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**Abstract**

This paper examines the long-term relationship between primary energy consumption and other key macroeconomic variables, including real GDP, labour force, capital stock and technology, using a panel dataset for 64 countries over the period 1965-2009. Deploying panel error correction models, we find that there is a positive relationship running from physical capital, GDP, and population to primary energy consumption. We observe however a negative relationship between total factor productivity and primary energy usage. Significant differences arise in the magnitude of the cointegration coefficients, when we allow for differences in geopolitics and wealth levels. We also argue that inference on the basis of a single model without taking model uncertainty into account can lead to biased conclusions. Consequently, we address this problem by applying simple model averaging techniques to the estimated panel cointegration models. We find that tackling the uncertainty associated with selecting a single model with model averaging techniques leads to a more accurate representation of the link between energy consumption and the other macroeconomic variables, and to a significantly increased out–of–sample forecast performance.

**JEL Classification:** C33, C52, Q41, Q43.

**Keywords:** Energy Consumption; Panel Cointegration Models; Model Averaging.

## 1 Introduction

The causality between energy consumption and real income has been an important research topic in recent years. Rising concerns about climate change and global warming associated with

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greenhouse gas emissions necessitate the modelling and prediction of primary energy consumption for the following decades. Despite of the growing number of studies, no consensus has been achieved on the direction and on the magnitude of the relationship between energy consumption and the gross domestic income. The absence of any clear consensus according to Apergis and Payne (2009b) can be attributed to the heterogeneity in climate conditions, varying energy consumption patterns, the structure and stages of economic development within a country, as well as to alternative econometric methodologies employed.

The present literature focuses foremost on the energy consumption–economic growth nexus and emphasises four different hypotheses (Apergis and Payne (2009b); Squalli (2007)): The growth hypothesis, the conservation hypothesis, the neutrality hypothesis, and the feedback hypothesis. The growth hypothesis treats energy as a factor of production, and thus carries the policy implications that a drastic reduction in energy consumption would also adversely impact economic growth. The neutrality hypothesis treats energy consumption as an insignificant part of economic output and thus assumes no causality between these variables, while the feedback hypothesis assumes a bidirectional causality running between energy consumption and economic growth. The conservation hypothesis asserts that the long–term relationship runs from economic growth to energy consumption but not the other way. Thus a reduction in energy consumption would not significantly affect economic growth.

The purpose of this paper however, is to establish the long–term relationship between primary energy consumption and a number of key macroeconomic variables under model uncertainty, in order to project future energy demand. Besides real income, the explanatory variables include population, physical capital and total factor productivity, which we examine in a panel dataset for 64 countries over the period 1965–2009. To the knowledge of the authors, this is the largest panel study on the subject up to now, and the only one taking model uncertainty related to different structural models into account. We employ panel error correction models, allowing for variation in the cointegrating coefficients, arising from the particularity of geopolitical regions and from the differing wealth levels of the panel members. We find a positive long–run relationship running from physical capital, GDP and population to primary energy consumption. Additionally, there is a negative relationship with total factor productivity, indicating, that the more GDP is explained by factors other than capital or population, the lower the primary energy consumption in this country. We also find significant differences in the magnitude of the cointegrating coefficients, when we allow for differences in geopolitics and wealth levels, which indicates that distinct energy consumption patterns are associated with the particular stages of economic development and with different political systems. In order to account for the model uncertainty caused by these differing results, we build two different model averages. The first average is based on out–of–sample forecast errors, while the second on the in–sample–fit of the models. In comparing the out–of–sample predicting ability of our models, we find the average models to have the highest long term predicting power. Using these averaged models, we hope to provide a useful tool for projecting future primary energy consumption in different parts of the world.

The paper is organised as follows: Section 2 gives a short overview of the connected literature.

Section 3 introduces the underlying methodology and our data, along with their long–run time series properties, and considers the issue of model uncertainty in the context of panel error correction specifications. Section 4 presents and explains our empirical results, and in Section 5 policy implications are derived.

## 2 Literature

Most of the literature agrees that cointegration exists between gross domestic product and energy consumption. At the same time the population and physical capital variables are treated less frequently in the models. Below we give a limited review of the continuously growing literature on the broad subject, however with highly contradicting and mixed results. It is worth noting that most studies however examine either individual countries, or employ a panel dataset limited to certain geographical areas.

The first studies addressing the subject usually focused on the energy–GDP nexus. Kraft and Kraft (1978) examined the subject with a vector autoregressive model (VAR) finding the relationship running from income to energy consumption in the United States. In a later study, Yu and Choi (1985) found the relationship also running from GDP to energy consumption. However, their results have been found spurious in later years. In the early 1990s many researchers turned to cointegration techniques to model the determinants of energy consumption. Stern (2000) for example established a cointegration relationship with the Johansen trace cointegration test for the USA postwar period. He comes to the conclusion that energy is limiting factor to growth in the US macroeconomy. In response, Oh and Lee (2004) extended the analysis of Stern, using the same variables. They tested for cointegration with the Johansen, Juselius maximum likelihood estimate (MLE) and used vector error correction models (VECM). They find a long run bidirectional relationship between energy consumption and GDP. Similar time series analyses like those of Soytas and Sari (2003) find bidirectional causality between energy consumption and GDP in Argentina, a long-term causality running from GDP to energy consumption in Italy & Korea, and the other way around in Turkey, France, Germany and Japan. Among others, these results show mixed evidence on the nature of this relationship. Lee and Chiu (2011) employ the Johansen cointegration technique to examine the relationship between nuclear energy consumption, oil prices and economic growth in six industrialised countries. They also arrive to mixed results, either GDP Granger causing nuclear energy consumption (Japan), or a bidirectional relationship (US, Canada, Germany), to no relationship at all (France, UK). These contradicting findings are not surprising in single time–series analyses.

During the last decade, researchers began to turn to panel cointegration methods, as panel methods bring a significant improvement in analysis over single time series. Despite of this, as the literature shows, different studies brought again contradicting empirical results. The findings of Wolde-Rufael (2006), for example support the bidirectional long term relationships for 17 African countries. A second study of Wolde-Rufael (2009) reexamines the relationships in the 17 countries while including labour and capital as additional variables, using a multivariate modified

Granger causality analysis of Toda and Yamamoto (1995). They find that in 15 countries capital and labour are the most important factors to output growth, while energy is comparatively less important and only a contributing factor in case of eleven countries to output growth. Apergis and Payne (2009b) using Pedroni cointegration and VECM for South American countries find that cointegration is present between real GDP, energy consumption, the labour force and real gross fixed capital formation. They also find evidence of short– and long–run causality running from energy consumption to economic growth. Another study of Apergis and Payne (2009a) employs the same variables and technique for the Commonwealth of Independent States (CIS) countries and discovers a bidirectional long–run relationship between energy consumption and GDP, supporting the feedback hypothesis.

An important case is those of the energy exporting countries. Squalli (2007) examined the relationship between energy use and growth in the OPEC countries: He found very mixed evidence, partly explained by different cultural, political and economic structures. The abundance in resources is not found to be a common factor determining the direction of long–term causality between energy and economic growth. He noted that an economy although growing, may be constrained by infrastructural, political or managerial obstacles which may put downward pressure on energy consumption. Political factors coupled with mismanagement or inadequate allocation of a country's income can result in widespread inefficiencies, poverty and reduced demand for goods and services including energy. Another reason for the negative relationships between energy consumption and economic growth in some countries is explained by the fact that growing economies may shift their production to less energy intensive sectors, which is line with the finding of Wolde-Rufael (2006).

As the review of the connected literature also shows, the modelling of primary energy consumption includes a large amount of uncertainty. The aim of this paper is to test the largest panel dataset at our disposal while examining the determinants of primary energy consumption, including less researched variables such as total factor productivity, population and capital. We address the inherent uncertainty in available models by applying simple model–averaging techniques to commonly used panel error correction equations. We wish to increase thus the predictive power of our models in forecasting future energy needs. As next we turn to the description of our data and the applied methodology.

## 3 Data and Methodology

The purpose of the paper is to establish the best model that can be deployed for future primary energy projections. In this section first we shall describe the source of our data, then we investigate the statistical properties of these variables to determine the best modelling choice.

### 3.1 Data Source and Description

Our panel dataset ranges from 1965 to 2009 for 64 countries.[1] For the majority of the countries a full dataset is available, however political changes, such as the breaking up of the USSR and the foundation of new sovereign states had shortened the availability of data, especially for the successor states of the ex–Soviet Union, where data are only accessible starting from the early or mid 1990s. Total primary energy consumption (E) was taken from the British Petrol (2010) *Statistical Review of World Energy* and is denoted in terms of million tons of oil equivalent (MTOE). The British Petrol (BP) statistics considers oil, gas, coal, nuclear and hydro energy usage. Total population (L) and real GDP (Y) are taken from the Penn World Table 7.0 (Heston, Summers, and Aten (2011)).

