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Greenhouse gases emissions, growth and the energy mix in Europe

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Abstract:

The importance of energy on greenhouse gases (GHG) emissions is reflected by the fact that 65% of said emissions in the World are currently due to the use and production of energy. However, most empirical emission models are found within the Environmental Kuznetz Curve (EKC) framework, which focuses on the relationship between emissions and economic development. Ang (2007, 2008) papers are some of the exceptions that simultaneously study the relationship between emissions, growth and energy. With respect to Ang's research, we contribute on two important aspects. First, while Ang uses a particular country as the study and use time series techniques, we take advantage of a panel data set of 24 European countries between 1990 and 2006 and use a Dynamic Panel Data (DPD) framework. Second, the impact of energy consumption on emissions would depend on the primary energy mix and on the final use of this energy, and we consider both factors in the model.

JEL: Q43, Q42, C23

Key Worlds: Greenhouse gases emissions, energy, energy mix, dynamic panel data models

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1. Introduction

The importance of energy on greenhouse gases (GHG) emissions is reflected by the fact that about 65% of said emissions in the World are currently due to the use and production of energy (IEA, 2008). This percentage rise up to 80% in the OECD or the European Union. However, most research on emissions determinants is found within the framework of the Environmental Kuznetz Curve (EKC), which only focuses on the relationship between emissions and economic activity and omits energy aspects from the analysis.

The objective of this paper is not to discuss the EKC hypothesis, on which there is already an extensive literature,[2] but to characterize the effects that alternative energy factors have on said emissions. To this goal, we extend Álvarez et al. (2005) and Brock and Taylor (2004, 2005) empirical models and include energy variables. These authors have adapted the neoclassical growth framework to a growth setting with emissions, and derive an estimating Dynamic Panel Data (DPD) equation for pollution, but they leave aside energy aspects. Thus, in addition to include the level of activity (measured by real per capita GDP), its quadratic term to control for a possible inverted U-shaped relationship between emissions and GDP, and fixed cross-section and temporal effects, we also consider an *aggregate energy term*, measured as total primary energy consumption per inhabitant, an *energy mix effect*, measured as the shares of alternative energy sources (coal, oil, gas, nuclear or renewable) with respect to total primary energy consumption, and an *energy sector effect*, measured as the distribution of final energy consumption (industry, transport, households or services.)

[2] The studies by Selden and Song (1994) and Grossman and Krueger (1995) are consistent with the EKC hypothesis, while other authors, such as Holtz-Eakin and Selden (1995) or, more recently, Huang et al. (2008), do not present evidence to support this hypothesis. In general, the EKC literature leads to inconclusive results about this hypothesis. Among the alternative pollutants, the most controversial is for CO2 emissions, which is the main GHG pollutant. Regarding this pollutant, most studies confirm that the EKC hypothesis remains a fragile concept (Brock and Taylor, 2004, 2005; Galeotti et al., 2009), which is consistent with our results. See also Dinda and Coondoo (2006), Dinda (2004) and Verbeke and Clercq (2006) for discussions about the EKC topic. We are also aware about the problems of testing the EKC hyphotesis (Wagner, 2008; Galeotti et al., 2009).

Ang (2007, 2008) are some of the few exceptions in the literature that have simultaneously studied the relationship between emissions, energy and growth.[3] These works examine the relationship among these variables under a dynamic framework for the case of France and Malaysia, respectively. With respect to Ang's research, our paper contributes on two important aspects. First, while Ang considers a particular country as the study and use time series techniques, we take advantage of a panel data set of 24 European countries between 1990 and 2006 and estimate a Dynamic Panel Data (DPD) model.[4] Second, Ang focuses on the effects of aggregate energy consumption on emissions. However, the impact of energy consumption on emissions would strongly depend on the primary energy mix and on the final use of this energy, and we consider both factors in our analysis.

Although it is not the main focus of the paper, the DPD model we estimate would allow us to test for GHG emissions convergence within EU countries between 1990 and 2006. There exists an extensive recent literature that analyse in more details this important subject. Strazicich and List (2003), Alby (2006), Westerlund and Basher (2008), Romero-Ávila (2008) have provided evidence of convergence (deterministic and stochastic) in CO2 emissions for different sets of industrialised countries using cross-sections and panel unit root tests.[5] Our empirical analysis is consistent with this convergence result within European countries.

