Modelling Primary Energy Consumption under Model Uncertainty[*]

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Abstract

The causality between energy consumption and real income in developed countries has been a important research topic in recent years. Rising concerns about climate change and global warming increase the pressure on policy makers to take action against greenhouse gas emissions. Unfortunately these efforts coincide with one of the largest global economic recessions in the past century. Establishing the link between energy consumption and other key macroeconomic variables like real GDP, labour force, capital stock and technology thus currently appears to be a particularly relevant research effort. Deploying panel error correction models, we find that there is a positive cointegrating 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. In this area of the literature, uncertainty about the choice of a statistical model is rarely considered. Whenever one model is opted over reasonable alternative models to represent knowledge about a specific process, model uncertainty occurs. We argue that inference on the basis of a single model without taking model uncertainty into account can lead to biased conclusions. Consequently we tackle this problem by applying simple model–averaging techniques to commonly used panel cointegration models. We find that taking into account 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 other macroeconomic variables and a significantly increased out–of–sample forecast performance.

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1 Introduction

Despite of the growing number of studies, no consensus has been achieved on the direction and magnitude of the relationship between energy consumption and economic growth. The absence of any clear consensus according to Apergis and Payne (2009b) can be contributed to the heterogeneity in climate conditions, varying energy consumption patterns, the structure and stages of economic development within a country, as well as 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.

This paper models the components of long term primary energy consumption (E) with the help of vector error correction models, allowing for heterogeneity of geopolitical regions and for the differing $\text{GDP}_{p.c.}$ levels of a panel dataset of 64 countries over a time span of 45 years. We find that there is a positive cointegrating relationship running from physical capital (K), GDP (Y) and population (L) to primary energy consumption. There is a negative cointegrating relationship with the total factor productivity (A), meaning 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. 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.

In the next sections we are going to give a sort overview of the connected literature. Then we introduce our data and the underlying assumptions. We conduct panel unit root tests and a Pedroni cointegration test on our data, and estimate the cointegrating relationship with vector error correction models, allowing for different GDPpc and geopolitical models.

2 Literature

Most of the literature agrees that cointegration exists between economic growth and energy consumption. The population and physical capital variables are treated less frequently in the equations. Below is a limited review of the continuously growing literature on the subject, however with highly contradicting and mixed results. It is worth noting that most studies examine either individual countries, or employ a panel cointegration of certain geographical areas or organisational units. To the knowledge of the authors, up to now no panel study including 64 different countries have been made.

Kraft and Kraft (1978) provided the first significant study with a vector autoregressive model (VAR) finding the relationship running from income to energy consumption in the United States. Yu and Choi (1985) find the relationship also running from GDP to energy consumption. The results have been found spurious in later years. Stern (2000) establishes a cointegration relationship with Johansen trace cointegration test for the USA postwar period and finds that energy Granger causes GDP either unidirectionally or a through mutually causative relationship. Stern comes to the conclusion that energy is limiting factor to growth in the US macroeconomy. Oh and Lee (2004) extends the analysis of Stern, using the same variables. They test for cointegration with the Johansen, Juselius maximum likelihood estimate (MLE) and use a vector error correction models (VECM) instead of a VAR model, as the VAR model is misspecified in the presence of a cointegration. VAR models may indicate short term relationships as long term relationships are removed by first differencing. They find a long run bidirectional relationship between energy consumption and GDP. Soytas and Sari (2003) find bidirectional casualties 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. Lee and Chiu (2011) employ the Johansen cointegration technique to examine the relationship between nuclear energy consumption, oil prices and economic growth in six different but industrialised countries. They arrive to very mixed results, either GDP Granger causing nuclear energy consumption (Japan), or a bidirectional relationship (US, Canada, Germany), to no relationship at all (France, UK).

Warr and Ayres (2006) develop a Resource Exergy Service (REXS) forecasting model for assessing the impact of natural resource consumption and technological change on economic growth. They build in energy as a factor of production (LINEX production function), and model technology with a logistic function. They forecast a serious decline in GDP growth, caused by the decreasing of the energy intensity of output (dematerialisation), and forecast that serious improvements in energy efficiency (usage) must be reached to counteract this process. Ayres and Warr argue that capital/energy services are continuously replacing labor in the production process, causing higher unemployment and thus propose to transfer tax from labor to natural resource consumption.