We calculated the physical capital stock (K) using the perpetual inventory method by Bernanke and Gurkaynak 2001. The method involves calculating the starting capital $K_{i,0}$ by dividing the initial investment (capital flow) at year one by the average annual growth rate around year one, and the average depreciation, which is uniformly assumed to be 6%.

$$K_{i,0} = \frac{I_{i,1}}{(g_{i,1} + \delta)} \tag{1}$$

where $K$ is the physical capital stock, $I$ denotes the initial investment (capital flow), $\delta$ is the average depreciation of the capital stock, $g_{i,1}$ is the average annual growth rate for country i around year one, while $i$ and $t$ are country and time indices, respectively.

Over a period of 40 years the capital stock converges to its present value, regardless of the starting capital stock. However, in case of the ex–Soviet member states, the reported growth rates in the transition period of the 1990s were often negative, therefore we judged the starting capital stock obtained by the above method to be misleading. When we encountered high negative growth rates, we substituted 2% for the average growth rate around year one, based on the world–wide average during the past century. Where applicable, the first five years of the capital series were eliminated, and the series was constructed by

$$K_{i,t} = K_{i,t-1}(1 - \delta) + I_{i,t}. \tag{2}$$

To assure that we have sufficient number of observations in case of the ex–Soviet states, we decided to use the first calculated capital stock value without excluding the initial five years. This was to ensure a sufficient number of time series observations for the panel cointegration modelling.

[1]Full list of the countries with their categorisation is found in Table 1.

**Table 1:** Country Classification & Descriptive Statistics

| | Region | Country | $GDP_{group}$ | $Ypc_{2009}$ | Δ Y (%) | | Δ E (%) | | Δ L (%) | | $1^{st}$ obs | $\mathcal{M}_{AV}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | | |
| 1 | | Australia | H | 41293.9 | 3.8 | 1.7 | 3.2 | 3.1 | 1.4 | 0.4 | 1965 | $\in$ |
| 2 | | Bangladesh | L | 1397.3 | 4.2 | 2.8 | 8.2 | 5.4 | 2.1 | 0.5 | 1965 | $\in$ |
| 3 | | China Version 1 | L | 7630.4 | 8.5 | 4.2 | 6.1 | 7.6 | 1.4 | 0.7 | 1965 | $\in$ |
| 4 | | Hong Kong | H | 36297.0 | 5.9 | 4.7 | 5.8 | 7.0 | 1.5 | 1.0 | 1965 | $\in$ |
| 5 | | India | L | 3238.4 | 5.4 | 3.5 | 5.1 | 2.8 | 1.9 | 0.3 | 1965 | $\in$ |
| 6 | | Indonesia | L | 4074.1 | 6.1 | 4.5 | 7.0 | 6.7 | 1.8 | 0.3 | 1965 | $\in$ |
| 7 | AS | Japan | MH | 30025.3 | 3.5 | 4.0 | 2.7 | 5.1 | 0.6 | 0.5 | 1965 | $\in$ |
| 8 | | Korea, Republic of | MH | 25052.6 | 7.2 | 4.7 | 8.7 | 6.2 | 1.2 | 0.6 | 1965 | $\in$ |
| 9 | | Malaysia | LM | 11309.5 | 6.9 | 5.2 | 7.9 | 6.4 | 2.4 | 0.5 | 1965 | $\in$ |
| 10 | | New Zealand | MH | 27878.3 | 2.4 | 3.0 | 2.3 | 3.3 | 1.1 | 0.5 | 1965 | $\in$ |
| 11 | | Pakistan | L | 2353.1 | 4.8 | 3.5 | 5.3 | 4.5 | 2.6 | 0.8 | 1965 | $\in$ |
| 12 | | Philippines | L | 2839.0 | 4.1 | 4.4 | 4.2 | 6.7 | 2.5 | 0.3 | 1965 | $\in$ |
| 13 | | Singapore | H | 47329.1 | 7.7 | 5.0 | 6.9 | 9.0 | 2.1 | 1.0 | 1965 | $\in$ |
| 14 | | Thailand | L | 7800.0 | 6.2 | 4.4 | 8.7 | 6.6 | 1.7 | 0.8 | 1965 | $\in$ |
| 15 | | Azerbaijan | L | 9619.0 | 8.8 | 13.1 | -2.5 | 8.0 | 0.6 | 0.2 | 1996 | $\notin$ |
| 16 | | Belarus | LM | 12782.0 | 6.5 | 5.8 | 0.1 | 5.4 | -0.3 | 0.4 | 1997 | $\notin$ |
| 17 | | Bulgaria | LM | 10922.5 | 3.3 | 5.1 | 0.1 | 6.3 | -0.4 | 0.8 | 1973 | $\notin$ |
| 18 | | Czech Republic | MH | 21972.1 | 2.0 | 4.8 | -1.1 | 4.6 | -0.0 | 0.1 | 1993 | $\notin$ |
| 19 | | Hungary | LM | 16521.4 | 2.1 | 3.4 | 0.7 | 4.0 | -0.1 | 0.4 | 1971 | $\notin$ |
| 20 | | Kazakhstan | LM | 11734.2 | 4.7 | 8.3 | 0.3 | 9.2 | -0.4 | 0.9 | 1994 | $\notin$ |
| 21 | | Lithuania | LM | 14187.3 | 3.6 | 7.1 | 0.4 | 9.4 | -0.2 | 0.1 | 1996 | $\notin$ |
| 22 | EE | Poland | LM | 16375.9 | 3.1 | 4.5 | 0.3 | 4.6 | 0.4 | 0.4 | 1973 | $\notin$ |
| 23 | | Romania | L | 9741.4 | 3.9 | 6.3 | 0.9 | 6.7 | 0.3 | 0.6 | 1965 | $\notin$ |
| 24 | | Russia | LM | 14644.8 | 0.7 | 8.1 | -1.5 | 3.6 | -0.3 | 0.3 | 1993 | $\notin$ |
| 25 | | Slovak Republic | LM | 19144.8 | 2.6 | 6.5 | -0.8 | 3.7 | 0.2 | 0.3 | 1990 | $\notin$ |
| 26 | | Turkey | L | 9919.4 | 4.4 | 4.1 | 5.6 | 6.0 | 2.0 | 0.4 | 1965 | $\notin$ |
| 27 | | Turkmenistan | L | 6934.9 | 3.9 | 9.7 | 5.0 | 8.9 | 1.4 | 0.3 | 1996 | $\notin$ |
| 28 | | Ukraine | L | 6413.9 | 0.5 | 9.4 | -2.8 | 5.2 | -0.8 | 0.1 | 1996 | $\notin$ |
| 29 | | Uzbekistan | L | 2384.1 | 3.0 | 5.3 | 0.5 | 4.3 | 1.6 | 0.6 | 1993 | $\notin$ |
| 30 | | Algeria | L | 6076.3 | 3.9 | 5.6 | 7.3 | 9.1 | 2.4 | 0.8 | 1965 | $\in$ |
| 31 | | Egypt | L | 4956.7 | 5.6 | 4.5 | 5.6 | 7.1 | 2.2 | 0.8 | 1965 | $\in$ |
| 32 | | Iran | LM | 10622.1 | 4.4 | 9.2 | 6.0 | 6.5 | 2.6 | 1.3 | 1965 | $\in$ |
| 33 | ME | Kuwait | H | 46756.5 | 5.0 | 20.2 | 7.0 | 26.2 | 2.9 | 15.8 | 1989 | $\notin$ |
| 34 | | Qatar | H | 159246.9 | 9.0 | 9.3 | 6.7 | 14.2 | 3.4 | 1.2 | 1989 | $\notin$ |
| 35 | | Saudi Arabia | MH | 21552.4 | 4.1 | 4.7 | 4.6 | 3.4 | 2.6 | 2.2 | 1989 | $\notin$ |
| 36 | | South Africa | L | 7587.6 | 3.3 | 2.9 | 3.4 | 4.0 | 2.1 | 0.8 | 1965 | $\in$ |
| 37 | | United Arab Emirates | H | 52869.2 | 6.9 | 4.9 | 6.2 | 7.3 | 5.4 | 0.8 | 1989 | $\notin$ |
| 38 | NA | Canada | H | 36234.5 | 3.1 | 2.1 | 2.4 | 2.8 | 1.2 | 0.3 | 1965 | $\in$ |
| 39 | | United States | H | 41143.9 | 2.9 | 2.3 | 1.3 | 2.8 | 1.0 | 0.1 | 1965 | $\in$ |
| 40 | | Argentina | LM | 11959.9 | 2.8 | 4.6 | 2.4 | 3.7 | 1.4 | 0.3 | 1965 | $\in$ |
| 41 | | Brazil | L | 8163.0 | 4.3 | 4.6 | 5.5 | 4.7 | 2.0 | 0.6 | 1965 | $\in$ |
| 42 | | Chile | LM | 12007.0 | 4.3 | 5.8 | 3.7 | 4.5 | 1.5 | 0.3 | 1965 | $\in$ |
| 43 | SA | Colombia | L | 7528.0 | 4.5 | 3.7 | 3.4 | 3.8 | 2.0 | 0.6 | 1965 | $\in$ |
| 44 | | Ecuador | L | 6170.9 | 4.3 | 4.9 | 7.0 | 8.0 | 2.4 | 0.6 | 1965 | $\in$ |
| 45 | | Mexico | LM | 11633.1 | 3.9 | 4.4 | 4.5 | 3.9 | 2.1 | 0.7 | 1965 | $\in$ |
| 46 | | Peru | L | 7279.0 | 3.3 | 5.9 | 3.1 | 6.3 | 2.1 | 0.7 | 1965 | $\in$ |
| 47 | | Venezuela | L | 9123.4 | 3.0 | 6.2 | 3.7 | 5.2 | 2.5 | 0.7 | 1965 | $\in$ |
| 48 | | Austria | H | 37415.2 | 2.8 | 2.2 | 1.7 | 3.4 | 0.3 | 0.4 | 1965 | $\in$ |
| 49 | | Belgium | MH | 34629.9 | 2.5 | 2.3 | 1.5 | 3.8 | 0.2 | 0.1 | 1965 | $\in$ |
| 50 | | Denmark | MH | 33931.8 | 2.2 | 2.4 | 0.9 | 7.7 | 0.3 | 0.2 | 1965 | $\in$ |
| 51 | | Finland | MH | 32187.2 | 2.8 | 3.5 | 2.2 | 4.7 | 0.3 | 0.2 | 1965 | $\in$ |
| 52 | | France | MH | 30837.3 | 2.7 | 2.0 | 1.8 | 3.5 | 0.6 | 0.2 | 1965 | $\in$ |
| 53 | | Germany | MH | 32493.5 | 2.0 | 2.0 | -0.1 | 2.9 | 0.1 | 0.4 | 1973 | $\in$ |
| 54 | | Greece | MH | 27304.1 | 3.2 | 3.5 | 3.8 | 5.7 | 0.5 | 0.4 | 1965 | $\in$ |
| 55 | | Iceland | H | 37212.4 | 3.5 | 5.2 | 3.7 | 8.6 | 1.1 | 0.4 | 1965 | $\in$ |
| 56 | WE | Ireland | MH | 33405.9 | 4.4 | 4.0 | 2.6 | 6.3 | 1.1 | 0.8 | 1965 | $\in$ |
| 57 | | Italy | MH | 27709.7 | 2.5 | 2.6 | 1.7 | 3.6 | 0.3 | 0.3 | 1965 | $\in$ |
| 58 | | Netherlands | H | 37052.2 | 2.8 | 1.9 | 2.3 | 4.8 | 0.7 | 0.2 | 1965 | $\in$ |
| 59 | | Norway | H | 49979.6 | 3.3 | 1.9 | 2.3 | 6.2 | 0.5 | 0.2 | 1965 | $\in$ |
| 60 | | Portugal | LM | 19904.0 | 3.5 | 4.1 | 3.9 | 4.7 | 0.4 | 0.7 | 1965 | $\in$ |
| 61 | | Spain | MH | 27648.9 | 3.4 | 2.6 | 3.8 | 4.2 | 0.8 | 0.5 | 1965 | $\in$ |
| 62 | | Sweden | H | 35246.4 | 2.1 | 2.1 | 0.9 | 4.5 | 0.4 | 0.3 | 1965 | $\in$ |
| 63 | | Switzerland | H | 39634.0 | 1.9 | 2.5 | 1.7 | 4.7 | 0.6 | 0.5 | 1965 | $\in$ |
| 64 | | United Kingdom | MH | 33406.8 | 2.3 | 2.1 | 0.1 | 2.9 | 0.3 | 0.2 | 1965 | $\in$ |