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[3] Marvao-Pereira and Marvao-Pereira (2009) uses a VAR model to estimate the impact of CO2 emissions from fuel combustion on economic activity in Portugal. It also stresses the importance of energy consumption in the analysis. Sadorsky (2009) emphasizes the relationship between renewable energy consumption and CO2 emissions in the G7 countries.

[4] Europe is positioned as one of the most active economic areas in terms of measures for combating GHG emissions, which makes this area an interesting case of study. In addition to ratifying the Kyoto Protocol in 2002, another prominent agreement was adopted by the EU parliament in December of 2008 (the 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 energy as a means to reach this objective: the framework for 2020 also establishes an improvement in energy efficiency by 20% and an increase in the share of renewable energy as a part of overall energy consumption by 20%.

[5] However, the emissions convergence hypothesis is not robust to the sample used. For instance, Alby (2006) also finds emissions divergence for an 88-country global sample over 1960–2000. Aldy (2007)

An additional contribution of the paper regards the estimation procedure. We find important differences among alternative estimation methods, which may even change energy policy recommendations. This finding emphasizes the importance of considering a convenient estimation procedure to estimate the relationship between emissions, energy and activity. 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 because of the endogeneity problem (Hsiao, 1986). Among others, Halkos (2003) and Metcalf (2008) address the endogeneity problem and use a *first-difference*-GMM estimator (Arellano and Bond, 1991). However, this procedure does not care about the *weak instruments problem*, which arises in a DPD model when time series are highly persistent, as it is the case for aggregate emissions, GDP and energy consumption (Blundell and Bond, 1998). Huang et al. (2008), which revisits the causal relationship between energy consumption and GDP, is an exception that properly handle both the endogeneity and the weak instruments problems by considering the *system*-GMM approach (Arellano and Bover, 1995; Blundell and Bond, 1998), which is the method used in our paper.[6]

The rest of the paper is organized as follows. The next section presents GHG emissions, energy and growth data for EU27 and motivates the use of an integrated dynamic framework to study emissions determinants. Section 3 presents the DPD model. Section 4 describes the system GMM methodology and compares their estimations with those of alternative, more traditional procedures. Section 5 shows more detailed results for the relationship between emissions and energy. The last section provides the final remarks.

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addresses the question of CO_2 emissions convergence by focusing on the U.S. states and finds also no evidence of convergence.

[6] 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.

2. Emissions, energy and growth in Europe

In this section we motivate the need to combine several theories to understand the performance between 1990 and 2006 of GHG emissions within EU countries. Data on GHG emissions, growth and energy are summarized in Tables A1-A3 in the Appendix.[7] Between 1990 and 2006, per capita GHG emissions fell by 0.75% in the EU27 (Table A1). With the exception of Italy, Finland and Austria, the richest countries in EU27 have reduced per capita emissions in this period, and of particular note are the UK and Germany, whose emissions have dropped more than 1% per year. On the other hand, emissions have increased by as much as 1.8% per year in Spain and Portugal. With regards to the Eastern European countries, except for Slovakia, every country have reduced its per capita emissions to a greater extent even than those of the richest EU economies, despite their per capita GDP levels being the lowest in the area. Per capita emissions in Estonia, Latvia and Lithuania, for example, fell by almost 4% per year. These facts suggest that the EKC hypothesis cannot explain alone the recent evolution of GHG emissions within EU27 countries.

The literature on growth and convergence (Barro and Sala-i-Martín, 1992) has recently been applied to the topic of emissions to address some of the EKC shortcoming (Brock and Taylor, 2004, 2005; Álvarez et al., 2005). Figure 1 shows the relationship between emissions growth between 1990 and 2006 and emission levels in 1990 (a β-convergence graphic), which summarizes the basic relationship of this model. Its negative relationship gives some evidence in favour of absolute β-convergence of GHG emissions; it suggests that countries with initial higher levels of emissions tend to reduce (increase) emissions more (less) than countries with lower initial levels. For example, it helps us to understand part of the emissions performance of

[7] We take all EU27 members except Luxemburg, Cyprus and Malta. Data on GHG emissions are obtained from the European Environment Agency (EEA), while Energy consumption data come from Eurostat (Energy statistics), measured in thousands of tons of CO2 equivalent and on tons of oil equivalent, respectively. Series on real GDP and population are obtained from *The Conference Board and Groningen Growth and Development Centre (2008),* expressed in 1990 US$ market prices converted at "*Geary-Khamis*" purchasing power parities and midyear population in thousands of persons, respectively.