Masih and Masih (1996) tested for cointegration in India, Pakistan, Malaysia, Singapore, Indonesia and in the Philippines. Using vector error correction models they find cointegrating relationships in case of India, Pakistan, and Indonesia. They find the causality running from energy to income in India, the opposite in Indonesia, and a mutual causality in Pakistan. Wolde-Rufael (2006) findings 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 labor and capital as additional variables, using a multivariate modified Granger causality analysis of Toda and Yamamoto. They find that in 15 countries capital and labor are the most important factors to output growth, while energy is comparatively not as important and only a contributing factor in case of eleven countries to output growth. Lee (2005) uses in his study a Pedroni cointegration and panel error correction models on 18 developing nations to find the long term relationship running from energy to GDP. He comes to the conclusion that energy conservation would harm economic growth in developing countries, and thus his results are similar to that of Masih and Masih (1998) and Asafu-Adjaye (2000). Apergis and Payne (2009b) using Pedroni cointegration and VECM for South American countries find that cointegration is present between RGDP, energy consumption, the labor 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 comes to find a bidirectional long run relationship between energy consumption and GDP, supporting the feedback hypothesis. Lee and Chien (2010) apply an aggregate production function to examine the dynamic linkages among energy consumption, capital stock, and real income (real GDP per capita) in G–7 counties. They find mixed results with the help of the Toda Yamamoto Granger causality tests, for the different countries.

Apart from those few studies described above further information can be found in the work of Narayan and Smyth (2008), Lee and Chang (2008), Squalli (2007), Asafu-Adjaye (2000), Fatai, Oxley, and Scrimgeour (2004) and Paul and Bhattacharya (2004).

3 Methodology

3.1 Unit Root and Cointegration Tests

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 are going to work with the Levin Lin Chu test (assuming a homogeneous autoregressive parameter (AP)), 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 AP), or test for stationarity 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, and more precisely on the alternatives allowing for a heterogeneous autoregressive parameter. 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.

The Levin–Lin Chu 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, we 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 (1999,2003), 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 and it builds upon the Fischer ρ–test (1932). The Fischer test “combines the observed significance levels (p–values) of the different tests, while the IPS test is based on combining the test statistics.”[1] If the test statistics are continuous, the significance levels $\Phi_i \quad (i = 1, 2, \dots N)$ are independent uniform variables and $-2log\Phi_i$ has a χ^2 (chi squared) distribution with two degrees of freedom. Maddala and Wu argue that the Fischer test does not have the limitations of the IPS. ”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. Also there is no restriction of the sample sizes for different samples.”[2]

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 (1999,2004) and Westerlund (2005) and the system tests of Larsson, Lyhagen, Löthrgen (2001) and the Breitung (2005) tests. All of these tests assume a cross sectionally independent panels. Hlouskova and Wagner test 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. Thus in accordance we have chosen the panel cointegration test by Pedroni (1999), which allows for testing for cointegration with multiple regressors. The

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[1] Maddala and Wu (1999).

[2] Maddala and Wu (1999).

Pedroni tests 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, although this cointegrating vector need not be the same for each member." (Pedroni 1999). Since the Pedroni test does not deal with the question of normalisation, it is expected that the researcher has a particular normalisation in mind.

According to Pedroni, 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 (Pedroni 1999).

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 test seems (whether ADF or ρ) seems to have a larger impact on the performance, then the dimension (between or within) of the test. The ADF tests of Pedroni have the highest power throughout, which is substantially larger than the power on the other tests in many cases".

Cross sectional correlation and additional cross unit cointegration are found by citeauthorhlouskova: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. Based on these results we take the results of the Pedroni ADF statistics to conclude that we can reject the null hypothesis of no cointegration, and treat the variables as cointegrated. The Pedroni tests do not, however give us the direction or magnitude of the cointegrating vectors.

3.2 Panel Cointegration Model

We have chosen to estimate the long term cointegrating relationship with the help of a panel error correction model. A classical autoregressive distributed lag (ADL) approach cannot be used, as we have found evidence of cross-cointegration between the explanatory I(1) variables (real GDP, capital, labor and technology).

Below you can see a small number of structural models with the highest plausibility, which have been selected from the array of all possible models. We estimate the cointegrating equation with full information maximum likelihood (FIML).

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

$$\begin{aligned}\Delta logE_{i,t} &= \alpha(logE_{i,t-1} - \beta_0 - \beta_1 logY_{i,t-1} - \beta_2 logL_{i,t-1}) \\ &\quad + \gamma_0 \Delta logE_{i,t-1} + \gamma_1 \Delta logY_{i,t-1} + \gamma_2 \Delta logL_{i,t-1} + \sum_{j=1}^{I} cD + \epsilon \end{aligned} \tag{1}$$

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

$$\begin{aligned} \Delta logE_{i,t} = \alpha(logE_{i,t-1} - \beta_0 - \beta_2 logL_{i,t-1} - \beta_3 logK_{i,t-1}) \\ + \gamma_0 \Delta logE_{i,t-1} + \gamma_2 \Delta logL_{i,t-1} + \gamma_3 \Delta logK_{i,t-1} + \sum_{j=1}^{I} cD + \epsilon \end{aligned} \tag{2}$$

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

$$\begin{aligned} \Delta logE_{i,t} = \alpha(logE_{i,t-1} - \beta_0 - \beta_2 logL_{i,t-1} - \beta_3 logK_{i,t-1} - \beta_4 logA_{i,t-1}) \\ + \gamma_0 \Delta logE_{i,t-1} + \gamma_2 \Delta logL_{i,t-1} + \gamma_3 \Delta logK_{i,t-1} + \gamma_4 \Delta logA_{i,t-1} + \sum_{j=1}^{I} cD + \epsilon \end{aligned} \tag{3}$$

Country effects (cD) and fixed effects for the different decades 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 control for 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 consists 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.