* Regional Classification: Asia & Pacific (AS), Eastern Europe & Eurasia (EE), Middle East & Africa (ME), North America (NA), South America & Mexico (SA) and Western Europe (WE). GDPpc Groups: Low Income (L) [$\leq 10K\$$], Middle-low Income (ML) [$10K\$ - 20K\$$], Middle-high Income (MH) [$20K\$ - 35K\$$] and High Income (H) [$\geq 35K\$$]. Source: Heston, Summers, and Aten 2011

The technology component (A) or total factor productivity was generated by the equation:

$$Y = AK^{\theta}L_F^{1-\theta} \tag{3}$$

of which taking the natural logarithms (log) and isolating $logA$, we get:

$$logA = logY - \theta logK - (1-\theta)logL_F$$

Where logA denotes the relative magnitude of the part of output not explained by the physical capital and labour force components. $A$ depends next to the level of technology, also on the structure of the economy and the stages of economic development.

Answering the question why we have excluded primary energy prices, more precisely crude oil prices form our models brings various answers. Firstly, bearing in mind that we wish to set up models that have a realistic predictive power, the practical unpredictability of oil or gas prices in the future would render our models unusable even in the short-term in forecasting energy consumption. Secondly, it would be very difficult to account for the various government subsidies and the effects of liberalised versus non–liberalised energy markets, and price caps in the various countries. Therefore our long-range models focus only on the main macroeconomic variables.

## 3.2 Unit Root and Cointegration Tests

While working with the above mentioned macroeconomic variables, we have to keep in mind that a large number of empirical studies have found at least some of them to be non-stationary. This raises the necessity of testing the order of integration of our data. Presently, a number of techniques exist to perform panel unit root tests, which generally show increased power over the single time series unit root test, such as the augmented Dickey Fuller test or the Phillips–Perron test. In this paper we work with the Levin Lin Chu test (assuming a homogeneous autoregressive parameter), as well with the Im–Pesaran–Shin tests, and the Fischer type augmented Dickey–Fuller test (ADF) tests of Maddala and Wu (both assuming a heterogeneous autoregressive parameter). Apart from these tests, the researcher could work with the Breitung test (homogeneous autoregressive parameter), or with stationarity tests such as the Hadri or Hadri–Larsson test. A large scale simulation carried out by Hlouskova and Wagner (2006) has shown however that panel stationarity tests perform significantly worse than the unit root tests, therefore we concentrate on the unit root tests, more precisely on the alternatives allowing for heterogeneous autoregressive parameters. Potential distortions by all tests might arise from panel cross sectional dependence, moving average roots in the processes, and by a low number of time dimensional observations.

**Table 2:** Unit Root Test Results*

| Variable | Order[o] | Model without $\alpha$ or $\delta t$ statistics | prob. | Model with $\alpha$ statistics | prob. | Model with $\alpha + \delta t$ statistics | prob. |
|---|---|---|---|---|---|---|---|
| Levin-Lin-Chu Test[1] | | | | | | | |
| logE | 0 | 9.51145 | 1.00000 | -13.00330 | 0.00000 | -2.36212 | 0.00910 |
| | 1 | -18.59190 | 0.00000 | -12.08320 | 0.00000 | -12.54330 | 0.00000 |
| logY | 0 | 18.27510 | 1.00000 | -8.90729 | 0.00000 | -3.51120 | 0.00020 |
| | 1 | -15.33870 | 0.00000 | -7.65853 | 0.00000 | -4.63588 | 0.00000 |
| logL | 0 | -1.15028 | 0.12500 | -11.48040 | 0.00000 | -6.03059 | 0.00000 |
| | 1 | -9.24682 | 0.00000 | -2.14263 | 0.01610 | -6.06629 | 0.00000 |
| logA | 0 | 10.55110 | 1.00000 | -9.35295 | 0.00000 | -0.57744 | 0.28180 |
| | 1 | -21.72620 | 0.00000 | -10.49420 | 0.00000 | -10.14430 | 0.00000 |
| logK | 0 | 8.86165 | 1.00000 | -6.74069 | 0.00000 | -8.49421 | 0.00000 |
| | 1 | -8.24533 | 0.00000 | -3.13923 | 0.00080 | -1.27233 | 0.10160 |
| Im-Pesaran-Shin (IPS) Test[2] | | | | | | | |
| logE | 0 | | | -5.97780 | 0.0000 | 1.22547 | 0.8898 |
| | 1 | | | -17.13820 | 0.0000 | -17.84800 | 0.0000 |
| logY | 0 | | | 1.51778 | 0.9355 | -1.38402 | 0.0832 |
| | 1 | | | -16.40110 | 0.0000 | -13.09920 | 0.0000 |
| logL | 0 | | | -3.15763 | 0.0008 | 4.73374 | 1.0000 |
| | 1 | | | -3.28343 | 0.0005 | -7.37387 | 0.0000 |
| logA | 0 | | | -2.37371 | 0.0088 | -0.52077 | 0.3013 |
| | 1 | | | -17.29060 | 0.0000 | -14.67920 | 0.0000 |
| logK | 0 | | | 4.63761 | 1.0000 | -1.48312 | 0.0690 |
| | 1 | | | -5.01166 | 0.0000 | -4.13264 | 0.0000 |
| Fischer's ADF(Chi Squared) test[3] | | | | | | | |
| logE | 0 | 27.30830 | 1.0000 | 287.75300 | 0.0000 | 120.41100 | 0.6708 |
| | 1 | 629.66500 | 0.0000 | 580.73000 | 0.0000 | 581.91200 | 0.0000 |
| logY | 0 | 3.78173 | 1.0000 | 137.93600 | 0.2588 | 161.85500 | 0.0230 |
| | 1 | 443.75900 | 0.0000 | 540.14100 | 0.0000 | 458.99700 | 0.0000 |
| logL | 0 | 82.33360 | 0.9994 | 225.92600 | 0.0000 | 132.80400 | 0.3676 |
| | 1 | 347.00100 | 0.0000 | 236.72800 | 0.0000 | 285.07900 | 0.0000 |
| logA | 0 | 15.19330 | 1.0000 | 197.64800 | 0.0001 | 152.11000 | 0.0718 |
| | 1 | 742.13300 | 0.0000 | 604.07600 | 0.0000 | 514.92500 | 0.0000 |
| logK | 0 | 15.56200 | 1.0000 | 109.87800 | 0.8747 | 183.01500 | 0.0010 |
| | 1 | 218.49500 | 0.0000 | 208.99600 | 0.0000 | 190.78300 | 0.0003 |
| ADF(Choi Z STAT) test[4] | | | | | | | |
| logE | 0 | 15.28990 | 1.0000 | -6.11318 | 0.0000 | 1.12677 | 0.8701 |
| | 1 | -18.49990 | 0.0000 | -16.64800 | 0.0000 | -16.55220 | 0.0000 |
| logY | 0 | 21.81730 | 1.0000 | 1.24574 | 0.8936 | -1.24405 | 0.1067 |
| | 1 | -14.13030 | 0.0000 | -16.16910 | 0.0000 | -12.77680 | 0.0000 |
| logL | 0 | 8.64210 | 1.0000 | -3.10694 | 0.0009 | 4.55995 | 1.0000 |
| | 1 | -10.71930 | 0.0000 | -3.11211 | 0.0009 | -7.10434 | 0.0000 |
| logA | 0 | 14.39400 | 1.0000 | -2.45686 | 0.0070 | -0.75519 | 0.2251 |
| | 1 | -20.49830 | 0.0000 | -17.10310 | 0.0000 | -14.50220 | 0.0000 |
| logK | 0 | 13.30290 | 1.0000 | 4.33435 | 1.0000 | -1.71567 | 0.0431 |
| | 1 | -6.07223 | 0.0000 | -5.30844 | 0.0000 | -4.64324 | 0.0000 |

