variables are exploited to find a set of instruments and construct a GMM-based estimator.[13] Their GMM approach (GMM-DIF) allows us to handle endogeneity, measurement errors and omitted variables problems. However, the GMM-DIF approach shows important bias problems when variables are persistent, which is the case of emissions, economic and energy macroeconomic variables. Under these circumstances, the instruments used in the GMM-DIF estimator have proven to be *weak* and the first difference estimator is poorly behaved. Arellano and Bover (1995) and Blundell and Bond (1998) propose an alternative GMM procedure which might overcome the *weak* instruments problem. This procedure estimates a system of equations in both first-differences and levels, where the instruments in the level equations are lagged first differences of the variables. In this paper we use the system GMM estimator (GMM-SYS) in its one-step version. In contrast to the two-step version, the one-step GMM estimator has standard errors that are asymptotically robust to heteroskedasticity and have been found to be more reliable for finite sample inference.[14]

4. RESULTS

The estimation approach consists of the one-step GMM estimator proposed by Arellano and Bover (1995) and developed by Blundell and Bond (1998). All variables are taken as deviations from period means so that we do not need to include time-specific

[13] See the technical appendix for more details on this point.

[14] See Blundell and Bond (1998), Blundell et al. (2000), Windmeijer (2005) and Bond (2002), among others.

constants and can omit the ξ term from equation (1)'. GMM results are shown for the one-step estimator case, with heteroskedasticity-consistent asymptotic standard errors reported.[15]

The most frequently used tests to validate the assumptions underlying GMM methods are the *m1*, *m2* and Sargan tests. If the disturbance ε_{it} in (1)' is not serially correlated, there should be evidence of negative first order serial correlation and no evidence of second order serial correlation in first difference residuals, ε_{it}-ε_{it-1}. The absence of serial correlation in these errors is also an indication that business cycle effects are not biasing our results in a significant way [Caselli et al. (1997)]. The *m1* and *m2* tests are based on the standardized average residuals autocovariance, which are asymptotically N(0,1) distributed under the null hypothesis of no autocorrelation. The Sargan test, in contrast, is distributed chi-squared with degrees of freedom equal to the number of moment restrictions minus the number of parameters estimated under the null hypothesis that moment conditions are valid. However, the Sargan test is less meaningful since it requires that the error terms be independently and identically distributed, which is not expected in our case. Hence, we will pay basically attention to the *m1* and *m2* tests. Specifically, as Arellano (2002) suggests, we include some lagged terms of regressors in (1) in order to improve the specification of the DPD model. In all models estimated, including one lagged term for the energy and the income variables is enough to pass the *m1* and the *m2* specification tests.

[15] For a given cross-sectional sample size, the use of too many instruments in models with endogenous regressors may result in seriously biased estimates (Álvarez and Arellano (2003)). Hence, even when computing speed is not an issue, these authors recommend not using the entire series history as instruments. We include instruments up to t-3. Including more instruments does not change results significantly.

We first find evidence supporting the good properties of the system GMM estimates. Following Blundell et al. (2000), Table 1 compares the results of alternative methods: the OLS pooling estimates (OLS-POOL), the Within Group estimates (WG), the GMM-DIF and the GMM-SYS. Associated with each parameter, the p-value of the t-test is shown. We show standard specification tests for each model. First, notice that the Haussman test rejects the null hypothesis of random effects at any standard level of significance. For any GMM estimate, we show the *m1* and the *m2* tests and conclude that moment conditions underlying GMM estimates seem to be robustly supported.

INSERT TABLE 1 ABOUT HERE

In the presence of country-specific effects, OLS seems to give an upward-biased estimate of the β coefficient in (1)', while WG appears to give a downwards-biased estimate of this coefficient. Using GMM-DIF, the β coefficient is barely higher than the WG estimates, suggesting the possibility of important finite sample bias due to the weak instruments problem. This comparison also highlights that the estimated coefficients of the GDP and energy regressors, which are of our main interest, differ significantly among the alternative procedures. Hence, using a method resulting in bias estimates (the WG or the GMM-DIF) will lead to misleading conclusions. For example, energy sector share coefficients are not significant under the WG and the GMM-DIF methods, while they are significant under GMM-SYS. Moreover, they are of opposite signs. Misleading conclusions would say that sector energy composition has no significant effect on GHG emissions. As another example, the EKC hypothesis is not rejected under WG and GMM-DIF, while it is rejected at standard levels of significance under GMM-SYS. Regarding the primary energy mix regressors, they are negative in all cases and under all methods. Recall that these coefficients are all expressed in terms of the Solid Fuel ratio. WG estimates indicate that nuclear energy is the most significant source for reducing GHG emissions, while renewables are in second position, with petroleum and gas also playing an important role in reducing emissions. Coefficients under GMM-SYS are, first of all, notably smaller than those estimated under WG and GMM-DIF estimates and, secondly, now the coefficient associated with renewables is the highest one, followed by that for nuclear, while those for gas and petroleum products are similar and almost negligible.

In summary, this comparison suggests that the WG estimates are severely biased, that there exists a problem with weak instruments and hence the GMM-DIF is also biased in the WG direction and that the GMM-SYS approach seems to be a convenient way to overcome the weak instrument problem. Hence, we will focus our attention on GMM-SYS estimates from now on.

We want to distinguish our results between alternative areas in the EU27: the EU10, the EU14 (all EU10 countries together with Spain, Portugal, Greece and Ireland) [16] and the EU East. In addition, we want to show the differences in the results when considering the pre-Kyoto (1990-1997) and the post-Kyoto (1998-2006) period. For each area and time period, we estimate a model like (1)' by one-step system GMM. Results are shown in Tables 2(a)-2(d) for the EU27, EU10, EU14 and EU East, respectively, for the 1990-2006, the 1990-1997 and the 1998-2006 period. As shown in the tables, the *m1* test supports a negative and significant first order correlation of the first difference residuals, while the *m2* test rejects the existence of second order correlation. A joint interpretation of these tests does not reject the hypothesis that the level disturbances are serially uncorrelated, hence GMM assumptions are satisfied. The p-value for the Sargan

[16] We do not consider the EU4 group alone because of the small dimension of the panel.

test is always very close to one, but this test is less reliable in our framework, as commented above.

INSERT TABLES 2(a)-2(d) ABOUT HERE

Most noteworthy in the results is that parameter β in (1)' is always significantly less than 1. The convergence parameter is given by β-1, hence there is evidence for the conditional convergence of GHG emissions for the EU27 countries for the time period in question. Whether we consider the EU27, or just the EU14 or EU10, the estimate for β-1 is approximately -0.1, independently of the period considered. This estimate represents a reduction in the differences in emissions for the EU27 countries of about 10% a year, as determined by the steady state for each country. If we consider only the countries of the East, the estimate for β-1 is around -0.5, which represents a conditioned convergence process for the emissions within Eastern European countries that is far above the convergence between the most developed countries and those in Eastern Europe.

Secondly, we note the minimal or zero evidence for the EKC hypothesis in the EU for the time period in question. This fact concurs with the evidence discussed in Section 2. In general, both the GDP coefficient and its square term are either very close to zero or negligible. This evidence, then, indicates that the differences in emissions observed among European countries are basically due to energy, technological or regulatory aspects. This paper focuses on the energy aspects, distinguishing between aggregate factors, differences in the primary energy mix and differences in the distribution of the end consumer.