3.3 Model Averaging

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.

Based on our vector error correction models, we have created for each country 3×3 models, three structural models, referring to the composition of the vector 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 GDP$_{p.c.}$ models for the wealth levels of different countries as of 2009.

First, the nine VECM 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, taking the coefficients from our Training Sample I, for the period 1985—1997 (called Training Sample II). We forecasted this 13 year period, and extracted the logarithm of forecasted primary energy consumption. We saved the forecast errors $\xi = logPC - logPC_{FC}$, as the difference between the logarithm of primary energy consumption values and the forecasted values, receiving thus 13 period of forecast errors. Subsequently, we estimated the VECM coefficients until 1985 and performed the out–of–sample forecast until 1997, saving the forecast errors. This rolling loop was repeated until the window in Training Sample II was closed. We have received thus the forecast errors associated with the different models taking 13 different time setting into account. After compiling the data, we had now a number 13 of one step ahead forecast errors, 12 two step ahead forecast errors, 9 three step ahead forecast errors etc. for each single country.

Model averaging is performed in this paper, by running two separate weighting procedures. In the first procedure, we assigned weights based on the out–of–sample predicting ability. By taking

$$w^{\xi}_{m,h} = \frac{\sum \xi^2_{m,t+h}}{\sum_{m=1}^{M} \sum \xi^2_{m,t+h}} \tag{4}$$

which assigned higher weights to models where the sum of the squared forecast errors was lower. We have as next estimated an out–of–sample forecast for 1998—2009 (called Competition Period), after running the nine vector error correction models for the period 1965—1997, from which we fixed the coefficients. After calculating 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 an one–step–ahead forecast error for the year 2009 was derived.

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:

$$w^{SSE}_{m} = \frac{-\frac{k}{2} \cdot log(obs) - \frac{obs}{2} \cdot log(SSE)}{\sum_{m=1}^{M} -\frac{k}{2} \cdot log(obs) - \frac{obs}{2} \cdot log(SSE)} \tag{5}$$

which assigned highest weights to the models with the best in–sample fit. Again, we took the out of sample forecast estimates for the Competition Period 1998—2009, and assigned the weights based on the residuals from the Training Periods.

4 Data and variable descriptions

Our panel dataset ranges from 1965 to 2009 for 64 countries.[3] For the majority of the series 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 successor states of the ex Soviet Union, where data are only available starting from the early or mid 1990s.

Total primary energy consumption was taken from the *Statistical Review of World Energy* and is denoted in terms of MTOE[4] (million tons of oil equivalent). The BP statistics considers oil, gas, coal, nuclear, hydro energy usage. Total population and real GDP are taken from the Penn World Table 7.0 (Heston, Summers, and Aten (2011)).

We calculated the physical capital stock using the perpetual inventory method by Bernanke and Gurkaynak. As 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

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[3] Full list of the countries with their categorisation is found at the end of this paper.

[4] $1TOE = 41.868GJ$

average depreciation, which is uniformly assumed to be 6%.

$$K_i, 0 = \frac{I_{i,1}}{(g_{i,1} + \delta)} \tag{6}$$

Over a period of 40 year the capital stock converges to its present value, regardless of the starting capital stock. However, in case of the ex–Soviet member states, depending on the reported growth rates, which are often negative, and the investment ratio, we judged starting capital stock to be misleading. Therefore in case of high negative average growth rates, we substituted 2% for average growth rate which has been 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

$$K_{i,t} = K_{i,t-1}(1 - \delta) + I_{i,t} \tag{7}$$

To assure that we have sufficient number of observations in case of the ex–Soviet states, we used the first calculable capital stock without excluding any initial values. This was to ensure a sufficient number of time series observations for the panel cointegration.

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

$$Y = AK^{\alpha}L^{1-\alpha} \tag{8}$$

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

$$logA = logY - \alpha logK - (1 - \alpha)logL$$

Where logA denotes the relative magnitude of the part of economic growth not explained by the physical capital and labor components. We denote A as the technology component, it is driven however not only by the level of technology, but also by 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 long term 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. Energy prices show a significant heterogeneity on a regional level.