[1] Test specification: $\Delta y_{i,t} = \rho y_{i,t-1} + \alpha_0 + \delta_t + \alpha_i + \theta_t + \epsilon_{i,t}$ (where $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T$) $H_0$: Existence of a Common Unit Root in the Series ($H_0 : \rho_i = \rho = 0$).

[2] Test specification: $\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \delta_t + \epsilon_{i,t}$ (where $\alpha_i = (1 - \phi_i), \rho_i = -(1 - \phi_i)$ and $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$). $H_0$: Existence of a Unit Root in the Series ($H_0 : \rho_i = 0$ for all $i$).

[3] Test specification: $-2 \sum_{i=1}^{N} log(\pi_i) \rightarrow \chi^2_{2N}$ $H_0$: Existence of a Common Unit Root in the Series.

[4] Test specification: $Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}(\pi_i) \rightarrow N(0, 1)$ $H_0$: Existence of a Common Unit Root in the Series.

[*] User Specified Lags: 1. Probabilities for Fisher tests are computed using an asymptotic Chi-squared distribution. All other tests assume asymptotic normality. Source: Own calculation.

[o] Order of differencing: 0=level, 1=$1^{st}$ difference

The Levin–Lin Chu Levin and Chu (2002) test involves the estimation of a pooled ordinary least squares (OLS) regression equation, for several sub cases (allowing for drifts or trends). The basic test assumes no serial correlation in the error terms. To correct for possible serial correlation in the error terms, one could include the lagged first differences when calculating the test statistics. As described above, the major drawback of the Levin–Lin Chu test is that it takes the autoregressive coefficient as homogeneous for all cross sections. The alternative hypothesis is argued to be too strong for most of the empirical applications.

Additionally we look at the Im–Pesaran–Shin (IPS) test Im, Pesaran, and Shin (2003), which allows for heterogeneity in the autoregressive coefficient of the different panel members. The basic framework described by Im, Pesaran, and Shin (2003) performs a unit root tests on each cross section units, instead of pooling the data. The test result is calculated by taking the mean of the individual unit root tests. One weakness of the test is that it only considers balanced panel cases. A second test that considers heterogeneity within the variables was proposed by Maddala and Wu (1999) and it builds upon the Fischer $\rho$–test (1932). The Fischer test conflates the significance levels (p–values) of the different tests, whereas the IPS test rests upon combining the respective test statistics. If the test statistics are continuous, the significance levels $\Phi_i \quad (i = 1, 2, \ldots, N)$ are independent uniform variables, and $-2log\Phi_i$ has a $\chi^2$ (chi squared) distribution with two degrees of freedom. The Fischer test proposed by Maddala and Wu (1999) does not have the limitations of the IPS. Not only is it appropriate for unbalanced panels, but it can be used with any unit root test, and even if the ADF test is used, the choice of the lag length for each sample can be separately determined. The results of the Levin–Lin–Chu panel unit root test statistics, the IPS test and the results of the Fischer's ADF test can be seen in Table 2.

Based on these results, we concluded that logE is a unit root process with a drift and deterministic trend, logY is a unit root process with a drift, logL is a unit root process with a drift and deterministic trend, logK is a unit root process with a drift, and logA is a unit root process with a drift and deterministic trend.

To ascertain the presence of a relationship between unit root processes, we have to test for cointegration in our data. While the presently known time series cointegration tests are widely used and known (Engle–Granger test, Johansen test), the panel cointegration literature is still developing. Hlouskova and Wagner (2010) examine in a large scale simulation four different panel cointegration tests, the so called single equation tests of Pedroni (1999); Pedroni (2004) and Westerlund (2005) and the system test of Larsson, Lyhagen, and Löthgren (2001) and the Breitung (2005) test. All of these tests assume a cross sectionally independent panel. Hlouskova and Wagner (2010) compare the performance of the tests with respect to the time series and cross sectional dimensions, with respect to the impact of stable autoregressive roots approaching the unit circle, the presence of an integrated of order two ($I(2)$) component and with respect to cross unit cointegrating relationship. Since all of these panel tests above consider cross sectionally independent panels, asymptotic results for the tests are achieved by applying sequential limit theory with first $T \to \infty$ then $N \to \infty$. Hlouskova and Wagner (2010) arrive to the conclusion that the Pedroni ADF statistics are by far the most robust test statistics of all the examined cointegration tests. We have thus chosen the panel cointegration test by Pedroni (1999), which allows testing for cointegration with multiple regressors. The Pedroni test allows for heterogeneity among panel members, while testing the null hypothesis of no cointegration against the alternative hypothesis, that for each member of the panel there exists a single cointegrating vector, athough, this cointegrating vector need not be the same for each member.

According to Pedroni (1999), the panel ADF $t$–statistics is most closely analogous to the Levin–Lin panel unit root statistics, applied to the estimated residuals of a cointegrating regression. The Group t–statistics is most closely analogous to the Im–Pesaran–Shin group mean unit root statistics applied to the estimated residuals of a cointegrating regression. Hlouskova and Wagner (2010) have also evaluated the performance of these statistics. Analysing the single equations (the seven Pedroni statistics) they come to the conclusion that the best performing are the two ADF tests of Pedroni. Also the type of the chosen test (whether ADF or $\rho$) seems to have a larger impact on the performance, then the dimension (between or within) of the test. Cross sectional correlation and additional cross unit cointegration are found by Hlouskova and Wagner (2010) to have a much weaker negative effect on the performance of the cointegrating tests as expected, especially in case of the Pedroni ADF tests.

**Table 3:** Pedroni Residual Cointegration Test

| | Test | Statistic | Prob. | Weighted Statistic | Prob. |
|---|---|---|---|---|---|
| 1 | Panel v-Statistic[1] | -1.159175 | 0.8768 | -3.642482 | 0.9999 |
| 2 | Panel rho-Statistic[1] | 3.615002 | 0.9998 | 3.015330 | 0.9987 |
| 3 | Panel PP-Statistic[1] | 0.046351 | 0.5185 | -3.937184 | 0.0000 |
| 4 | Panel ADF-Statistic[1] | 1.135961 | 0.8720 | -3.903896 | 0.0000 |
| 5 | Group rho-Statistic[2] | 5.5166 | 1.0000 | | |
| 6 | Group PP-Statistic[2] | -6.1803 | 0.0000 | | |
| 7 | Group ADF-Statistic[2] | -2.1817 | 0.0146 | | |

[*] Test specification: $y_{i,t} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \cdots + \beta_{Mi} x_{Mi,t} + e_{i,t}$ (for $t = 1, 2, \ldots, T; i = 1, 2, \ldots, N$ and $m = 1, 2, \ldots, M$). Sample: 1965—2009. Included observations: 2880. Cross-sections included: 64. $H_0$: No cointegration. Trend assumption: Deterministic intercept and trend. User-specified lag length: 1. Newey-West automatic bandwidth selection and Bartlett kernel. T = number of observations over time, N=number of individual members in panel, M=number of regression variables. Source: Own calculation.
[1] Alternative hypothesis: common AR coefs (within-dimension).
[2] Alternative hypothesis: individual AR coefs (between-dimension).