The elasticity associated with aggregate primary energy consumption is significantly higher than zero but less than one in every case analyzed. The differences in aggregate energy consumption, then, would explain a great deal, but not all, of the differences present in emission levels. For the EU27, and even if only the EU10 or EU14 are considered, this elasticity is around 0.8 and 0.9 and does not change over the time periods analyzed. As for the countries of the East, this elasticity, which was near 0.9 in the pre-Kyoto period, fell to almost 0.6 afterward. The important changes in production processes, technology and energy usage seen by these economies in recent years might have resulted in drastically reduced emissions and would explain the smaller elasticity.

According to our estimates, in addition to aggregate energy consumption, differences in the primary energy mix also play an important role in explaining the variations in emissions among EU countries. Recall that the energy type omitted from the regression was coal, meaning the estimated coefficients for the other energy sources are in reference to this source. The estimated coefficients are negative for every case, which would indicate that a change in the coal energy mix toward any other alternative energy source would favor a reduction in emissions. A comparison of the coefficients for the various energy sources would indicate how the increased use of a particular energy source is most beneficial for the environment: the more negative the coefficient, the greater the positive effect on emissions of a one percentage point change in the mix.[17]

Various points stand out in this regard. First, the lower coefficient is usually associated with renewables, followed by nuclear and lastly by natural gas and petroleum, which all have very similar coefficients. In the majority of cases, the magnitude of the coefficient

[17] The increase in the energy mix of a certain source of energy could be due to a greater use of said energy type in existing economic sectors or to a change in the production structure, where the new sectors demand one source of energy use over another. Regardless of the reason, all that matters to our model is the resulting shift in the energy mix.

for renewables is almost double that for gas or petroleum. For the countries of the East, the energy mix coefficients are almost unchanged when comparing estimates for the pre- and post-Kyoto periods. For the most advanced countries, however, whether considered as the EU10 or EU14, significant changes are evident. For the four energy types in question, the estimated coefficients for the post-Kyoto period are considerably more negative than for pre-Kyoto. Given that the coefficient associated with aggregate energy consumption was almost unchanged for this group of countries, these results point to significant advances in the efficiency and/or use of these energy sources in recent years which has made them less polluting.

Lastly, let us consider the effects the changes in the final energy distribution have on emissions. Recall that the variable omitted was from the services and farm sector, meaning the estimated coefficients are in reference to those sectors.[18] Although the changes in these ratios were not as significant as those in the primary energy mix for the period in question, certain results still merit consideration.

Let us first focus on the term associated with transport, whose final consumption has grown the most in the EU and which is currently the most important in the EU14 countries (see Table A3). The transportation sector has undergone two very important changes in recent years, which could have offsetting effects on emissions. On the one hand, technological and regulatory advances have resulted in improved emissions data for this sector. On the other, the higher degree of mobility induced by economic development and derived from technological improvements (the rebound effect) have the opposite effect. For the entire set of EU27 countries, the coefficient associated with

[18] As noted for the primary energy mix, a change in these ratios could be due to a change in the energy usage of existing sectors or to a sector shift within the economy. These differences are not considered in this paper either. All that matters to our model is the shift that has taken place in the distribution of final energy consumers.

the transportation sector is, in general, small and negligible. If analyzed by groups, however, we note, on the one hand, a significantly negative coefficient for the EU10 and EU14 countries for the post-Kyoto period, indicative of improved technology and regulation in the sector during this period and their favorable effect on emissions despite its increased contribution to energy consumption; and, on the other, the estimate is positive and significant for the countries of the East for both the pre- and post-Kyoto periods, which implies that advances in technology and regulation have not offset the increased mobility resulting from greater developments in the field. In the EU14, the relevant coefficient for the pre-Kyoto period is negligible.

The coefficient associated with industry is not significant for the EU27 as a whole or for the EU10 or EU14. It is significant and positive, though smaller than that associated with transportation, for the countries of the East. Among the most developed countries, industry is shifting toward a greater use of technology and less energy consumption and emissions, which has brought its emissions on a par with those of the service sector in many cases. In Eastern Europe, despite the rapid renewal of industry, it has not reached the level of the most advanced countries. This change is apparent in that the industry coefficient for the post-Kyoto period is smaller and closer to zero than the associated pre-Kyoto coefficient.

Lastly, we note that the coefficient associated with final consumption by household is not significant in most cases, save for the most developed countries in the post-Kyoto period, in which it is negative, though smaller than for the transportation sector. For this time period, regulatory measures aimed at more rational energy usage, weather-sealing improvements in construction that favor reduced household energy consumption, and technological advances in appliances and lighting are all allowing for more sustainable growth in terms of emissions.

FINAL REMARKS

This paper has proposed and estimated a panel dynamic model for EU27, for the 1990 and 2006 period, that relates GHG emissions with real GDP, aggregate energy consumption, the primary energy mix and the energy distribution for end consumers. This paper's main contributions have been two-fold. The first is the use of a dynamic panel to simultaneously assess the EU27 in terms of emissions, growth and energy. The second is methodological, since the most generalized procedures for estimating in this type of literature tend to exhibit endogeneity problems and biased estimates for finite samples. We use in this paper the system GMM approach proposed by Arellano and Bond (1995) and Blundell and Bond (1998), which has been shown to solve many of the problems that arise in traditional procedures. From a methodological standpoint, our results prove the relevance of considering a suitable estimation method, since we found notable differences when comparing the findings provided by alternative, less reliable methods.

The main findings of this paper are summarized as follows. First, our results indicate that between 1990 and 2006, there is clear evidence for the existence of conditional convergence in terms of GHG emissions among the EU27 countries. These symptoms are robust when different sub-groups of countries and time periods are considered. In this regard, no notable differences were detected between the pre-Kyoto (1990-1997) and the post-Kyoto (1998-2006) periods.

Secondly, we found no evidence in favor of the EKC hypothesis over the course of this same time period for the EU27 countries. This fact is due, in part, to the transition experienced by the countries of the East in recent years and which has resulted in a drastic reduction in their emissions, despite being countries with per capita GDP levels markedly lower than those of the Western European economies. Nevertheless, when only the most developed countries are considered (EU15), the EKC hypothesis also fails. Hence, our results indicate that once emissions by energy and convergence factor are taken into account, there is no evidence for the existence of an inverted-U relationship in Europe between emissions and real GDP.

The third relevant result involves the relationship between total energy and emissions. The elasticity between aggregate energy consumption and emissions is significantly greater than zero, but also below unity. This indicates that a 20% reduction in energy consumption (as suggested by the 20/20/20 plan) would not be sufficient to achieve the 20% emissions reduction goal. An additional boost in efficiency or a shift in the energy mix toward less polluting energies would be required to achieve the emissions goal, which is the ultimate objective.

Fourth, our findings highlight how merely shifting the energy mix toward renewable sources (and, to a lesser extent, nuclear) would yield significant reductions in per capita emissions. Technological advances that may be occurring in the usage and consumption processes for the natural gas and petroleum products still seem to be small with respect to solid fuels.

As for the energy consumption distribution of end users, our results emphasize the positive effect of the industrial, transportation and residential sectors in the most developed countries. The transformation of industry and its efficiency gains in many

European countries, along with technological advances in the transportation and residential sectors, appear to favor a reduction in emissions. The evidence is not as clear in Europe's less developed countries, which must still make a substantial effort to improve in this area.