Estonia or the Czech Republic, which had very high emission levels in 1990 and then it may explain part of the substantial drop in their emissions despite having a small per capita GDP. This theory, however, falls well short of being complete, as evidenced by the fact that the scatter plot dispersion is quite high - R^2 is only 0.26. Notice the cases of Latvia, Lithuania or Romania, whose drops in emissions are much greater than those associated with their 1990 levels; or the cases of Spain, Greece or Ireland, whose emissions growth are clearly above those associated with their 1990 levels. The poor economic growth experienced of the formers and the high growth of the latter (see Table A1) could explain part of these differences.

FIGURE 1 ABOUT HERE

However, there are still important cases which cannot be explained even by combining the growth-convergence and the EKC theories. For example, let us compare the UK with Finland in Figure 1. Both economies were at similar emission levels in 1990 and had comparable annual per capita growth between 1990 and 2006 (about 2% per year). And yet the UK lowered its emissions to a much greater extent than Finland. The key to their differences may be that while energy consumption of the UK grew by just 0.2% per year during this period, Finland's energy consumption increased by 1.4% per year (Table A1). The case of Spain is also noteworthy, 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 examples has been to illustrate the pressing need to simultaneously consider economic and energy aspects in emissions models (Ang, 2007; 2008). However, we want also to emphasize that the effect of energy usage on emissions depends on the type of energy used and on the distribution of final energy consumption. Thus, we also consider energy consumption by type of primary sources (solid fuels, oil and petroleum products, gas, nuclear, and renewable) and by type of final consumers (industry, transport, households, agriculture, and services). Regarding the primary energy mix, the overriding trend in Europe has been for a reduction in energy consumption derived from solid fuels and, to a lesser extent, petroleum products (see Table A2). 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 of final energy consumption by type of end users (see Table A3), industry and transport represent almost 30% each, while households amount to around 25%. With the exception of Finland, industry's share of energy consumption has decreased in all EU countries, showing an annual rate of -0.4% for the whole EU27. These drops have been particularly significant for the countries of the East, where industry has undergone a considerable renovation. Consumption in transport has increased by slightly over 0.3 p.p. a year in the EU27, although these changes have been driven by the East countries. Finally, household energy usage has grown by almost 0.1 p.p. a year in the area. While no clear pattern exists for this ratio in the EU15, it has grown in most Eastern countries.

3. A DPD model of emissions, energy and growth

In this section we present a DPD model for pollution emissions. The estimated equation is built on Brock and Taylor (2004, 2005) and Álvarez et al. (2005) equations, so as to propose the following DPD model that relates pollution, GDP and energy variables:

$$p_{it} = \alpha_i + \xi_t + \beta p_{it-1} + \lambda_1 y_{it} + \lambda_2 y_{it}^2 + \theta e_{it} + \sum_{j=1}^{J-1} \delta_j m_{jit} + \sum_{k=1}^{K-1} \varphi_k s_{kit} + \varepsilon_{it} \quad \textbf{(1)}$$

$$t = 1990, 1991, ..., 2006; i = 1, 2, ..., 24.$$

The p_{it} variable is the log of per capita GHG emissions, and its lagged level controls for short-term dynamics and conditional convergence.[8] 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; ξ_t is a period-specific constant, which captures productivity, regulatory or economic changes that are common to all countries;[9] 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); the e_{it} term is the log of per capita primary energy consumption, which measures an *aggregate energy use effect*; the m_{jit} variables show the distribution of *primary* energy consumption among the alternative energy sources, which capture a primary *energy mix effect*; the s_{kit} variables show the shares of *final* energy consumption of end consumers, which capture a final *energy composition effect*.