Based on the results of the Pedroni ADF and the Phillips–Perron (PP) t–statistic, we conclude that we can reject the null hypothesis of no cointegration, and treat the variables as cointegrated. The detailed Pedroni test statistics can be seen in Table 3. Although the Pedroni test ascertains whether or not cointegration is present among the variables of the panel dataset, it does not deal with the normalisation of the cointegrating vector. It is expected thus, that the researcher has a particular normalisation in mind.

## 3.3 Panel Cointegration Model

Since the Pedroni tests do not give us the direction or magnitude of the cointegrating vectors, we have chosen to estimate the long term cointegrating relationship with the help of a panel error correction model. A classical autoregressive distributed lag (ARDL) approach cannot be used, as we have found evidence of cross–cointegration between the explanatory I(1) variables (real GDP, capital, labour and technology), which would lead to identification problems according to Pesaran and Shin (1995, 1997).

After normalising the cointegrating vector on the natural logartihm of primary energy consumption, we have tested all possible combinations of the models with the explanatory variables Y, L, K, A. We have chosen three models with the highest economic plausibility. We estimate these panel error correction equations with full information maximum likelihood (FIML).

1. The EC model of primary energy consumption on GDP and on population ($E.YL$)

$$\begin{aligned}\Delta logE_{i,t} = \alpha(logE_{i,t-1} - \beta_0 - \beta_1 logY_{i,t-1} - \beta_2 logL_{i,t-1}) \\ + \gamma_0 \Delta logE_{i,t-1} + \gamma_1 \Delta logY_{i,t-1} + \gamma_2 \Delta logL_{i,t-1} + \mu_i + \lambda_t + \epsilon_{i,t}\end{aligned} \tag{4}$$

2. The EC model of primary energy consumption on population and physical capital ($E.LK$)

$$\begin{aligned}\Delta logE_{i,t} = \alpha(logE_{i,t-1} - \beta_0 - \beta_2 logL_{i,t-1} - \beta_3 logK_{i,t-1}) \\ + \gamma_0 \Delta logE_{i,t-1} + \gamma_2 \Delta logL_{i,t-1} + \gamma_3 \Delta logK_{i,t-1} + \mu_i + \lambda_t + \epsilon_{i,t}\end{aligned} \tag{5}$$

3. The EC model of primary energy consumption on population, physical capital and technology ($E.LKA$)

$$\begin{aligned}\Delta logE_{i,t} = \alpha(logE_{i,t-1} - \beta_0 - \beta_2 logL_{i,t-1} - \beta_3 logK_{i,t-1} - \beta_4 logA_{i,t-1}) \\ + \gamma_0 \Delta logE_{i,t-1} + \gamma_2 \Delta logL_{i,t-1} + \gamma_3 \Delta logK_{i,t-1} + \gamma_4 \Delta logA_{i,t-1} + \mu_i + \lambda_t + \epsilon_{i,t}\end{aligned} \tag{6}$$

Country fixed effects ($\mu_i$) and fixed effects for the different decades ($\lambda_t$) are included. As significant differences in the patterns of energy consumption may be attributable to the different levels of economic development and different geopolitical developments, we decided to take into account these effects. We created regional groups including Asia & Pacific (AS), Eastern Europe & Eurasia (EE), Middle East & Africa (ME), North America (NA), South America & Mexico (SA) and Western Europe (WE), while the gross domestic product per capita groups accounting for wealth effect consist of low income (L) [$\leq 10K\$$], middle-low income (ML) [$10K\$ - 20K\$$], middle-high income (MH) [$20K\$ - 35K\$$] and high income (H) [$\geq 35K\$$] countries. We test the above models on the different regions and income clusters.

## 3.4 Model Averaging

Since some countries of our dataset such as those in the Eastern Europe & Eurasia group, and parts of the Middle East & Africa group have data often starting around or after 1990, we have —

for the purposes of model averaging — excluded these countries from our sample. In the evaluation of the out–of–sample performance of our models, we reduced the dataset to 45 countries, which have full data available from 1965 to 2009.

In answering the question, what is the best possible model for forecasting future primary energy consumption, we have to deal with the problem of model uncertainty, which we address by performing simple model averaging techniques. Based on our panel error correction models, we have created for each country $3 \times 3$ models, three structural models, referring to the composition of the error correction model, including the $E.YL$, $E.LK$ and $E.LKA$ models, and three attribute models, including world, geopolitical and wealth level dummies. Regional models control for the worldwide geopolitical differences, while $\text{GDP}_{p.c.}$ models for the wealth levels of different countries as of 2009.

First, the nine panel ECM models for each country as defined above were estimated for a period between 1965—1984 (called Training Sample I). Next, we have performed an out–of–sample rolling forecast, by taking the coefficients from our Training Sample I, for the period 1985—1997 (called Training Sample II). We have forecasted this 13–year period, and saved the forecast errors $\xi = logPC - logPC_{FC}$, as the difference between the logarithm of primary energy consumption and the forecasted values, obtaining thus 13 period of forecast errors. Next, we repeated the previous steps by setting our Training Sample I to include the period 1965-1985, estimated our nine EC models and saved the coefficients. We have also reset our Training Sample II to include 1986-1997, and performed the out-of sample forecasts with the coefficients we fixed for the period 1965-1985. We saved the forecast errors as specified above for this 12-year period. This rolling loop was repeated 13 times, until the window in Training Sample II was closed. We have obtained thus the forecast errors associated with the different models taking 13 different time setting into account. After compiling the data, we had now 13 one step ahead forecast errors, 12 two step ahead forecast errors, 11 three step ahead forecast errors, etc. for each single country.

After testing how good our different models were at explaining and forecasting primary energy consumption, we performed a model averaging attempting to prove that an averaged model will have a significantly better out–of–sample predicting ability than any single (individual) model. Model averaging is performed in this paper by running two separate weighting procedures. In the first procedure, we assigned weights to the different models based on the out–of–sample predicting ability. By taking

$$w^{\xi}_{m,h} = \frac{1/\sum \xi^2_{m,t+h}}{\sum_{m=1}^{M} 1/\sum \xi^2_{m,t+h}} \tag{7}$$

which assigned higher weights to models where the sum of the squared forecast errors in Training Sample II was lower.

A second approach to model weighing was to assign weights based on the residuals, or the in–sample–fit of the models for the period 1965—1997. Applying the weighting scheme of Sala-i-

Martin, Doppelhofer, and Miller (2004) leads to the following formula:

$$w_m^{SSE} = \frac{-\frac{k_m}{2} \cdot log(n_m) - \frac{n_m}{2} \cdot log(SSE_m)}{\sum_{m=1}^{M} -\frac{k_m}{2} \cdot log(n_m) - \frac{n_m}{2} \cdot log(SSE_m)} \tag{8}$$

which assigned highest weights to the models with the best in–sample fit. The symbols are defined as follows: $\xi^2$ denotes the squared forecast errors, $m$ is one specific model out of the whole model space $M$, $h$ specifies the forecast horizon, $SSE$ stands for the sum of the squared residuals, $n$ represents the number of observations and $k$ the number of estimated parameters.

Next, we have re–estimated the models for the period 1965–1997 and fixed the coefficients from the basic models, to which we assigned the weights calculated above. We have–based on the coefficients from the period 1965-1997–performed an out–of–sample rolling forecast for 1998—2009 (called Competition Period) with the nine structural models. The forecast errors of the different models were then weighted by the weights from above. After performing the forecasts and saving the resulting weighted forecast errors, this algorithm was repeated by extending the training sample and curtailing the forecast period by one year until only a one–step–ahead forecast error for the year 2009 was derived. Finally, we were able to compare the predicting ability of the averaged models to those of the individual models, using the results of the Competition Period.

## 4 Empirical results: Determinants of Primary Energy Consumption

We estimated the three basic panel error correction models described in Section 3.3 on our entire data set. The coefficients of the long-term cointegrating relationship can be seen in Table 4. Examining the results, we see that the error correction adjustment parameter is always highly significant, and negative, meaning that the relationship tends to a long–run equilibrium.