Although the EU seems to be progressing in the right direction, it is still far from achieving its goals for 2020. What is more, reducing energy use will not be enough. It is necessary to continue with industrial renovation and with technological advances in the transportation and residential sectors, combined with measures to reduce mobility via private transportation as well as our dependence on petroleum, coal and natural gas and shift toward less polluting energies.

As a final caveat, our findings indicate that a smooth transition from a nonrenewable to a renewable energy system is yielding reduced GHG emissions within the EU15 economies. This important result highlights the need to promote research on the economic political mechanisms behind a possible change in the energy system, and on how to accelerate this process.

REFERENCES

1. Álvarez, J. and M. Arellano (2003). The time series and cross-section asymptotics of dynamic panel data estimators, *Econometrica* 71(4), 1121-1159.
2. Álvarez, F., Marrero, G.A. and L.A. Puch (2005). Air pollution and the macroeconomy across European countries, *Working Papers* 2005-10, FEDEA.
3. Anderson, T.W. and C. Hsiao (1982). Formulation and Estimation of Dynamic Models Using Panel Data, *Journal of Econometrics*, 18, 47-82.
4. Ang, J. (2007). CO2 emissions, energy consumption, and output in France. Energy Policy 35, 4772-4778.
5. Arellano, M. (2002). Sargan's instrumental variables estimation and the Generalized Method of Moments, *Journal of Business & Economic Statistics, American Statistical Association*, vol. 20(4), 450-59.
6. Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies*, 58, 277-297.
7. Arellano, M. and S. Bond (1998). Dynamic panel data estimation using DPD98 for GAUSS. http://www.ifs.org.uk/staff/steve_b.shtml.
8. Arellano, M. and O. Bover (1995). Another look at the instrumental-variable estimation of error-components models. *Journal of Econometrics* 68, pp. 29–52.
9. Barro, R.J. and X. Sala-i-Martin (1992). Convergence, *Journal of Political Economy*, 100(2), 223-51.
10. Barro, R.J. (2000). Inequality and Growth in a Panel of Countries, *Journal of Economic Growth*, 5(1), 5-32.
11. Blundell, R. and S. Bond (1998). Initial conditions and moment restrictions in Dynamic Panel Data models, *Journal of Econometrics*, 87, 115-143.
12. Blundell, R.W. and S. Bond (2000). GMM estimation with persistent panel data: an application to production functions. *Econometric Reviews* 19, 321–340.
13. Blundell, R.W., Bond, S.R. and F. Windmeijer (2000). Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator. In: Baltagi, B., Editor, 2000. *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, Advances in Econometrics Vol. 15, JAI Press, Elsevier Science, Amsterdam, pp. 53–91.

14. Bond, S., Hoeffler, A. and J. Temple (2001). GMM Estimation of Empirical Growth Models, *Economics Papers* 2001-W21, Economics Group, Nuffield College, University of Oxford.
15. Bond, S. (2002). Dynamic panel data models: a guide to microdata methods and practice, *Portuguese Economic Journal*, 1, 141-162.
16. Brock, W.A. and M.S. Taylor (2004). The Green Solow Model. NBER Working Papers 10557, *National Bureau of Economic Research*.
17. Brock, W.A. and Taylor, M.S (2005). Economic Growth and the Environment: A Review of Theory and Empirics, Handbook of Economic Growth, in: Philippe Aghion & Steven Durlauf (ed.), *Handbook of Economic Growth*, edition 1, volume 1, 1749-1821, Elsevier.
18. Cánova, F. and A.Marcet (1995). The Poor Stay Poor: Non-Convergence Across Countries and Regions, *CEPR Discussion Papers* 1265, C.E.P.R. Discussion Papers.
19. Caselli, F., G. Esquivel and F. Lefort. (1996). Reopening the convergence debate: a new look at cross-country growth empirics. *Journal of Economic Growth*, 1, 363-389.
20. Coondoo, D. and S. Dinda (2008). The carbon dioxide emission and income: a temporal analysis of cross-country distributional patterns. *Ecological Economics* 65, 375-385.
21. Chamberlain, G., (1984). Panel Data, in: Z. Griliches and M. Intriligator (Eds.), *Handbook of Econometrics*, Vol. 2, North-Holland, 1247-1318.
22. De la Fuente, A. (2002). On the sources of convergence: A close look at the Spanish regions*, European Economic Review*, 46(3), 569-599.
23. Dinda, S. (2004). Environmental Kuznets Curve Hypothesis: A Survey, *Ecological Economics*, 49(4), 431-455.
24. Dinda, S. and D. Coondoo (2006). Income and emission: a panel data-based cointegration analysis. *Ecological Economics* 57, 167-181.
25. Forbes, K. (2000). A reassessment of the relationship between inequality and growth. *American Economic Review*, 90(4), 869-887.
26. Grossman, G. and A. Krueger (1995). Economic growth and the environment, *Quarterly Journal of Economics* 110(2) 353-377.

27. Halkos, G.E. (2003). Environmental Kuznets Curve for sulphur: evidence using GMM estimation and random coefficient panel data models, *Environment and Development Economics*, 8, 581-601.
28. Holtz-Eakin, D., Newey, W. and H. S. Rosen (1988). Estimating Vector Autoregressions with Panel Data, *Econometrica*, 56(6), 1371-1395.
29. Holtz-Eakin, D. and T. Selden (1995). Stoking the fires? CO2 emissions and economic growth, *Journal of Public Economics* 57(1) 85-101.
30. Hsiao, C. (1986). Analysis of Panel Data, New York, Cambridge University Press.
31. Huang B.N., M.J. Hwang and C.W. Yang (2008). Causal relationship between energy consumption and GDP growth revisited: A dynamic panel data approach, *Ecological Economics* 67 (1), 41-54.
32. Islam. N. (1995). Growth Empirics: A Panel Data Approach, *The Quarterly Journal of Economics*, 110, 4 1127-1170.
33. Levine, R., Loayza, N. and T. Beck (2000). Financial intermediation and growth: causality and causes, *Journal of Monetary Economics*, 46(1), 31-77.
34. Metcalf, G. (2008). An empirical analysis of energy intensity and its determinants at the state level. *The Energy Journal* 29, 1-26.
35. Selden, T.M. and D. Song (1994). Environmental quality and development: Is there a Kuznets curve for air pollution emissions? *Journal of Environmental Economics and Management* 27 147-162.
36. Schmalensee, R., T. M. Stoker and R.A. Judson (1998). World Carbon Dioxide Emissions: 1950-2050, *The Review of Economics and Statistics*, 80(1), 15-27.
37. Shioji, E. (2001). Public capital and economic growth: a convergence Approach, *Journal of Economic Growth* 6, 205-227.
38. Stokey, N. (1998). Are there limits to growth?, *International Economic Review* 39(1), 1-31.
39. Stern, D. (2004). The rise and fall of the environmental Kuznets curve. *World Development* 32, 1419-1439.
40. Stern, D. (2007). The economics of climate change: the Stern Review, Cambridge University Press.
41. Tahvonen, O. and S. Salob (2001). Economic growth and transitions between renewable and nonrenewable energy resources, *European Economic Review* 45, 8, 1379-1398.