For primary energy, we use the following broad and standard classification of the IEA: oil, gas, nuclear, renewable and coal. Thus, $J=5$ and each m_j is defined as the ratio between each energy consumption source and total primary consumption, with $\sum_{j=1}^{J} m_{jit} = 1, \forall i, t$. In a similar way, for final energy consumption, we consider final consumption in the industry sector, in the transport sector, in the household and in *other* sectors (mainly, agriculture and services). Thus, $K=4$ and each s_k is defined as the ratio between the amount of energy used by each final consumer and total final consumption, with $\sum_{k=1}^{K} s_{kit} = 1, \forall i, t$. In order to avoid multicolinearity problems in estimating (1), we have to omit one m_j and one s_k variable. The omitted energy source is coal (in principle, the most polluting one), thus remaining δ_j coefficients are referred to the coal ratio (all other variables equal). For final consumption, the

[8] Although it is not our main goal, 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.

[9] Time dummies allow the removal of universal time related shocks from the errors. Since the GMM procedure will assume that the errors are only correlated within individuals and not across them, time dummies make this assumption more credible.

omitted sectors are the agriculture and the services (the *other* sectors category), which represent less than 15% of total final energy consumption. Thus, remaining φ_k coefficients are referred to the *other* sectors category (all other variables equal).

Finally, ε_{it} in (1) encompasses effects of a random nature and not considered in the model. Following Arellano and Bond (1991), Arellano and Bover (1995) and Bundell and Bond (1998), we assume that α_i and ε_{it} are independently distributed across i and have the standard error components structure,

A1) $$\begin{aligned} &E(\alpha_i \varepsilon_{it}) = 0; E(\varepsilon_{it}) = 0, \text{for } i = 1,\ldots,N \text{ and } t = 2,\ldots,T; \\ &E(\varepsilon_{it}\varepsilon_{is}) = 0, \text{ for } i = 1,\ldots,N \text{ and } \forall t \neq s. \end{aligned}$$

Additionally, there is the standard assumption concerning the initial condition in emissions, p_{i1}:

A2) $$E(p_{i1}\varepsilon_{it}) = 0, \text{ for } i = 1,\ldots,N \text{ and } t = 2,\ldots,T.$$

These assumptions would imply moment restrictions that are sufficient to identify and estimate (1) consistently using a GMM-based approach for $T \geq 3$ (see Blundell and Bond, 1998, among others).[10]

4. GMM estimation of DPD empirical pollution models

The easiest way to estimate a panel data model like (1) is to ignore any unobserved country specific heterogeneity – i.e., set $\alpha_i=\alpha$ for all i in (1)- and then apply OLS to pooled data (OLS-POOL). However, this strategy may result in seriously biased – more concretely, upward-biased - estimates of the coefficient associated to the dynamic term [i.e., the β in equation (1)] when country heterogeneity exists (Hsiao, 1986; Bond et al., 2001). In our case, the reason is because the resulting error term would be clearly correlated with the variable p_{it-1} in the right hand side of (1). The standard alternative is the Within Groups (WG), fixed effects, estimator, which wipes out the α_i by transformation. However, the transformed variable $y_{it-1} - \overline{y}_{i.-1}$, with $\overline{y}_{i.-1} = \sum_{t=2}^{T} y_{it-1}/(T-1)$, is still correlated with the transformed error $\varepsilon_{it} - \overline{\varepsilon}_{i.}$,

[10] See the technical appendix for additional assumptions about the regressors in (1).

$\bar{\varepsilon}_{i.} = \sum_{t=2}^{T} \varepsilon_{it} /(T-1)$, because $\bar{\varepsilon}_{i.}$ contains ε_{it-1} and it is clearly correlated with y_{it-1} by construction (Anderson and Hsiao, 1982; Hsiao, 1986). As opposed to the OLS-POOL, the WG estimates have been proved to yield relatively low values (i.e., it is downward biased) for the β in a model like (1). Therefore, a kind of instrumental variables approach must be used in order to overcome these bias problems.