Since, as noted before, some of our dataset such as the Eastern Europe & Eurasia dataset, and some of the Middle East & Africa dataset 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.

5 Empirical results: Determinants of Primary Energy Consumption

We tested for the presence of a unit root in the main variables with the help the Levin–Lin–Chu test, Im–Pesaran–Shin test and the Fischer–ADF test, proposed by Maddala and Wu. The corresponding test statistics can be found in the Appendix (Tables 4 - 6). 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 determinist trend, logA is a unit root process with a drift and deterministic trend.

The existence of the cointegration relationship is ascertained by deploying the Pedroni cointegration test for panel data. We used the results of the panel ADF t–statistic and the panel Phillips–Perron (PP) t–statistic, both of which rejected the null hypothesis of no cointegration. The detailed Pedroni test statistics can be seen in the Appendix (Table 7).

We ran the three structural vector error correction models described earlier, normalised on the logarithm of primary energy consumption. The coefficients of the long term cointegrating relationship can be seen in Table 1

Looking at the data we see that the error correction adjustment parameter is always highly significant, and negative, meaning that the relationship tends to a long term equilibrium.

The population variable is always highly significant and takes on values between 0.92 to 1.17, implying a positive cointegrating relationship and that increases in energy consumption go hand in hand with population increase. As our dataset 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 sufficient and representative to capture the long term cointegrating effects. These results let us conclude that population growth will significantly increase worldwide energy needs.

The technology variable (A) is negatively cointegrated with energy consumption, a result that we have expected. One of the policy implications of the above findings is that countries with high population growth will have to put emphasis on —technology development, moving into less energy intensive and knowledge driven sectors. Both RGDP and Physical capital have a negative value in the error correction term and are significant at 5% level. This indicates a positive cointegrating relationship, with a coefficient value of 0.29 and 0.34, meaning a 1% increase in cumulated physical capital would increase energy consumption by 0.29%. If both capital and real GDP were included into the cointegrating equation GDP would become insignificant and negatively cointegrated with energy consumption. This could be attributed to high multicollinearity between capital accumulation and real GDP.

Energy consumption based on the E.LK model is mostly going to be driven 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. Economic growth plays a smaller role, which is a surprise, as 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 1: Estimated Long–Run Coefficients

		Model	α		β_0		β_1		β_2		β_3		β_4	
1	W	*E.LK*	-0.044	***	-11.923	***			1.176	***	0.293	**		
2		*E.LKA*	-0.044	***	-10.987	***			0.922	***	0.493	***	-0.417	*
3		*E.YL*	-0.040	***	-11.432	***	0.337	**	1.099	***				
4	WE	*E.LK*	-0.073	***	-16.492	***			1.770	**	0.295			
5		*E.LKA*	-0.075	***	-16.636	***			1.612	**	0.483	**	-0.365	
6		*E.YL*	-0.068	***	-16.913	***	0.185		1.998	***				
7	EE	*E.LK*	-0.096	***	-20.552	***			3.250	***	-0.580	**		
8		*E.LKA*	-0.077	***	-19.447	***			3.050	***	-0.483		-0.640	*
9		*E.YL*	-0.065	***	-20.251	***	-1.047	**	3.654	***				
10	NA	*E.LK*	-0.185	***	-37.660	**			5.116	****	-1.104	**		
11		*E.LKA*	-0.134	**	-33.242				4.614	*	-1.005		0.084	
12		*E.YL*	-0.142	***	-18.828		-0.649		2.960					
13	AS	*E.LK*	-0.049	***	-15.489	***			1.467	**	0.425	**		
14		*E.LKA*	-0.053	***	-16.544	***			1.497	***	0.470	**	0.018	
15		*E.YL*	-0.047	***	-14.437	**	0.592	**	1.175	*				
16	SA	*E.LK*	-0.063	***	-13.647	*			1.939	***	-0.206			
17		*E.LKA*	-0.072	***	-15.414	**			2.136	***	-0.354		0.916	*
18		*E.YL*	-0.093	***	-15.656	***	0.401	**	1.378	***				
19	ME	*E.LK*	-0.087	***	10.699				-1.978	*	1.015	*		
20		*E.LKA*	-0.072	***	15.707				-3.012		1.552	*	-0.907	
21		*E.YL*	-0.064	*	15.749		0.570		-1.786					
22	L	*E.LK*	-0.042	***	-16.910	***			1.544	***	0.354	*		
23		*E.LKA*	-0.042	***	-17.844	***			1.583	**	0.406		-0.099	
24		*E.YL*	-0.041	***	-21.336	***	0.589	***	1.740	***				
25	ML	*E.LK*	-0.016		-23.842				6.155		-2.587			
26		*E.LKA*	-0.013		-30.948				7.311		-3.143		1.212	
27		*E.YL*	-0.027	***	-6.303	***	-0.264		1.339	***				
28	MH	*E.LK*	-0.049	***	-20.406	**			2.482	**	0.109			
29		*E.LKA*	-0.052	***	-19.178	**			2.249	**	0.229		-0.272	
30		*E.YL*	-0.047	***	-17.357	**	0.155		2.098	*				
31	H	*E.LK*	-0.127	***	-1.889				-0.546		0.981	***		
32		*E.LKA*	-0.121	***	-2.949				-0.635		1.216	***	-0.628	
33		*E.YL*	-0.104	***	3.015		1.064	***	-0.991	*				