42. Verbeke, T. and M. De Clercq (2006). The income-environment relationship: Evidence from a binary response model, *Ecological Economics*, 59(4), 419-428.
43. Wagner, M. (2008). The carbon Kuznets curve: a cloudy picture emitted by bad econometrics?, *Resource and Energy Economics*, 30(3), 388-408.
44. Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators, *Journal of Econometrics* 126, 1, 25-51.

Table 1. Alternative estimates of DPD emissions model for EU27

	OLS-POOL		***WG-Fixed effects***		***GMM1-DIF***		***GMM1-SYS***	
	estimates	*p-value*	*estimates*	*p-value*	*estimates*	*p-value*	*estimates*	*p-value*
Lag of emissions	0.930	0.000	0.422	0.000	0.377	0.000	0.821	0.000
GDP	0.103	0.044	0.304	0.000	0.321	0.001	0.146	0.213
Lag of GDP	-0.120	0.010	0.031	0.465	0.014	0.830	-0.110	0.328
GDP2	0.004	0.472	-0.075	0.000	-0.078	0.000	-0.005	0.588
Energy Consumption	0.829	0.000	0.875	0.000	0.839	0.000	0.770	0.000
Lag of Energy	-0.784	0.000	-0.335	0.000	-0.259	0.001	-0.653	0.000
Petroleum mix	-0.022	0.405	-0.313	0.000	-0.315	0.000	-0.104	0.063
Gas mix	-0.053	0.009	-0.224	0.000	-0.177	0.028	-0.082	0.016
Nuclear mix	-0.105	0.000	-0.745	0.000	-0.754	0.000	-0.261	0.001
Renewables mix	-0.130	0.000	-0.616	0.000	-0.602	0.000	-0.315	0.000
Industry share	0.046	0.233	-0.119	0.087	-0.058	0.480	0.172	0.036
Transport share	0.064	0.242	-0.057	0.538	0.028	0.793	0.198	0.082
Households share	0.024	0.617	-0.113	0.106	-0.098	0.206	0.111	0.155
R2	0.993	--	0.948	--	--	--	--	--
Hausman, random effect test	--	--	268.650	0.000	--	--	--	--
m1-test	--	--	--	--	-3.846	0.000	-6.283	0.000
m2-test	--	--	--	--	0.326	0.744	0.197	0.844

Note: '*WG*' is Within Groups estimation, *OLS-POOL* is OLS applied to the entire pool of data. For GMM estimates, we take as instruments the lagged levels of *y* and the endogenous regressors dated t-2 and earlier. We use the lagged difference of *y* and all regressors dated *t-1* as additional instruments in the system GMM estimation. For the GMM-DIF and GMM-SYS we report its one-step estimation. The null of the Haussman test is the existence of random effects. The null of the *m1* and *m2* test is the absence of first- and second-order serial correlation of first-difference residuals. The inclusion of a lagged energy consumption and GDP term is required to pass the m1 and m2 test. The number of cross sections is 24 (all EU27 countries except Luxembourg, Malta and Cyprus) and the number of time periods is 17 (1990-2006).

Table 2(a). System GMM estimates of DPD emissions model for EU27

	EU27, 1990-2006		***EU27, 1997-2006***		***EU27, 1990-1997***	
	estimates	*p-value*	*estimates*	*p-value*	*estimates*	*p-value*
Lag of emissions	0.821	0.000	0.821	0.000	0.825	0.000
GDP	0.146	0.213	0.269	0.095	-0.135	0.302
Lag of GDP	-0.110	0.328	-0.329	0.037	0.073	0.401
GDP2	-0.005	0.588	0.012	0.473	0.020	0.073
Energy Consumption	0.770	0.000	0.683	0.000	0.914	0.000
Lag of Energy	-0.653	0.000	-0.555	0.000	-0.792	0.000
Petroleum mix	-0.104	0.063	-0.059	0.282	-0.082	0.394
Gas mix	-0.082	0.016	-0.122	0.019	-0.082	0.131
Nuclear mix	-0.261	0.001	-0.277	0.000	-0.251	0.005
Renewables mix	-0.315	0.000	-0.331	0.000	-0.350	0.016
Industry share	0.172	0.036	0.030	0.781	0.156	0.098
Transport share	0.198	0.082	0.051	0.689	0.090	0.545
Households share	0.111	0.155	-0.067	0.584	0.104	0.331
m1-test	-6.283	0.000	-5.691	0.000	-4.158	0.000
m2-test	0.197	0.844	-1.896	0.058	0.513	0.608

Note: The null of the m1 and m2 test is the absence of first- and second-order serial correlation between regressors and residuals, respectively. GMM results are for the one-step estimator case, with heteroskedasticity-consistent asymptotic standard errors reported. Variables are taken as deviations from period means.

Table 2(b). System GMM estimates of DPD emissions model for EU10

	UE10, 1990-2006		*UE10, 1997-2006*		*UE10, 1990-1997*	
	estimates	*p-value*	*estimates*	*p-value*	*estimates*	*p-value*
Lag of emissions	0.829	0.000	0.794	0.000	0.833	0.000
GDP	0.045	0.837	-0.208	0.371	-0.386	0.429
Lag of GDP	0.299	0.128	0.274	0.218	0.152	0.377
GDP2	-0.059	0.008	0.015	0.753	0.063	0.457
Energy Consumption	0.904	0.000	0.883	0.000	0.878	0.000
Lag of Energy	-0.850	0.000	-0.909	0.000	-0.801	0.000
Petroleum mix	-0.273	0.033	-0.467	0.015	-0.301	0.060
Gas mix	-0.194	0.009	-0.499	0.002	-0.142	0.041
Nuclear mix	-0.312	0.007	-0.499	0.006	-0.304	0.007
Renewables mix	-0.350	0.001	-0.732	0.002	-0.303	0.049
Industry share	-0.027	0.749	0.050	0.517	0.210	0.263
Transport share	-0.207	0.267	-0.391	0.009	0.057	0.889
Households share	-0.006	0.960	-0.198	0.085	0.080	0.683
m1-test	-5.024	0.000	-4.199	0.001	-5.625	0.080
m2-test	0.508	0.611	0.563	0.574	0.040	0.968

Note: the UE10 area includes Belgium, Denmark, Germany, France, Italy, Austria, The Netherlands, Finland, Sweden and United Kingdom. See Note in Table (2a).

Table 2(c). System GMM estimates of DPD emissions model for EU14

	UE14, 1990-2006		*UE14, 1997-2006*		*UE14, 1990-1997*	
	estimates	*p-value*	*estimates*	*p-value*	*estimates*	*p-value*
Lag of emissions	0.902	0.000	0.835	0.000	0.921	0.000
GDP	0.093	0.555	-0.009	0.964	0.225	0.577
Lag of GDP	0.025	0.881	-0.114	0.548	0.057	0.726
GDP2	-0.021	0.120	0.051	0.010	-0.058	0.331
Energy Consumption	0.914	0.000	0.810	0.000	0.908	0.000
Lag of Energy	-0.853	0.000	-0.836	0.000	-0.837	0.000
Petroleum mix	-0.105	0.039	-0.365	0.001	-0.045	0.525
Gas mix	-0.136	0.000	-0.499	0.000	-0.061	0.147
Nuclear mix	-0.218	0.001	-0.457	0.000	-0.163	0.000
Renewables mix	-0.199	0.000	-0.684	0.000	-0.089	0.409
Industry share	-0.048	0.309	0.012	0.799	-0.061	0.576
Transport share	-0.032	0.770	-0.308	0.012	-0.056	0.802
Households share	-0.004	0.960	-0.241	0.017	0.026	0.818
m1-test	-5.854	0.000	-5.903	0.000	-4.158	0.000
m2-test	1.433	0.152	0.655	0.513	0.513	0.608