The world models (W) were estimated for the complete panel. We find the parameter on the population variable always highly significant, taking on values between 0.92 to 1.17, implying a positive relationship and that increases in energy consumption go hand in hand with population increase. As our data set contains not only countries of the European Union and North America, but also regions with dynamic population growth in the past like China, India, South–East Asia, and South America, we are confident that the sample is sufficiently representative to capture the long–term cointegrating effects. These results let us conclude that population growth will significantly increase worldwide energy needs. The parameter on the technology variable (A) is significant at 10% and negative, a result that we have expected. Both real GDP and physical capital are significant at 5% level. Our results indicate a positive long–run relationship, with a coefficient value of 0.29 and 0.34, meaning that a 1% increase in accumulated physical capital would increase energy consumption by 0.29% in the long run. If both capital and real income were included in the cointegrating equation, GDP would become insignificant with a negative sign. This could be attributed to the high multicollinearity between physical capital accumulation and real income.

Energy consumption based on the E.LK model is mostly propelled by population increases and to a lesser extent by physical capital accumulation. Similarly, in the E.YL model, energy consumption is driven by population growth with a factor higher than one. GDP plays a smaller role, thus our model would project high primary energy demand growth also for relatively poor countries with high rates of population growth but low rates of GDP growth.

**Table 4:** Estimated Long–Run Coefficients

| | | Model | $\alpha$ | | $\beta_0$ | | $\beta_1$ | | $\beta_2$ | | $\beta_3$ | | $\beta_4$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | *E.LK* | -0.044 | *** | -11.923 | *** | | | 1.176 | *** | 0.293 | ** | | |
| 2 | W | *E.LKA* | -0.044 | *** | -10.987 | *** | | | 0.922 | *** | 0.493 | *** | -0.417 | * |
| 3 | | *E.YL* | -0.040 | *** | -11.432 | *** | 0.337 | ** | 1.099 | *** | | | | |
| 4 | | *E.LK* | -0.073 | *** | -16.492 | *** | | | 1.770 | ** | 0.295 | | | |
| 5 | WE | *E.LKA* | -0.075 | *** | -16.636 | *** | | | 1.612 | ** | 0.483 | ** | -0.365 | |
| 6 | | *E.YL* | -0.068 | *** | -16.913 | *** | 0.185 | | 1.998 | *** | | | | |
| 7 | | *E.LK* | -0.096 | *** | -20.552 | *** | | | 3.250 | *** | -0.580 | ** | | |
| 8 | EE | *E.LKA* | -0.077 | *** | -19.447 | *** | | | 3.050 | *** | -0.483 | | -0.640 | * |
| 9 | | *E.YL* | -0.065 | *** | -20.251 | *** | -1.047 | ** | 3.654 | *** | | | | |
| 10 | | *E.LK* | -0.185 | *** | -37.660 | ** | | | 5.116 | *** | -1.104 | ** | | |
| 11 | NA | *E.LKA* | -0.134 | ** | -33.242 | | | | 4.614 | * | -1.005 | | 0.084 | |
| 12 | | *E.YL* | -0.142 | *** | -18.828 | | -0.649 | | 2.960 | | | | | |
| 13 | | *E.LK* | -0.049 | *** | -15.489 | *** | | | 1.467 | ** | 0.425 | ** | | |
| 14 | AS | *E.LKA* | -0.053 | *** | -16.544 | *** | | | 1.497 | *** | 0.470 | ** | 0.018 | |
| 15 | | *E.YL* | -0.047 | *** | -14.437 | ** | 0.592 | ** | 1.175 | * | | | | |
| 16 | | *E.LK* | -0.063 | *** | -13.647 | * | | | 1.939 | *** | -0.206 | | | |
| 17 | SA | *E.LKA* | -0.072 | *** | -15.414 | ** | | | 2.136 | *** | -0.354 | | 0.916 | * |
| 18 | | *E.YL* | -0.093 | *** | -15.656 | *** | 0.401 | ** | 1.378 | *** | | | | |
| 19 | | *E.LK* | -0.087 | *** | 10.699 | | | | -1.978 | * | 1.015 | * | | |
| 20 | ME | *E.LKA* | -0.072 | *** | 15.707 | | | | -3.012 | | 1.552 | * | -0.907 | |
| 21 | | *E.YL* | -0.064 | * | 15.749 | | 0.570 | | -1.786 | | | | | |
| 22 | | *E.LK* | -0.042 | *** | -16.910 | *** | | | 1.544 | *** | 0.354 | * | | |
| 23 | L | *E.LKA* | -0.042 | *** | -17.844 | *** | | | 1.583 | ** | 0.406 | | -0.099 | |
| 24 | | *E.YL* | -0.041 | *** | -21.336 | *** | 0.589 | *** | 1.740 | *** | | | | |
| 25 | | *E.LK* | -0.016 | | -23.842 | | | | 6.155 | | -2.587 | | | |
| 26 | ML | *E.LKA* | -0.013 | | -30.948 | | | | 7.311 | | -3.143 | | 1.212 | |
| 27 | | *E.YL* | -0.027 | *** | -6.303 | *** | -0.264 | | 1.339 | *** | | | | |
| 28 | | *E.LK* | -0.049 | *** | -20.406 | ** | | | 2.482 | ** | 0.109 | | | |
| 29 | MH | *E.LKA* | -0.052 | *** | -19.178 | ** | | | 2.249 | ** | 0.229 | | -0.272 | |
| 30 | | *E.YL* | -0.047 | *** | -17.357 | ** | 0.155 | | 2.098 | * | | | | |
| 31 | | *E.LK* | -0.127 | *** | -1.889 | | | | -0.546 | | 0.981 | *** | | |
| 32 | H | *E.LKA* | -0.121 | *** | -2.949 | | | | -0.635 | | 1.216 | *** | -0.628 | |
| 33 | | *E.YL* | -0.104 | *** | 3.015 | | 1.064 | *** | -0.991 | * | | | | |

* Coefficients: $\beta_1$: Y, $\beta_2$: L, $\beta_3$: K, $\beta_4$: A. Regional Classification: Asia & Pacific (AS), Eastern Europe & Eurasia (EE), Middle East & Africa (ME), North America (NA), South America & Mexico (SA) and Western Europe (WE). GDPpc Groups: Low Income (L) [$\leq 10K\$$], Middle-low Income (ML) [$10K\$ - 20K\$$], Middle-high Income (MH) [$20K\$ - 35K\$$] and High Income (H) [$\geq 35K\$$]. Source: Own calculation. Significance levels: $\leq$ 10% ($*$), $\leq$ 5% ($**$) & $\leq$ 1% ($***$).

E.LKA is perhaps our most interesting model because it includes the total factor productivity variable ($A$), which is rarely examined in the literature. The basic premise that primary energy consumption will be mostly affected by population growth stays the same. However, we see a negative long–run relationship between total factor productivity and primary energy consumption. This implies that technological development (in energy efficiency) reduces energy consumption, but can also mean that richer economies move away from capital and labour intensive industries towards more knowledge based and less energy intensive sectors.

## 4.1 Worldwide differences in the Cointegrating Relation

To examine the possible differences arising from different geographic and historical background, we have constructed six groups of economies, on which we estimate the three basic error correction models. Four wealth categories have been built to account for the low, mid–low, mid–high and high real income per capita levels of the countries. Some geopolitical groups such as Western Europe, Eastern Europe & Eurasia, or South–Central America are fairly homogeneous with respect to the real income per capita levels, others regions like the Asia Pacific region and the Middle–East & North Africa region are much more mixed. The methodology is as described above, country fixed effects and time dummies are included in each group to control for the heterogeneity between the different countries.

First we investigate the West European relationships which shows similar results to the world model, with a significant and negative adjustment term, indicating an adjustment to the cointegration relationship. We find as expected a positive long–term relationship running from population as well as from capital accumulation, GDP to primary energy consumption. The cointegrating coefficient on the technology variable is negative as expected, although it is statistically not significant. The reaction of primary energy consumption to population growth is much higher than in the worldwide model, a result that originates from comparatively low population growth of the region. It is very interesting that while some countries like the United Kingdom, Germany, Sweden, or Denmark had a peak in energy consumption around the early 1990s and ever since strongly falling consumption levels, other countries, such as France, Spain, Italy, Greece, Portugal show continuous increases in primary energy consumption, while displaying similar development in real income or capital accumulation as Germany. The lower primary energy consumption pattern in the first group could be attributed partly to deindustrialisation in these countries, but also to massive improvements in energy efficiency.

The Eastern European and Eurasian cointegrating coefficients show different magnitude and directions than those of West Europe. Examining the period starting in the 1990s, the negative error correction term confirms the adjustment to the cointegrating relationship. We see a positive long–term relationship between population and primary energy consumption while the models indicate a negative relationship between real GDP or capital and energy consumption. We must be careful not to draw long–term conclusions from these results, as they reflect the turbulent transition period of the 1990s, with fluctuating GDP and capital stock data. The continuous increase in primary energy consumption up to 1990, was followed by a sharp decrease of almost 30% until the end of our observation period, accompanied by a slight population decrease in most countries. One explanation for the drop in primary energy consumption are the effects of market liberalisation. Energy was very cheaply available throughout the pre 1990s, mostly from the oil and gas rich countries of the Warsaw Pact. As the prices were regulated by the state, they would not follow the international price development and would if at all affect the economy through the supply side (Reynolds and Kolodziej (2008)). Next to the adjustment to market prices the region saw inevitable increases in energy efficiency, however the rate of technological improvement was not homogeneous across the countries. Deindustrialisation and the shift to less energy intensive sectors after the transition could also have contributed to the change of energy consumption patterns. The coefficient on the technology variable is negative and slightly significant, indicating increases in efficiency and a structural transition. The true extent and direction of the relationship would be visible only after a few decades at the present market or quasi–market conditions. As we have a very special region here, we cannot in any way generalise these findings, save to countries that would experience similar economic and structural transition.