[*] Coefficients: β_1: Y, β_2: L, β_3: K, β_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). GDP 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, our most interesting model includes the technology variable A. The basic premise that primary energy consumption will be mostly affected by population growth stays the same. We see however that the technology variable is negatively cointegrated with energy consumption. The higher our total factor productivity (or the part of GDP growth not explained by capital and labor) the lower our energy consumption. This shows a technology effect, but can also mean that richer economies move away from more capital and labor intensive industries towards more knowledge based and less energy intensive sectors.

5.1 Worldwide differences in the Cointegrating Relation

To examine the possible differences arising from different geographic and historical background we have constructed six groups, where we test the three models. Four wealth cathegories have been built to account for the low, mid-low, mid-high and hight RGDPpc levels of the countries. Some geopolitical groups such as West Europe , East Europe & Eurasia, or South-Central America are fairly homogeneous with respect to the RGDPpc 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 shall look at the West European relationships which shows similar results to the general model, with a significant and negative adjustment term, indicating a cointegration relationship. We find as expected a positive cointegrating relationship between primary energy consumption and population growth as well as with capital accumulation and with GDP growth. The cointegrating term on the technology variable is negative as expected, although it is statistically not significant. The reaction of primary energy consumption on population growth is much higher than in the worldwide model, which is explained by looking at the increases in energy consumption and in population growth over the period. While total West European energy consumption increased with about 67% (from864 MTOE to 1450 MTOE), population growth was only 20% (340 million to 409 Million). 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 three to five fold increases in primary energy consumption, while showing a similar growth in real RGDP or capital accumulation as Germany.

Looking at the Eastern European and Eurasian numbers, the relationships show different magnitude and directions. While analysing these numbers we have to keep in mind that with the exception of Turkey, all of these countries were part of the Soviet Union or the Warsaw Pact, with different economic systems and development than West Europe. The question of data availability is also significant, as we have a full 45 year series only for Romania and Turkey, and out of our fifteen countries, more than ten have GDP and capital time series data only after 1990. Energy consumption and population data are available for longer periods.

Looking at our results we see a negative adjustment term, which confirms the cointegrating relationship. Population is significantly and positively correlated with energy consumption while real GDP or capital shows a negative cointegrating relationship. Looking at the energy consumption of the Eastern Block, we see a continuous increase in energy consumption up to 1990, then a sharp decrease of almost 30% until the end of our observation period We have also a slight population decrease in all countries except in Turkey, Turkmenistan and Uzbekistan. Most of the population increase in the period however comes from Turkey.

It is likely that the sharp drop in energy consumption comes from the liberalisation of the energy markets. Energy was very cheaply available throughout the pre 1990 period 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)). Any serious supply shortage is however not seen from our energy consumption data leading up to 1990. The decreasing energy consumption along with the decreasing population gives us a positive cointegrating relationship. When examining the RGDP and the capital stock data, it also becomes evident, that while there was a significant fall in RGDP during the transition period, economic growth recovered quickly. Both economic growth and capital accumulation show a positive trend starting from the late 1990s, causing a significant negative cointegrating relationship between energy consumption and these variables. We must be very careful however drawing any conclusion from this, as the relationship is more attributable to decreased energy demand due to the adjustment to the energy market prices, to a drastic increase in end energy efficiency, and to the shift away to less energy intensive sectors after the transition. The technology variable is negatively cointegrated and slightly significant, indicating the above efficiency and 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 make similar economic and structural transition.

Examining the North American region of the United States and Canada, the results are by no means easily interpretable, either in a panel set, or individually by the way of a Johansen cointegration. Looking purely at the numbers, we see that energy consumption , population, but also RGDP and growth were exhibiting a stable growth.