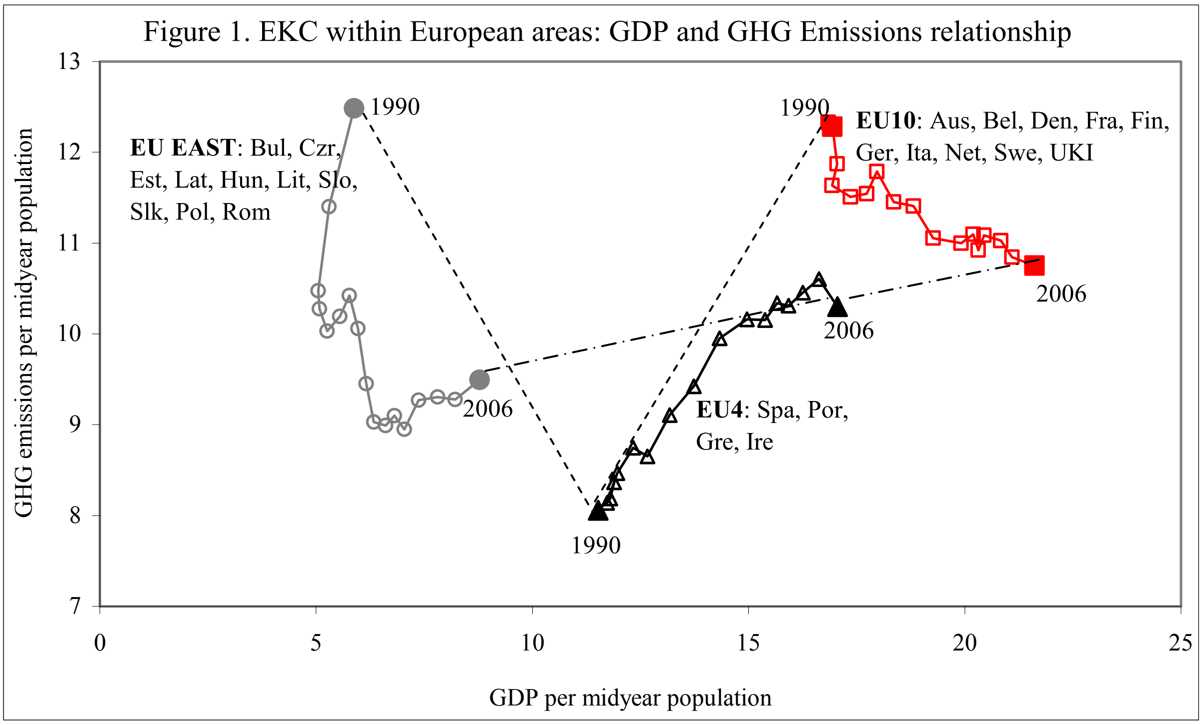
Note: the EU14 area includes EU10 and Spain, Greece, Portugal and Ireland. See Note in Table (2a).

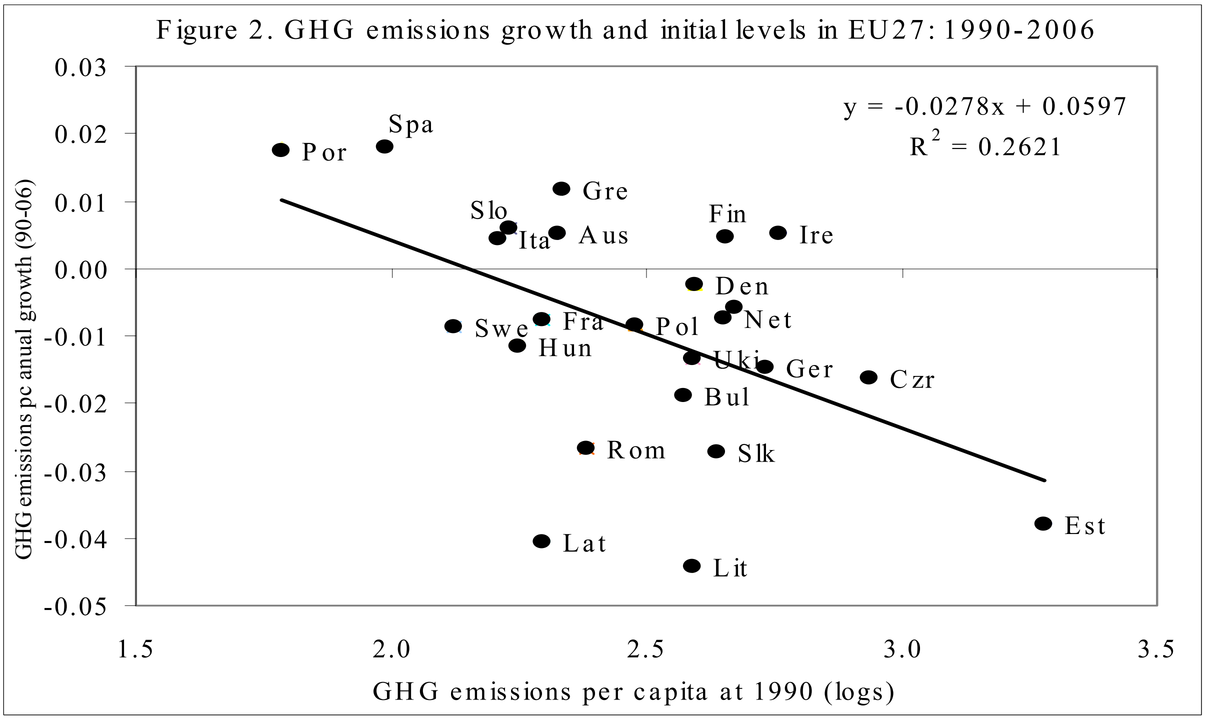
Table 2(d). System GMM estimates of DPD emissions model for EU East

	UE EAST, 1990-2006		*UE EAST, 1997-2006*		*UE EAST, 1990-1997*	
	estimates	*p-value*	*estimates*	*p-value*	*estimates*	*p-value*
Lag of emissions	0.539	0.000	0.529	0.000	0.507	0.000
GDP	0.026	0.727	0.123	0.425	-0.246	0.018
Lag of GDP	-0.006	0.919	-0.198	0.116	0.144	0.008
GDP2	-0.013	0.197	0.004	0.684	0.016	0.408
Energy Consumption	0.697	0.000	0.598	0.000	0.892	0.000
Lag of Energy	-0.356	0.000	-0.241	0.000	-0.460	0.000
Petroleum mix	-0.243	0.000	-0.310	0.006	-0.165	0.058
Gas mix	-0.252	0.000	-0.260	0.000	-0.279	0.000
Nuclear mix	-0.587	0.000	-0.611	0.000	-0.603	0.000
Renewables mix	-0.691	0.000	-0.706	0.000	-0.729	0.000
Industry share	0.277	0.000	0.163	0.167	0.290	0.007
Transport share	0.645	0.000	0.681	0.000	0.446	0.000
Households share	0.007	0.871	-0.176	0.118	0.110	0.288
m1-test	-3.665	0.000	-3.284	0.001	-1.751	0.080
m2-test	-1.179	0.239	-1.498	0.134	0.370	0.711

Note: The UE East area includes Bulgaria, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia and Slovakia. See Note in Table (2a).