Anderson and Hsiao (1982) once suggested first differencing equation (1) to remove the fixed effect and then using $\Delta p_{it-2} = (p_{it-2} - p_{it-3})$ or simply p_{it-2} as an instrument for $\Delta p_{it-1} = (p_{it-1} - p_{it-2})$. These instruments are not correlated with $\Delta\varepsilon_{it} = (\varepsilon_{it} - \varepsilon_{it-1})$ as long as the errors are serially uncorrelated (assumption A1). This instrumental variable estimation would lead to consistent but not necessarily efficient estimates. Moreover, it can suffer from important finite sample bias problems. Holtz-Eakin et al. (1988) and Arellano and Bond (1991) pointed out these problems and propose an alternative, more efficient, GMM-based approach (the GMM-DIF). Using the first difference model, the basic idea is to employ the levels of the series lagged two periods or more (i.e., p_{it-s}, for $s \geq 2$) as instruments in the GMM procedure to overcome the problem of $E(\Delta p_{it-1}\Delta\varepsilon_{it}) \neq 0$.[11] However, the GMM-DIF approach has important finite sample bias problems when variables are highly persistent (Alonso-Borrego and Arellano, 1999; Blundell and Bond, 1998), which is the case of GHG emissions, GDP and energy time series. Under these conditions, lagged levels of the variables are only *weak* instruments for subsequent first-differences, and the GMM-DIF estimator would be poorly behaved. To overcome this problem, Arellano and Bover (1995) and Blundell and Bond (1998) propose an alternative GMM procedure, the system GMM (GMM-SYS). This procedure estimates a system

[11] GMM-based approaches have important advantages over other panel data methods. First of all, the use of instrumental variables in the GMM procedure allows parameters to be estimated consistently in models with endogenous right-hand-side variables (Arellano and Bond, 1991; Blundell and Bond, 1998), such as GDP or energy consumption. Second, estimates will no longer be biased by omitted variables that are constant over time - country-specific fixed effects (Holtz-Eakin et al., 1988). Third, the use of instruments potentially allows consistent estimation even in the presence of transient measurement errors (Bond et al., 2001).

of equations in both first-differences and levels, where the instruments in the level equations are lagged first differences of the variables.[12]

Using simulations, Blundell et al. (2000) or Bond et al. (2001) show that the weak instruments problem may be serious in practice, and suggest how these problems may be detected: GMM-DIF bias is in the WG direction, and the β coefficient then would be simmilar to the WG estimates and far below that of OLS-POOL; using GMM-SYS, the β coefficient would be between that of OLS-POOL (upward-biased) and that of WG (downward biased). They also highlights that the estimated coefficients of the other regressors (GDP and energy variables in or case) may also be badly estimated under OLS-POOL, WG or GMM-DIF, which may lead to misleading conclusions.

Following this *practical rule*, we estimate model (1) by OLS-POOL, WG, GMM-DIF and GMM-SYS for EU-27, from 1990 to 2006. As it is standard in the literature, all variables are taken as deviations from period means so that we do not need to include time-specific constants and can omit the ξ term from (1). GMM estimates are shown for the one-step estimator case, with heteroskedasticity-consistent asymptotic standard errors reported.[13] Results are shown in Table 1. Associated with each parameter, the p-value of the individually significance t-test is shown. We show also standard specification tests for each model. First, notice that the Haussman test rejects the null hypothesis of random effects at any standard level

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[12] Using Monte Carlo simulations, Blundell and Bond (1998) and Bond et al. (2001) have shown that these instruments are still informative even for persistent time series. See the technical Appendix for more details about the GMM-SYS procedure.

[13] 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. As regards to the set of instruments used in GMM-SYS, Álvarez and Arellano (2003) points out that the use of too many instruments in models with endogenous regressors may result in seriously biased estimates in practice, and they recommend not using the entire series history as instruments. For each time period and equations, we use instruments up to *t-3*. Nevertheless, including more lags does not change results significantly. See Blundell and Bond (1998), Blundell et al. (2000) and Bond et al. (2001) for more details on these points.