The adjustment parameter is large negative and significant, showing a cointegrating relationship. Physical capital and RGDP however have an unexpected prefix, that is not justified by the data, or any structural development, or characteristics. RGDP is not significant, capital is only significant in the ELK model. One possible explanation for the findings of the model could be the two oil crises of 1974&75, and 1979&80. Primary energy consumption shows a decline a cumulative 6,5% decline in 74&75 compared to 1973, before it starts rising again. Similarly we observe a 11% decline in primary energy consumption between 1980 and 1983, due to the second oil crisis, but also to the vast energy efficiency measures and market inventions resulting from the period. Real GDP dips slightly in 1974 and 1980, then is growing. Capital stock exhibits no negative trend over the period. It is possible that the two periods and the opposite movement of the capital stock and energy consumption cause the negative cointegrating relationship. We have two years with decreasing energy consumption afterwards, 2001 and 2009, the latter clearly attributable to the financial crisis. The aftermath of 9/11 along with the sluggish US economy could have caused a slight decrease in primary energy consumption in 2001. Capital stock increase was not affected. We tested the models by excluding the years of the oil crises, however the results are not significantly different.

The South and Central American data, to which group also Mexico was classified give us the expected relationships for population and RGDP but not for capital or the technology variable.

The adjustment parameter is negative and significant as expected, so is the population variable. We find the capital stock and the technology variable however highly questionable and at 5% none of them are significant. Energy consumption for the listed countries increased almost sixfold from 108 MTOE to 622 MTOE over the period of 45 years, while the population increase was 2,38 fold (203 million to 481 million). Both real GDP and capital data has increased on average between 4 to 6 fold, except for Peru, Chile and Ecuador, where due to the fluctuating GDP numbers, capital stock increase was much less over the period. It is due to this fluctuating capital stock that the physical capital variable is likely to be insignificant and of the unexpected sign. The last model (E.YL) is however significant, and is similar to our worldwide model, meaning a population increase of 1% would cause a 1.38% increase in energy consumption, while a 1% increase in RGDP would result in a 0.4% increase in primary energy consumption in the long term.

An exciting region is the Asia Pacific, as it includes both planned economies such as China, and market economies like Australia, or Japan. The energy consumption increase is dominated in real numbers by China and India. The group had an 8.7 fold increase in primary energy consumption over the period, with significant (up to 10 fold or more) increases coming from China, Hong Kong India, Indonesia, South Korea, Malaysia, Pakistan, Singapore and Thailand. Japan, Australia and New Zealand had with similar rates of population increase only modest increases in energy consumption. Real GDP and capital levels increased significantly, 10 to 15 times the starting values in 1965, population doubled from 1661 million to 3460 million. All models show a negative cointegrating relationship between energy consumption and population, RGDP and physical capital. The 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 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 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.

Another 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 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 similar to the finding of Wolde-Rufael (2006).

5.2 GDP level differences in the Cointegrating Relation

Now, similarly let us turn to the different "wealth" groups, where countries were sorted based on their $\mathrm{GDP}_{p.c.}$ levels as of 2009 (see Appendix, Table 3).

One interesting finding is, that in case of high GDPpc level countries, the main driving force behind energy consumption becomes GDP or physical capital, the population variable becomes insignificant and has the 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.

An important topic issue is the often disputed question of the economic growth – energy nexus. As noted earlier, the major purpose of this paper is to examine 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 on 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 dependent variable was economic growth ($\Delta logY$), the explaining variables in the error correction term were energy consumption, physical capital and labor. 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 is, 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 abundant, the economy exhibits the behaviour of a modern growth engine. Warr and Ayres 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.

5.3 Model Averaging and Forecast Performance

Seeing the differing parameter results from our various models, the necessity of model evaluation and selection surfaced.

After calculating 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 8 shows the weights assigned to the different models in the different periods based on the forecasting errors $\xi^2_{m,t+1}$ and the residuals SSE.

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 2.

Table 2: 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
MOD^{SSE}_{AV}	1.03	2.11	3.00	3.78	4.36	4.70	4.82	4.89	4.78	4.42
MOD^{ξ}_{AV}	1.03	2.11	2.99	3.78	4.36	4.69	4.82	4.89	4.78	4.42

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-Mariano 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 Appendix (Table 9 and 10). If we compare the results, we see that in general (but not for each period) the averaged models have a significantly better predicting ability.

6 Conclusion

In this paper we have looked at the long term relationship between primary energy consumption, GDP, physical capital, technology and population based on a panel dataset for 64 countries over 45 years. We have found that that primary energy consumption is positively cointegrated with population, GDP and physical capital, but negatively with the technology variable.

Examining the technology variable, we see that our world model exhibits a negative and slightly significant cointegrating relationship between energy consumption 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 households as well as to the higher part of knowledge based and non-energy intensive production in GDP. 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. Thus, 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. It is important that fast growing countries should anticipate increased energy needs, and implement energy efficient technologies from the beginning on.

The examined panel error correction models show significant differences in the long term coefficients, when controlling for geopolitics and varying wealth levels. We account for model uncertainty caused by the differences in the long term parameters by building two simple 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.