GRAPHICAL APPENDIX





DATA **APPENDIX. GHG Emissions, Energy and Macroeconomic data for EU27**

Table A1. Emissions, level of activity and total energy consumption (data are expressed in per capita terms)

	GHG Emissions		Real GDP		Primary energy	
	2006	90-06 anual growth, %	2006	90-06 anual growth, %	2006	90-06 anual growth, %
BEL	13.2	-0.59	22.7	1.74	5.8	1.11
DEN	12.9	-0.23	24.9	1.87	3.8	0.61
GER	12.2	-1.49	20.0	1.27	4.2	-0.36
FRA	8.8	-0.78	22.4	1.35	4.4	0.61
ITA	9.8	0.44	19.8	1.22	3.2	1.05
NET	12.6	-0.74	23.6	1.95	4.9	0.45
AUS	11.1	0.51	22.7	1.86	4.2	1.51
FIN	15.3	0.47	23.2	1.99	7.2	1.35
SWE	7.3	-0.87	24.2	1.99	5.6	0.17
UKI	10.8	-1.35	23.0	2.11	3.8	0.19
IRE	17.2	0.51	27.8	5.35	3.8	1.68
GRE	12.5	1.17	15.4	2.70	2.9	1.81
SPA	9.7	1.79	17.1	2.20	3.2	2.18
POR	7.8	1.72	14.3	1.72	2.4	1.89
BUL	9.7	-1.91	7.8	2.07	2.8	-0.77
CZR	14.5	-1.65	11.8	1.74	4.5	-0.32
EST	14.3	-3.88	20.8	4.07	4.1	-2.72
LAT	5.1	-4.16	13.6	1.95	2.0	-2.38
LIT	6.5	-4.53	10.4	1.12	2.4	-3.84
HUN	7.9	-1.15	9.3	2.28	2.8	0.04
POL	10.4	-0.85	9.1	3.58	2.5	-0.18
ROM	7.0	-2.71	4.3	1.29	1.8	-2.62
SLO	10.2	0.58	16.5	2.62	3.7	1.72
SLK	9.0	-2.77	11.0	2.20	3.5	-0.88
EU27	***10.5***	***-0.76***	***18.3***	***1.83***	***3.7***	***0.33***

Table A.2. Primary energy consumption mix by energy sources (% of total primary energy consumption)

	Solid Fuels		Oil and Petroleum products		Total Gas		Nuclear		Total Renewables	
	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %
BEL	8.5	-0.78	39.2	0.07	24.8	0.50	19.9	-0.13	2.9	0.10
DEN	26.2	-0.49	39.4	-0.40	21.7	0.72	0.0	0.00	15.6	0.55
GER	23.6	-0.83	35.7	0.02	22.8	0.46	12.4	0.11	6.0	0.28
FRA	4.8	-0.24	33.8	-0.31	14.5	0.19	42.5	0.43	6.3	-0.05
ITA	9.0	-0.04	44.7	-0.88	37.2	0.74	0.0	0.00	7.0	0.18
NET	9.8	-0.23	40.6	0.21	42.6	-0.17	1.1	-0.01	3.6	0.14
AUS	11.7	-0.27	42.3	-0.04	21.9	0.08	0.0	0.00	21.4	0.09
FIN	19.7	0.08	29.0	-0.34	10.2	0.15	15.6	-0.10	22.7	0.23
SWE	5.3	-0.02	28.7	-0.14	1.7	0.03	34.0	-0.23	29.1	0.27
UKI	18.0	-0.78	35.8	-0.16	35.3	0.81	8.5	0.04	1.9	0.09
IRE	15.7	-1.10	54.8	0.50	25.9	0.47	0.0	0.00	2.7	0.07
GRE	26.6	-0.60	57.8	-0.01	8.7	0.51	0.0	0.00	5.7	0.05
SPA	12.4	-0.54	48.9	-0.14	21.6	1.00	10.8	-0.28	6.6	-0.03
POR	13.1	-0.11	53.6	-0.80	14.4	0.90	0.0	0.00	17.0	-0.11
BUL	33.9	0.17	24.9	-0.59	14.1	-0.32	24.5	0.68	5.5	0.31
CZR	45.2	-1.18	21.7	0.21	16.4	0.35	14.5	0.49	4.3	0.25
EST	56.1	-0.25	20.4	-0.54	14.9	0.16	0.0	0.00	9.8	0.32
LAT	1.9	-0.44	32.0	-0.75	30.4	0.03	0.0	0.00	31.0	1.11
LIT	3.3	-0.11	32.3	-0.67	29.1	0.00	26.5	-0.06	9.3	0.46
HUN	11.2	-0.60	28.2	-0.15	41.3	0.64	12.5	0.01	4.6	0.17
POL	58.0	-1.08	24.7	0.70	12.6	0.23	0.0	0.00	5.1	0.22
ROM	23.2	0.24	26.5	-0.22	35.7	-0.60	3.6	0.22	11.7	0.48
SLO	21.3	-0.53	36.2	0.28	12.2	-0.10	19.5	-0.13	10.5	0.37
SLK	23.6	-0.84	19.5	-0.04	28.6	0.27	24.7	0.62	4.6	0.19
EU27	***17.8***	***-0.59***	***36.9***	***-0.07***	***24.0***	***0.39***	***14.0***	***0.11***	***7.1***	***0.17***

Table A.3. Final energy consumption shares by type of consumers (% of final energy consumption)

	Industry		Transport		Households		Agriculture		Others (services included)	
	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %	2006	90-06 anual p.p. change, %
BEL	37.8	-0.09	25.2	0.07	23.4	-0.17	1.9	0.02	11.7	0.17
DEN	18.7	-0.09	34.2	0.28	28.3	-0.06	5.8	-0.15	13.1	0.02
GER	24.9	-0.41	28.4	0.16	31.0	0.33	1.2	-0.01	14.5	-0.07
FRA	22.2	-0.28	32.2	0.09	28.3	0.10	2.0	-0.02	15.2	0.12
ITA	29.1	-0.29	33.8	0.16	22.9	-0.10	2.6	-0.02	11.6	0.25
NET	26.4	-0.18	30.7	0.41	19.7	-0.22	7.8	-0.01	15.4	-0.01
AUS	32.7	-0.04	28.6	0.30	24.8	-0.35	2.2	-0.08	11.7	0.16
FIN	49.8	0.35	18.6	-0.08	18.5	-0.37	2.9	-0.08	10.2	0.19
SWE	38.4	-0.03	25.8	0.12	21.1	-0.02	2.4	-0.03	12.4	-0.05
UKI	22.3	-0.20	37.2	0.25	27.9	0.01	0.6	-0.02	12.0	-0.04
IRE	21.1	-0.16	41.2	0.89	23.5	-0.57	1.9	-0.09	12.2	-0.07
GRE	19.6	-0.47	39.6	-0.03	25.6	0.29	5.5	-0.10	9.7	0.31
SPA	31.2	-0.26	42.2	0.18	15.3	-0.07	2.8	0.00	8.5	0.16
POR	30.7	-0.58	38.5	0.43	17.3	-0.13	1.7	-0.13	11.8	0.42
BUL	38.2	-1.09	27.6	0.75	21.7	0.49	3.0	-0.12	9.4	-0.03
CZR	36.1	-0.90	24.1	0.96	24.8	0.03	2.1	-0.17	12.9	0.08
EST	22.2	-1.46	28.7	0.92	31.7	0.66	3.4	-0.52	13.9	0.40
LAT	17.6	-0.83	28.0	0.68	35.5	0.67	3.7	-0.37	15.1	-0.14
LIT	22.3	-0.75	31.8	0.70	30.3	0.70	2.4	-0.37	13.1	-0.29
HUN	19.1	-0.93	26.1	0.64	34.5	0.08	2.3	-0.22	17.9	0.43
POL	28.8	-0.84	22.3	0.62	31.9	0.09	7.2	0.12	9.8	0.01
ROM	38.4	-1.86	17.6	0.35	31.7	1.26	1.1	-0.32	11.2	0.56
SLO	34.4	-0.57	31.4	0.24	23.4	-0.12	1.5	0.09	9.3	0.36
SLK	42.3	-0.20	17.2	0.46	21.7	0.41	1.3	-0.21	17.6	-0.46
EU27	***27.6***	***-0.41***	***31.5***	***0.33***	***25.9***	***0.07***	***3.1***	***-0.04***	***12.6***	***0.06***