The model results of the North American region of the United States and Canada are by no means easily interpretable. The adjustment parameter is negative and significant, indicating adjustment to the cointegrating relationship. Physical capital and real GDP however have an unexpected sign, that is not justified by the data, or by any structural development. Real GDP is not significant, capital is only significant in the E.LK model. One possible explanation for the findings of the model could be structural breaks caused by the the two oil crises of 1974&75, and 1979&80. It is also possible that the periodically opposite movement of the capital stock and energy consumption results in the negative relationship. [2]

The South and Central American data, to which group also Mexico was classified, give us the expected relationships for population and real GDP but not for capital or the technology variable. The adjustment parameter is negative and significant as expected, so is the coefficient of the population variable. We do not find the cointegrating coefficients on capital stock and the technology variable at 5% significant. It could be due to the fluctuating capital stock that the physical capital variable is insignificant and of the unexpected sign. The E.YL model, where all long–term coefficients are significant shows similarities to our worldwide model, indicating that a population increase of 1% would cause a 1.38% increase in energy consumption, while a 1% increase in real GDP would result in a 0.4% increase in primary energy consumption in the long term.

The Asia Pacific region includes both planned economies such as China, and market economies like Australia or Japan. The energy consumption increase is dominated by China, South-East Asia and India, whereas Japan, Australia and New Zealand had only modest increases in energy consumption. All models show an adjustment to the cointegrating relationship between energy consumption and population, real income and physical capital. The coefficient of technology variable has not the expected sign but it is also not significant. The region shows similar patterns of economic development, population growth and energy consumption regardless of the political and economic structures. While energy prices are regulated in China as they were regulated in the Soviet Union, in contrast to the USSR, energy consumption does react to the second oil crisis. This is possibly attributable to the fact that China is heavily dependent on energy imports of certain minerals, while the USSR was not.

The Middle East and Africa region is very heterogeneous and includes both some Middle

[2] We tested the models by excluding the years of the oil crises, however the results are not significantly different.

East and some African countries. Physical capital shows a positive relationship with energy consumption. Since for half of the dataset the time series only start in 1989, we have only an often turbulent time period to judge, therefore much caution is advised in this case.

## 4.2 GDP level differences in the Cointegrating Relation

Now, similarly let us turn to the different "wealth" groups, where countries were sorted based on their $GDP_{p.c.}$ levels as of 2009, seen in Table 1. One interesting finding is that in case of high GDP per capita level countries, the main driving force behind energy consumption becomes GDP or physical capital, the population variable becomes insignificant and has an unexpected sign. This implies that for rich countries, increases in energy consumption can be expected, even though the population is not expected to increase significantly. This could, but need not implicate evidence for a rebound effect in energy consumption.

An important topic is the often disputed question of the real income — energy nexus. As noted earlier, the major purpose of this paper is to identify the determinants of energy consumption, to be able to predict it later with the help of the different models. However, since most of the literature up to now was interested in the effect of energy consumption on economic growth, we have also looked at it in our panel setting. The method was the same as for energy consumption, the error correction models were normalised on economic growth ($\Delta logY$), the explaining variables in the error correction term were energy consumption, physical capital and labour. Interestingly, after the inclusion of country specific effects, we did not find a significant relationship running from energy consumption to GDP, that is a very surprising result at the moment. Energy would be only significant without the inclusion of country specific effects, which assumption is economically highly problematic. One possible explanation that energy has been, since the beginning of the Industrial Revolution readily available at a very low cost, and therefore constituted no significant constraint to economic growth. Stern and Kander (2011) simulate with CES functions the role of energy in determining output. They find that in case of energy services scarcity, output will be strongly constrained, with growth resulting in a Malthusian steady state. When energy services are however abundant, the economy exhibits the behaviour of a modern growth engine. Warr and Ayres (2006) come also to the conclusion that energy scarcity will drastically reduce economic growth in the near future. From our results it is however not possible to either support or refute these hypotheses. It is widely known that high oil prices have caused macroeconomic problems during the oil crises, however at the same time most of the notable technological improvements towards energy efficiency also arise from this period.

## 4.3 Model Averaging and Forecast Performance

Seeing the differing parameter results from our various models, the necessity of model evaluation and selection surfaced. Instead of choosing one single model to project primary energy consumption for the future, we turned to model averaging techniques, and attempted to prove that an averaged model will have a significantly better out-of-sample predicting ability than any single individual model. After extracting the squared forecast errors for one– to ten–step–ahead forecasts and the squared residuals for the Training Periods, the model weights were assigned based on the performance of these models. Table 5 shows the weights assigned to the different models in the different periods based on the forecasting errors ($\xi^2_{m,t+1}$) and the in–sample–fit of the models ($SSE$).

**Table 5:** Model Weights based on $\sum \xi^2$ and $SSE$ respectively

| | $w^{\xi}_{m,t+1}$ | $w^{\xi}_{m,t+2}$ | $w^{\xi}_{m,t+3}$ | $w^{\xi}_{m,t+4}$ | $w^{\xi}_{m,t+5}$ | $w^{\xi}_{m,t+6}$ | $w^{\xi}_{m,t+7}$ | $w^{\xi}_{m,t+8}$ | $w^{\xi}_{m,t+9}$ | $w^{\xi}_{m,t+10}$ | $w^{SSE}_{m}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $E.LKA_W$ | 0.118 | 0.123 | 0.125 | 0.125 | 0.125 | 0.124 | 0.124 | 0.124 | 0.124 | 0.125 | 0.106 |
| $E.LK_W$ | 0.117 | 0.119 | 0.122 | 0.124 | 0.125 | 0.128 | 0.131 | 0.135 | 0.138 | 0.143 | 0.107 |
| $E.YL_W$ | 0.116 | 0.116 | 0.114 | 0.110 | 0.105 | 0.101 | 0.097 | 0.095 | 0.093 | 0.093 | 0.107 |
| $E.LKA_R$ | 0.108 | 0.105 | 0.105 | 0.105 | 0.104 | 0.104 | 0.104 | 0.104 | 0.107 | 0.108 | 0.115 |
| $E.LK_R$ | 0.107 | 0.102 | 0.101 | 0.100 | 0.098 | 0.098 | 0.098 | 0.098 | 0.101 | 0.106 | 0.114 |
| $E.YL_R$ | 0.112 | 0.112 | 0.115 | 0.118 | 0.119 | 0.120 | 0.118 | 0.117 | 0.114 | 0.110 | 0.114 |
| $E.LKA_G$ | 0.107 | 0.110 | 0.108 | 0.108 | 0.110 | 0.110 | 0.110 | 0.108 | 0.105 | 0.100 | 0.112 |
| $E.LK_G$ | 0.107 | 0.105 | 0.104 | 0.104 | 0.106 | 0.108 | 0.110 | 0.109 | 0.108 | 0.106 | 0.112 |
| $E.YL_G$ | 0.108 | 0.108 | 0.106 | 0.106 | 0.106 | 0.107 | 0.109 | 0.110 | 0.110 | 0.108 | 0.112 |

Generally, the world models received the highest weights based on the forecast errors from the rolling out–of–sample forecasts, while the other models fared better when we took the in–sample performance. As next, we compared the out–of–sample forecast performance of the nine panel error correction models with the two average models in the Competition Period. The weights for the average models were assigned to the forecast errors of the different models. The corresponding results are found in Table 6.