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Appendix

Table 3: Country Classification

	Country	1^{st} obs	Regions	$\text{GDP}_{p.c.}$ (2009)	GDP_{group}
1	Algeria	1965	ME	6076.33	L
2	Argentina	1965	SA	11959.85	LM
3	Australia	1965	AS	41293.94	H
4	Austria	1965	WE	37415.16	H
5	Azerbaijan	1996	EE	9618.98	L
6	Bangladesh	1965	AS	1397.32	L
7	Belarus	1997	EE	12782.00	LM
8	Belgium	1965	WE	34629.88	MH
9	Brazil	1965	SA	8162.99	L
10	Bulgaria	1973	EE	10922.52	LM
11	Canada	1965	NA	36234.51	H
12	Chile	1965	SA	12007.01	LM
13	China Version 1	1965	AS	7630.38	L
14	Colombia	1965	SA	7528.01	L
15	Czech Republic	1993	EE	21972.14	MH
16	Denmark	1965	WE	33931.78	MH
17	Ecuador	1965	SA	6170.90	L
18	Egypt	1965	ME	4956.72	L
19	Finland	1965	WE	32187.19	MH
20	France	1965	WE	30837.27	MH
21	Germany	1973	WE	32493.50	MH
22	Greece	1965	WE	27304.14	MH
23	Hong Kong	1965	AS	36297.04	H
24	Hungary	1971	EE	16521.37	LM
25	Iceland	1965	WE	37212.38	H
26	India	1965	AS	3238.41	L
27	Indonesia	1965	AS	4074.12	L
28	Iran	1965	ME	10622.12	LM
29	Ireland	1965	WE	33405.91	MH
30	Italy	1965	WE	27709.72	MH
31	Japan	1965	AS	30025.27	MH
32	Kazakhstan	1994	EE	11734.19	LM
33	Korea, Republic of	1965	AS	25052.58	MH
34	Kuwait	1989	ME	46756.46	H
35	Lithuania	1996	EE	14187.31	LM
36	Malaysia	1965	AS	11309.50	LM
37	Mexico	1965	SA	11633.15	LM
38	Netherlands	1965	WE	37052.19	H
39	New Zealand	1965	AS	27878.35	MH
40	Norway	1965	WE	49979.56	H
41	Pakistan	1965	AS	2353.11	L
42	Peru	1965	SA	7279.03	L
43	Philippines	1965	AS	2839.00	L
44	Poland	1973	EE	16375.87	LM
45	Portugal	1965	WE	19903.95	LM
46	Qatar	1989	ME	159246.88	H
47	Romania	1965	EE	9741.42	L
48	Russia	1993	EE	14644.75	LM
49	Saudi Arabia	1989	ME	21552.40	MH
50	Singapore	1965	AS	47329.09	H
51	Slovak Republic	1990	EE	19144.84	LM
52	South Africa	1965	ME	7587.59	L
53	Spain	1965	WE	27648.93	MH
54	Sweden	1965	WE	35246.42	H
55	Switzerland	1965	WE	39634.00	H
56	Thailand	1965	AS	7800.00	L
57	Turkey	1965	EE	9919.36	L
58	Turkmenistan	1996	EE	6934.92	L
59	Ukraine	1996	EE	6413.86	L
60	United Arab Emirates	1989	ME	52869.25	H
61	United Kingdom	1965	WE	33406.76	MH
62	United States	1965	NA	41143.93	H
63	Uzbekistan	1993	EE	2384.09	L
64	Venezuela	1965	SA	9123.44	L

[*] Regional Classification: Asia & Pacific (AS), Eastern Europe & Eurasia (EE), Middle East & Africa (ME), North America (NA), South America & Mexico (SA) and Western Europe (WE). GDP 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

Table 4: Unit Root Test Results — Levin-Lin-Chu Test

	Variable	lags	Model without α or δ_t	X	Model with α	X.1	Model with $\alpha + \delta_t$	X.2
1			statistics	prob.	statistics	prob.	statistics	prob.
2	logE	0	9.51145	1.00000	-13.00330	0.00000	-2.36212	0.00910
3		1	-18.59190	0.00000	-12.08320	0.00000	-12.54330	0.00000
4	logY	0	18.27510	1.00000	-8.90729	0.00000	-3.51120	0.00020
5		1	-15.33870	0.00000	-7.65853	0.00000	-4.63588	0.00000
6	logL	0	-1.15028	0.12500	-11.48040	0.00000	-6.03059	0.00000
7		1	-9.24682	0.00000	-2.14263	0.01610	-6.06629	0.00000
8	logA	0	10.55110	1.00000	-9.35295	0.00000	-0.57744	0.28180
9		1	-21.72620	0.00000	-10.49420	0.00000	-10.14430	0.00000
10	logK	0	8.86165	1.00000	-6.74069	0.00000	-8.49421	0.00000
11		1	-8.24533	0.00000	-3.13923	0.00080	-1.27233	0.10160

[*] H0: Existence of a Common Unit Root in the Series. User Specified Lags: 1. The probabilities were calculated assuming asymptotic normality. Source: Own calculation.