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.[14]

TABLE 1 ABOUT HERE

As commented above, the theory would say that, in the presence of country-specific effects, pooling OLS would give an upward-biased estimate of β in (1), while the WG estimate of β would be downwards-biased. Indeed, estimations are 0.930 and 0.422, respectively, which are consistent with the theory. Moreover, GMM-DIF estimate of β is 0.377, similar to that of WG and far below that of OLS-POOL, which is also consistent with the finite sample bias coming from the weak instruments problem. Finally, notice that the GMM-SYS estimate of β is 0.821, between those of OLS-POOL and GMM-DIF, which suggests that instruments including in the GMM-SYS are very informative and it is a convenient way to overcome the weak instruments problem. Moreover, notice that the *m1* and *m2* tests behave better for GMM-SYS than for GMM-DIF.

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. For example, energy sector share coefficients (the φ_k) are not significant under the WG and the GMM-DIF methods, while they are significant under GMM-SYS. Moreover, they are of opposite signs. Thus, misleading conclusions would say that sector energy composition has no

[14] 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 ε_{it}-ε_{it-1}. 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. Moreover, as Arellano (2002) suggests, we have also included 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 *m2* specification tests.

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 coal. WG estimates indicate that nuclear energy is the most significant source for reducing GHG emissions, while renewable energies are in second position, with petroleum and natural gas also playing an important role in reducing emissions. Coefficients under GMM-SYS are, first of all, smaller in magnitude than those estimated under WG and GMM-DIF; secondly, now the coefficient associated with renewable sources is the most important one, followed by that for nuclear, while those for gas and petroleum products are similar.

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

5. Estimation results and determinants of GHG emissions

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) 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 model (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 test is always very close to one, but this test is less reliable in our framework, as commented in the previous section.

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

The estimation of β in (1) is always smaller than 1 (i.e., its highest estimate is 0.921 for EU14 and the 1990-1997 period). Hence, since the convergence parameter is given by β-1, these estimates support the existence of conditional convergence of GHG emissions within 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 between approximately -0.20 and -0.10, independently of the period considered. This estimate represents a reduction in the differences in emissions for the EU27 countries of about 10%-20% 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 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, which is consistent with the discussion made in Section 2. Recall that this finding depends strongly on the estimation procedure, as discussed in the previous section. 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 other factors, such as energy, technological or regulatory aspects. This paper focuses on energy aspects, distinguishing between aggregate factors, the primary energy mix and the distribution of final energy consumption.

The elasticity associated with aggregate 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 this smaller elasticity.

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, given all other things in the estimated equation equal. 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 substitution from coal to the alternative source.[15]

Various points stand out in this regard. First, the most negative estimate is usually associated with renewable energies, followed by nuclear and lastly by natural gas and petroleum, which all have very similar coefficients. In the majority of cases, the magnitudes of the coefficient for renewable 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

[15] 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.

efficiency and/or use of these energy sources (specially for natural gas and renewable sources) in recent years which has made them less polluting.

Finally, we also consider the effects that changes in the final energy distribution have on emissions. Recall that now the variable omitted was from the services and farm sector, meaning the estimated coefficients are in reference to these sectors.[16] 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 (recall from 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 hand, 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 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 would imply 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

[16] As noted for the primary energy mix (see previous footnote), 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.

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 sample (EU10 and the post-Kyoto 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.

6. Final Remarks

This paper has proposed and estimated a panel dynamic model for EU27, for the 1990 and 2006 period, which relates GHG emissions with real GDP, aggregate energy consumption, the primary energy mix and the energy distribution for final consumers. This paper's main contributions have been two-fold. The first is the use of a dynamic panel framework to simultaneously assess the performance of main EU27 counties in terms of emissions, growth and energy. The second is methodological. We use in this paper the system GMM approach proposed by Arellano and Bover (1995) and Blundell and Bond (1998), which has been shown to solve many of the problems that arise in traditional DPD estimation procedures (endogeneity and weak instruments problem). From a methodological standpoint, our results show 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 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 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. Advances that may be occurring in the usage and consumption processes for gas and petroleum products are seem to be significant 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. This fact 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.