TECHNICAL APPENDIX: ESTIMATING DPD EMISSION MODEL BY SYSTEM GMM

The most common way to estimate a dynamic model like (1) is to ignore any unobserved regional heterogenerity – i.e., $\alpha_i = \alpha$ for all i - and then apply OLS to pooled data (OLS-POOL). This strategy may result in seriously biased estimates when regional heterogeneity exists [Hsiao (1986)]. Standard alternatives are fixed- or random-effects methods, which assume region-specific terms. The random-effects model is used when the α_i term is uncorrelated with the other explanatory variables, which is unexpected in our case. Indeed, the Haussman test rejects the random-effects hypothesis at any standard level of significance in the models we estimate in Section 5. Hence, we will focus on fixed-effects models hereinafter.

The fixed effect treatment normally uses the within group estimator (WG) [Hsiao (1986)], which has been applied to multiple frameworks.[19] As opposed to OLS-POOL estimates, the WG estimates yield relatively low values for the estimated parameter of the dynamic term in (1). The reason for this result is that the within transformation in dynamic models implies a 1/T correlation of order between the lagged dependent and the error term, which leads to biased estimates.[20] Hence, a kind of instrumental variables approach must be used in order to overcome the bias problem.[21] Holtz-Eakin et al. (1988) and Arellano and Bond (1991) point out this fact and propose a GMM-based estimation. The current response of these authors is to first difference the model equation, remove the fixed effect term and then use the following orthogonality conditions, which, under assumptions (A1) and (A2), are valid for the first differences model:

$$E\left[y_{it-s} \Delta \varepsilon_{it}\right] = 0,\ t = 3, \ldots, T \ and \ \ 2 \le s \le t-1,\ for\ i = 1, \ldots, N, \qquad \textbf{(3)}$$

Assuming a condition similar to (A2) for endogenous regressors,

---

[19] Islam (1995), Canova and Marcet (1995), De la Fuente (1996) or Barro (2000), among many others, have applied the WG method to growth models.

[20] Nickell (1981); Anderson and Hsiao (1982); Hsiao (1986)

[21] Since explanatory variables are not strictly exogenous, the traditional Chamberlain method [Chamberlain (1984)] for panel dynamics models also yields inconsistent estimates.

A3: $E\left[e_{i1}\varepsilon_{it}\right]=E\left[m_{ji1}\varepsilon_{it}\right]=E\left[s_{ki1}\varepsilon_{it}\right]=0,\ i=1,...,N;t=2,...,T;\ j=1,2,3,4;k=1,2,3,$

we have additional moment conditions for the *e*, m_j and s_k variables,

$$\begin{aligned}&E\left[e_{it-s}\Delta\varepsilon_{it}\right]=E\left[m_{jit-s}\Delta\varepsilon_{it}\right]=E\left[s_{kit-s}\Delta\varepsilon_{it}\right]=0,\\&t=3,...,T;i=1,...,N;s=2,3,...t;\ j=1,2,3,4;k=1,2,3.\end{aligned} \tag{4}$$

The conditions in (3) and (4) can be written more compactly as

$$E\left[Z_{iDIF}^{'}\Delta\varepsilon_i\right]=0,\ i=1,...,N, \tag{5}$$

where $\Delta\varepsilon_i=\left(\Delta\varepsilon_{i3},\Delta\varepsilon_{i4},...,\Delta\varepsilon_{iT}\right)^{'}$ and Z_{iDIF} is a *(T-2)*x*L* matrix, with *L* the total number of orthogonality conditions in (3)-(4), and given by[22]

$$Z_{iDIF}=\begin{pmatrix} y_{i1}e_{i1}m_{i1}s_{i2} & 0 & \cdots & 0\\ 0 & y_{i1}y_{i2}e_{i1}e_{i2}m_{i1}m_{i2}s_{i1}s_{i2} & \cdots & .\\ . & \cdots & \cdots & .\\ . & \cdots & \cdots & .\\ 0 & \cdots & 0 & y_{i1}\ldots y_{iT-2}e_{i1}\ldots e_{iT-2}m_{i1}\ldots m_{iT-2}s_{i1}\ldots s_{iT-2}\end{pmatrix} \tag{6}$$

These are the moment conditions exploited by the standard first differenced GMM estimator (GMM-DIF.) However, the GMM-DIF estimator has been found to have large finite sample bias and poor precision when the set of instruments is *weak*.[23] The problem of weak instruments in DPD models arises when: i) time series are persistent, ii) the variance of the individual fixed effect term is relatively high and iii) the number of time series observations is small (17 in our case). These features are present in our case, specially i) and iii). To address this problem, Arellano and Bover (1995) and Blundell and Bond (1998) assume conditions in addition to A1, A2 and A3 [see also Bond et al. (2001)]:

A4: $E\left[\alpha_i\Delta y_{i2}\right]=0,\ i=1,...,N$,

[22] For simplicity, we consider the case of J=1 and K=1. The matrix Zi for J=4 and K=3 is straightforward.

[23] See Blundell and Bond (1998), among many others.

A5: $E\left[\alpha_i \Delta e_{i2}\right] = E\left\lfloor \alpha_i \Delta m_{ji2}\right\rfloor = E\left[\alpha_i \Delta s_{ki2}\right] = 0, i = 1,..., N, j = 1,2,3,4;\ k = 1,2,3.$

which allows the use of additional moment conditions for the model in levels,

$$E\left[u_{it}\Delta y_{it-1}\right] = 0,\ t = 3,..., T; i = 1,2,...N, , \tag{7}$$

$$\begin{gathered} E\left[u_{it}\Delta e_{it-1}\right] = E\left\lfloor u_{it}\Delta m_{jit-1}\right\rfloor = E\left[u_{it}\Delta s_{it-1}\right] = 0, \\ t = 3,..., T; i = 1,..., N; j = 1,2,3,4; k = 1,2,3. \end{gathered} \tag{8}$$

which stay informative even for high persistent time series. Their proposal consists of a stacked system of all (T-2) equations in first differences and (T-2) equations in levels for *t=3,4,…,T*, and combine restrictions (3), (4), (7) and (8) to form a linear system GMM estimator (GMM-SYS) based on the following instrument matrix:

$$Z_i = \begin{pmatrix} Z_{iDIF} & 0 & ... & ... & 0 \\ 0 & \Delta y_{i2}\Delta e_{i2}\Delta m_{i2}\Delta s_{i2} & ... & ... & . \\ . & ... & \Delta y_{i3}\Delta e_{i3}\Delta m_{i3}\Delta s_{i3} & ... & . \\ . & ... & ... & ... & 0 \\ 0 & 0 & ... & 0 & \Delta y_{iT-1}\Delta e_{iT-1}\Delta m_{iT-1}\Delta s_{iT-1} \end{pmatrix} \tag{9}$$

where Z_{iDIF} is given by (6). Monte Carlo analysis has shown that using GMM-SYS greatly reduces the finite sample bias and improves the precision of the estimator in the presence of weak instruments.