Table 5: Unit Root Test Results — Im-Pesaran-Shin (IPS) Test

	Variable	lags	Model with α	X	Model with $\alpha + \delta_t$	X.1
1			statistics	prob.	statistics	prob.
2	logE	0	-5.97780	0.0000	1.22547	0.8898
3		1	-17.13820	0.0000	-17.84800	0.0000
4	logY	0	1.51778	0.9355	-1.38402	0.0832
5		1	-16.40110	0.0000	-13.09920	0.0000
6	logL	0	-3.15763	0.0008	4.73374	1.0000
7		1	-3.28343	0.0005	-7.37387	0.0000
8	logA	0	-2.37371	0.0088	-0.52077	0.3013
9		1	-17.29060	0.0000	-14.67920	0.0000
10	logK	0	4.63761	1.0000	-1.48312	0.0690
11		1	-5.01166	0.0000	-4.13264	0.0000

[*] H0: Existence of a Unit Root in the Series . User Specified Lags: 1. The probabilities were calculated assuming asymptotic normality. Source: Own calculation.

Table 6: Unit Root Test Results — Fischer's ADF(Choi Z STAT) test

	Variable	lags	Model without α or δ_t	X	Model with α	X.1	Model with $\alpha + \delta_t$	X.2
1			statistics	prob.	statistics	prob.	statistics	prob.
2	logE	0	15.28990	1.0000	-6.11318	0.0000	1.12677	0.8701
3		1	-18.49990	0.0000	-16.64800	0.0000	-16.55220	0.0000
4	logY	0	21.81730	1.0000	1.24574	0.8936	-1.24405	0.1067
5		1	-14.13030	0.0000	-16.16910	0.0000	-12.77680	0.0000
6	logP	0	8.64210	1.0000	-3.10694	0.0009	4.55995	1.0000
7		1	-10.71930	0.0000	-3.11211	0.0009	-7.10434	0.0000
8	logA	0	14.39400	1.0000	-2.45686	0.0070	-0.75519	0.2251
9		1	-20.49830	0.0000	-17.10310	0.0000	-14.50220	0.0000
10	logK	0	13.30290	1.0000	4.33435	1.0000	-1.71567	0.0431
11		1	-6.07223	0.0000	-5.30844	0.0000	-4.64324	0.0000

[*] H0: Existence of a Common Unit Root in the Series. User Specified Lags: 1. Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality. Source: Own calculation.

Table 7: Pedroni Residual Cointegration Test

	Test	Statistic	Prob.	Weighted Statistic	Prob.
1	Panel v-Statistic	-1,159175	0.8768	-3,642482	0.9999
2	Panel rho-Statistic	3.615002	0.9998	3.015330	0.9987
3	Panel PP-Statistic	0.046351	0.5185	-3,937184	0.0000
4	Panel ADF-Statistic	1.135961	0.8720	-3,903896	0.0000

* Sample: 1965 2009. Included observations: 2880. Cross-sections included: 64. Null Hypothesis: No cointegration. Trend assumption: Deterministic intercept and trend. User-specified lag length: 1. Newey-West automatic bandwidth selection and Bartlett kernel. Alternative hypothesis: common AR coefs. (within-dimension) Source: Own calculation.

Table 8: 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

Table 9: p-Values — Diebold–Mariano Test — AV Model$_{\xi}$

	$\sum \xi^2_{t+1}$	$\sum \xi^2_{t+2}$	$\sum \xi^2_{t+3}$	$\sum \xi^2_{t+4}$	$\sum \xi^2_{t+5}$	$\sum \xi^2_{t+6}$	$\sum \xi^2_{t+7}$	$\sum \xi^2_{t+8}$	$\sum \xi^2_{t+9}$	$\sum \xi^2_{t+10}$
$E.LKA_W$	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

Table 10: p-Values — Diebold–Mariano Test — AV Model$_{SSE}$

	$\sum \xi^2_{t+1}$	$\sum \xi^2_{t+2}$	$\sum \xi^2_{t+3}$	$\sum \xi^2_{t+4}$	$\sum \xi^2_{t+5}$	$\sum \xi^2_{t+6}$	$\sum \xi^2_{t+7}$	$\sum \xi^2_{t+8}$	$\sum \xi^2_{t+9}$	$\sum \xi^2_{t+10}$
$E.LKA_W$	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