**Table 6:** Forecast Errors in the Competition Period

| | $\sum \xi^2_{t+1}$ | $\sum \xi^2_{t+2}$ | $\sum \xi^2_{t+3}$ | $\sum \xi^2_{t+4}$ | $\sum \xi^2_{t+5}$ | $\sum \xi^2_{t+6}$ | $\sum \xi^2_{t+7}$ | $\sum \xi^2_{t+8}$ | $\sum \xi^2_{t+9}$ | $\sum \xi^2_{t+10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $E.LKA_W$ | 1.08 | 2.23 | 3.19 | 4.10 | 4.72 | 5.08 | 5.26 | 5.41 | 5.38 | 5.05 |
| $E.LK_W$ | 1.08 | 2.28 | 3.25 | 4.15 | 4.81 | 5.16 | 5.30 | 5.41 | 5.30 | 4.97 |
| $E.YL_W$ | 1.03 | 2.11 | 3.00 | 3.84 | 4.42 | 4.75 | 4.92 | 5.08 | 5.09 | 4.82 |
| $E.LKA_R$ | 1.12 | 2.39 | 3.51 | 4.54 | 5.36 | 5.86 | 6.04 | 6.08 | 5.87 | 5.34 |
| $E.LK_R$ | 1.10 | 2.33 | 3.36 | 4.29 | 5.04 | 5.48 | 5.61 | 5.62 | 5.36 | 4.86 |
| $E.YL_R$ | 1.06 | 2.21 | 3.22 | 4.19 | 4.94 | 5.48 | 5.81 | 6.03 | 6.01 | 5.55 |
| $E.LKA_G$ | 1.10 | 2.31 | 3.42 | 4.39 | 5.21 | 5.77 | 6.09 | 6.28 | 6.14 | 5.69 |
| $E.LK_G$ | 1.07 | 2.23 | 3.22 | 4.07 | 4.77 | 5.22 | 5.41 | 5.46 | 5.24 | 4.74 |
| $E.YL_G$ | 1.03 | 2.10 | 3.08 | 4.00 | 4.75 | 5.29 | 5.59 | 5.71 | 5.56 | 5.04 |
| $\text{MOD}^{SSE}_{AV}$ | 1.03 | 2.11 | 3.00 | 3.78 | 4.36 | 4.70 | 4.82 | 4.89 | 4.78 | 4.42 |
| $\text{MOD}^{\xi}_{AV}$ | 1.03 | 2.11 | 2.99 | 3.78 | 4.36 | 4.69 | 4.82 | 4.89 | 4.78 | 4.42 |

* $\sum \xi^2_{t+h}$ denotes the sum of squared forecast errors $\xi$, at the forecast horizon $h$. Source: Own calculation.

Starting with the 3rd step–ahead out–of–sample forecast values, we found that both average models outperform the individual models, until the end of the examined period. We used the Diebold and Mariano (1995) test to examine whether the results of our models are significantly different in predicting power form the average models. The null hypothesis states that the two forecasts have the same forecasting accuracy. The results of the Diebold-Mariano test can be found in Table 7. If we compare the results, we see that in general (but not for each period), the averaged models have a significantly better predicting ability.

**Table 7:** p-Values — Diebold–Mariano Test

| | $\sum\xi^2_{t+1}$ | $\sum\xi^2_{t+2}$ | $\sum\xi^2_{t+3}$ | $\sum\xi^2_{t+4}$ | $\sum\xi^2_{t+5}$ | $\sum\xi^2_{t+6}$ | $\sum\xi^2_{t+7}$ | $\sum\xi^2_{t+8}$ | $\sum\xi^2_{t+9}$ | $\sum\xi^2_{t+10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| AV Model$_{\xi}$ | | | | | | | | | | |
| $E.LKA_W$ | 0.44 | 0.02 | 0.06 | 0.06 | 0.11 | 0.18 | 0.20 | 0.19 | 0.16 | 0.19 |
| $E.LK_W$ | 0.38 | 0.01 | 0.05 | 0.06 | 0.08 | 0.14 | 0.20 | 0.21 | 0.25 | 0.28 |
| $E.YL_W$ | 0.94 | 0.93 | 0.97 | 0.75 | 0.82 | 0.84 | 0.74 | 0.58 | 0.40 | 0.29 |
| $E.LKA_R$ | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.03 | 0.08 | 0.14 |
| $E.LK_R$ | 0.23 | 0.00 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.07 | 0.20 | 0.34 |
| $E.YL_R$ | 0.57 | 0.18 | 0.18 | 0.16 | 0.19 | 0.18 | 0.15 | 0.12 | 0.07 | 0.03 |
| $E.LKA_G$ | 0.24 | 0.05 | 0.03 | 0.03 | 0.03 | 0.04 | 0.04 | 0.04 | 0.06 | 0.08 |
| $E.LK_G$ | 0.54 | 0.12 | 0.15 | 0.24 | 0.22 | 0.21 | 0.21 | 0.24 | 0.38 | 0.53 |
| $E.YL_G$ | 0.90 | 0.85 | 0.52 | 0.32 | 0.20 | 0.12 | 0.09 | 0.12 | 0.20 | 0.35 |
| AV Model$_{SSE}$ | | | | | | | | | | |
| $E.LKA_W$ | 0.44 | 0.03 | 0.08 | 0.07 | 0.13 | 0.20 | 0.22 | 0.20 | 0.17 | 0.20 |
| $E.LK_W$ | 0.38 | 0.01 | 0.05 | 0.07 | 0.10 | 0.15 | 0.22 | 0.23 | 0.26 | 0.30 |
| $E.YL_W$ | 0.95 | 0.94 | 0.98 | 0.75 | 0.83 | 0.86 | 0.76 | 0.59 | 0.41 | 0.30 |
| $E.LKA_R$ | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.03 | 0.08 | 0.14 |
| $E.LK_R$ | 0.23 | 0.00 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.08 | 0.19 | 0.33 |
| $E.YL_R$ | 0.56 | 0.18 | 0.18 | 0.16 | 0.19 | 0.18 | 0.15 | 0.12 | 0.07 | 0.02 |
| $E.LKA_G$ | 0.24 | 0.05 | 0.02 | 0.03 | 0.03 | 0.04 | 0.04 | 0.04 | 0.06 | 0.08 |
| $E.LK_G$ | 0.54 | 0.12 | 0.14 | 0.24 | 0.22 | 0.21 | 0.21 | 0.24 | 0.37 | 0.52 |
| $E.YL_G$ | 0.90 | 0.86 | 0.52 | 0.32 | 0.20 | 0.12 | 0.09 | 0.12 | 0.20 | 0.34 |

* Test specification: $S = \frac{1}{T_0}\sum_{t=t_0}^{T} d_t/\sqrt{\gamma_0 + 2\sum_{j=1}^{\infty} cov(d_t, d_{t-j})}$ (where $d = L(\xi^a_{t+h}) - L(\xi^b_{t+h})$). The probabilities were calculated assuming asymptotic normality. Source: Own calculation.

Looking at the averaged coefficients in Table8, we have to keep in mind that the coefficients on GDP, capital and technology are unexpectedly low, because of the three structural models averaged, GDP is only included in one model. Physical capital is present in two, while the total factor productivity in one model. Population is the only variable we included in estimating all three models. When a variable is not included in a structural model, the corresponding coefficients are automatically taken as zero for the purpose of model averaging. The parameters conditional on inclusion can be seen in the third and fourth row of Table 8. These estimates, obtained from the two model–averaging techniques, could be used thus to project worldwide primary energy consumption for future periods.

The main finding of this paper remains the same after taking model uncertainty into account, that population increase could be the major driver of energy consumption in the future, with income and capital playing a propelling but somewhat smaller role. Technology improvements will certainly contribute to the reduction of energy consumption levels.

**Table 8:** Coefficient Estimates obtained by Model Averaging

| | | Model | $\alpha$ | $\beta_0$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ |
|---|---|---|---|---|---|---|---|---|
| 1 | $\mathcal{M}$ | *SSE* | -0.057 | -13.295 | 0.128 | 1.390 | 0.167 | -0.061 |
| 2 | | $\xi$ | -0.057 | -13.163 | 0.120 | 1.364 | 0.184 | -0.075 |
| *Conditional on inclusion:* | | | | | | | | |
| 3 | $\mathcal{M}$ | *SSE* | -0.057 | -13.295 | 0.384 | 1.390 | 0.250 | -0.184 |
| 4 | | $\xi$ | -0.057 | -13.163 | 0.386 | 1.364 | 0.268 | -0.212 |

* Coefficients: $\beta_1$: Y, $\beta_2$: L, $\beta_3$: K, $\beta_4$: A. Source: Own calculation.

## 5 Conclusion and Policy Implications

Establishing the determinants of long-term primary energy consumption with high predictive long-term accuracy is a very challenging but crucially important task. We have, while seeing the inherent uncertainty connected to modelling in general, attempted to decrease it. To our knowledge, not only is this the largest panel cointegration study on the subject, but also no other study has applied model averaging techniques to a large number of panel error correction models before. This allows for considerable flexibility for policy makers, who can utilize both the regional and wealth level results of specific regions for future predictions, and also the optimal coefficient estimates, which we obtained by model averaging.

Although we find population and income to be the major drivers of energy consumption, examining the total factor productivity variable, we see that our world, but also the average models exhibit a negative and slightly significant relationship between energy use and technology. Implicitly, a higher technology component in economic growth reduces primary energy consumption. This might be attributable to the structure and development stage of the economies, to the higher efficiency in energy use by the industry and the households, as well as to the higher part of knowledge based and non–energy intensive production in GDP, including the de-industrialisation in developed countries.

Presently highly growing countries like India, China, the Caspian area and Africa will have to deal with the questions of infrastructure and industry expansion, therefore will experience enhanced energy needs. It is important that fast growing countries should anticipate increased energy demand, and implement energy efficient technologies from the beginning on. Therefore, it would be advisable to invest as much as possible in energy research at universities and research institutes or to support energy efficiencies at industry level.

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