Given instrument matrix Z, the linear GMM estimator is

$$\left(\Delta X' Z H_N Z' \Delta X\right)^{-1}\left(\Delta X' Z H_N Z' \Delta Y\right)$$

where two different choices of H_N result in two different GMM estimators. The one-step estimator sets

$$H_{N,GMM\,1} = \left(\frac{1}{N}\sum_{i=1}^{N} Z_i' H Z_i\right)^{-1},$$

where the H matrix is a (T-2) square matrix with 2's on the main diagonal, -1 on the first off-diagonals and zeros elsewhere. The two-step GMM estimator uses

$$H_{N,GMM\ 2} = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i^{'} \Delta \hat{u}_i \Delta \hat{u}_i^{'} Z_i \right)^{-1},$$

where estimated residuals are from a consistent one-step estimator (i.e., the one-step), which is an asymptotically efficient GMM estimator.

Under spherical disturbances, GMM1 and GMM2 are equivalent in the first-difference model. Otherwise, GMM2 is more efficient. However, Monte Carlo studies have shown that the efficiency gains of the two-step estimator are generally small. It also has the problem of converging to its asymptotic distribution relatively slowly. Hence, in finite samples, its variance-covariance matrix can be seriously biased. Moreover, for the case where the total number of instruments is large relative to the cross-section dimension of the panel, there may be computational problems in calculating the two-step estimates and serious estimation errors may arise [Arellano and Bond (1998); Doran and Schmidt (2006)]. With this in mind, most empirical works with a relatively small cross-section dimension report results of the one-step GMM estimator, which has standard errors that are asymptotically robust to heteroskedasticity and have been found to be more reliable for finite sample inference [Blundell and Bond (1998), Blundell et al. (2000); Windmeijer (2005); Bond (2002)]. This is the strategy considered in this paper.

ÚLTIMOS DOCUMENTOS DE TRABAJO

2009-16: "Greenhouse Gases Emissions, Growth and the Energy Mix in Europe: A Dynamic Panel Data Aproach", **Gustavo A. Marrero**.
2009-15: "Impact of the Rise in immigrant unemployment on public finances", **Pablo Vazquez, Mario Alloza, Raquel Vegas y Stefano Bertozzi**.
2009-14: "Responding to Financial Pressures. The Effect of Managed Care on Hospitals´ Provision of Charity Care", **Núria Mas**.
2009-13: "Domestic Transport Cost Reductions and Firms' Export Behaviour", **Pedro Albarran, Raquel Carrasco y Adelheid Holl**.
2009-12: "Compatibility with Firm Dominance", **María Fernanda Viecens**.
2009-11: "Pricing Strategies in Two-Sided Platforms: The Role of Sellers' Competition", **María Fernanda Viecens**.
2009-10: "Scheduled Service Versus Personal Transportation: the Role of Distance", **Volodymyr Bilotkach, Xavier Fageda y Ricardo Flores-Fillol**.
2009-09: "Social Preferences and Strategic Uncertainty: An Experiment on Markets and Contracts", **Antonio Cabrales, Rafaele Miniaci, Marco Piovesan y Giovanni Ponti**.
2009-08: "Hidden Information, Bargaining Power and Efficiency: An Experiment", **Antonio Cabrales, Gary Charness y Marie Claire Villeval**.
2009-07: "Democracy and the curse of natural resources", **Antonio Cabrales y Esther Hauk**.
2009-06: "Social Interactions and Spillovers: Incentives,Segregation and Topology", **Antonio Cabrales, Antoni Calvó-Armengol e Yves Zenou**.
2009-05: "Chance Constrained Programming with one Discrete Random Variable in Each Constraint",**Emilio Cerdá Tena y Julio Moreno Lorente**.
2009-04: "Economic Value of Weather Forecasting Systems Information: A Risk Aversion Approach", **Emilio Cerdá Tena y Sonia Quiroga Gómez**.
2009-03: "Population Ageing, Inequality and the Political Economy of Public Education", **Francisco Martínez-Mora**.
2009-02: "Real Wages over the Business Cycle: OECD Evidence from the Time and Frequency Domains", **Julian Messina, Chiara Strozzi y Jarkko Turunen**.
2009-01: "The Determinants Of Misreporting Weight And Height: The Role Of Social Norms", **Joan Gil y Toni Mora**.
2008-42: "Social Security Incentives, Exit from the Workforce and Entry of the Young", **Michele Boldrin, Pilar García-Gómez y Sergi Jiménez-Martín**.
2008-41: "The Evolution and Main Determinants of Productivity in Brazilian Electricity Distribution 1998-2005: an Empirical Analysis", **Francisco Javier Ramos-Real, Beatriz Tovar, Mariana Iootty, Edmar Fagundes de Almeida y Helder Queiroz Pinto Jr.**.
2008-40: "Immigration and Housing Prices in Spain", **Simón Sosvilla**.
2008-39: "Modeling the Immigration Shock", **Ana Montes y Michele Boldrin**.
2008-38: "Immigration and the Demand for Health in Spain", **Sergi Jiménez, Natalia Jorgensen y José María Labeaga**.
2008-37: "Immigration and Students' Achievement in Spain", **Natalia Zinovyeva, Florentino Felgueroso y Pablo Vázquez**.
2008-36: "Immigration and Social Security in Spain", **Clara Isabel González, J. Ignacio Conde-Ruiz y Michele Boldrin**.
2008-35: "Complements or Substitutes? Immigrant and Native Task Specialization in Spain", **Catalina Amuedo-Dorantes y Sara de la Rica**.
2008-34: "Immigration and Crime in Spain, 1999-2006", **Cesar Alonso, Nuno Garoupa, Marcelo Perera y Pablo Vázquez**.
2008-33: "A Social Network Approach to Spanish Immigration: An Analysis of Immigration into Spain 1998-2006", **Rickard Sandell**.
2008-32: "The Consequences on Job Satisfaction of Job-Worker Educational and Skill Mismatches in the Spanish Labour Market: a Panel Analysis", **Lourdes Badillo Amador, Ángel López Nicolás y Luis E. Vila**.
2008-31: "Students'assessment of higher education in Spain", **César Alonso-Borrego**, **Antonio Romero-Medina**.
2008-30: "Body image and food disorders: Evidence from a sample of European women", **Joan Costa-Font y Mireia Jofre-Bonet**.
2008-29: "Aggregation and Dissemination of Information in Experimental Asset Markets in the Presence of a Manipulator", **HelenaVeiga y Marc Vorsatz**.