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TABLES:

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: GMM results are for the one-step system- GMM estimator case, with heteroskedasticity-consistent asymptotic standard errors reported. Variables are taken as deviations from period means. We take as instruments the lagged levels of *y* and the endogenous regressors dated t-2 and earlier, and we also use the lagged difference of *y* and all regressors dated *t-1* as additional instruments in the system GMM estimation. 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(b). System GMM estimates of DPD emissions model for EU10

	EU10, 1990-2006		***EU10, 1997-2006***		***EU10, 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 EU10 area includes Belgium, Denmark, Germany, France, Italy, Austria, The Netherlands, Finland, Sweden and United Kingdom. See Note in Table 2(a).

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

	EU14, 1990-2006		*EU14, 1997-2006*		*EU14, 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 2(a).

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

	EU EAST, 1990-2006		***EU EAST, 1997-2006***		***EU 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 EU East area includes Bulgaria, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia and Slovakia. See Note in Table 2(a).

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 (% of 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. Distribution of final energy consumption (% of final 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 model by system GMM

Holtz-Eakin et al. (1988) and Arellano and Bond (1991) propose a GMM procedure to estimate DPD models. To simplify notation, let's suppose that all variables are measured as deviation of their time sample mean. Hence, we can omit ξ_t from the equation (1). We should first difference equation (1) and remove the fixed effect term,

$$\Delta p_{it} = \beta \Delta p_{it-1} + \lambda_1 \Delta y_{it} + \lambda_2 \Delta y_{it}^2 + \theta \Delta e_{it} + \sum_{j=1}^{J-1} \delta_j \Delta m_{jit} + \sum_{k=1}^{K-1} \varphi_k \Delta s_{kit} + \Delta \varepsilon_{it}\,, \qquad \textbf{(1')}$$

and then use the following orthogonal conditions, which, under assumptions (A1) and (A2), are valid for the first differences model (1'):

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

Assuming conditions similar to (A2) for the regressors (the y, e, m_j and s_k variables),[17]

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

we have additional moment conditions for each regressor,[18]

$$E\left[y_{it-s}\Delta\varepsilon_{it}\right] = E\left[e_{it-s}\Delta\varepsilon_{it}\right] = E\left[m_{jit-s}\Delta\varepsilon_{it}\right] = E\left[s_{kit-s}\Delta\varepsilon_{it}\right] = 0$$
$$\forall i; t = 3,\ldots,T;\ s = 2,\ldots,t;\ j = 1,2,3,4; k = 1,2,3. \qquad \textbf{(3)}$$

The conditions in (2) and (3) can be written more compactly as

$$E\left[Z_{iDIF}^{'}\Delta\varepsilon_i\right] = 0,\ i = 1,\ldots,N, \qquad \textbf{(4)}$$

where $\Delta\varepsilon_i = \left(\Delta\varepsilon_{i3}, \Delta\varepsilon_{i4}, \ldots, \Delta\varepsilon_{iT}\right)'$ and Z_{iDIF} is a *(T-2)*xL matrix, with L the total number of orthogonal conditions in (2)-(3), and given by[19]

---

[17] To simplify notation, I have omitted the expression for y^2. Nevertheless, in practice, including the instruments for y together with those for y^2 could lead to numerical problems in the estimation process.

[18] These conditions are defined assuming y, e, m_j and s_k to be endogenous regressors. See Bond et al. (2001) or Bond (2002), among others, for a discussion about the differences of these moment conditions when regressors are endogenous or exogenous.

[19] For simplicity, we consider the case for *j=1* and *k=1*. The matrix *Zi* for *j=1,2,3,4* and *k=1,2,3* is straightforward.

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

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*. 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: $E\left[\alpha_i \Delta p_{i2}\right] = 0,\ \forall i$,

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

which allows the use of additional moment conditions for the model in levels (1),

$$
E\left[u_{it}\Delta p_{it-1}\right] = 0,\ \forall i; t = 3,\ldots,T \ , \quad \textbf{(7)}
$$

$$
\begin{aligned} &E\left[u_{it}\Delta y_{it-1}\right] = E\left[u_{it}\Delta e_{it-1}\right] = E\left[u_{it}\Delta m_{jit-1}\right] = E\left[u_{it}\Delta s_{it-1}\right] = 0 \\ &\forall i; t = 3,\ldots,T;\ j = 1,2,3,4; k = 1,2,3 \end{aligned} \ , \quad \textbf{(8)}
$$

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:

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

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.

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 (as it is in our case), 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.