Primary Energy Use and Economic Growth in Sub-Saharan Africa: A Spatial Panel Data Approach

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Very Preliminary Version

Abstract

Primary energies being essentially endowments in natural resources, primary energy use is likely subject to spatial interactions among the neighbouring Sub-Saharan African countries engaged in regional cooperation, in economic integration processes and in competition. Consequently, stressing the existence of spatial spillovers while investigating the energy-economic growth nexus is the main focus of this paper. By testing for spatial dependence and estimating spatial regression models, we derive first empirical results supporting the existence of a strong link between energy consumption and income per capita. Furthermore, our findings highlight positive spatial externalities among neighbouring countries in primary energy consumption.

Keywords: Primary energy use, Income, Spatial effects, Sub-Saharan Africa

JEL Classification: C23, O55, Q43, Q56

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1. Introduction

In the last 50 years, the accelerated degradation of environmental quality associated with increases in human population have alarmed international organizations and scientists about the future of the planet. This explains the establishment in the 1950's of the International Union for Conservation of Nature (IUCN in 1948), of the Resources for the Future (RFF in 1952), and in the 1970's of the International Energy Agency (IEA in 1974) and the International Association for Energy Economics (IAEE in 1977), accompanied by several international agreements on environmental resources management. Thus, following the founding works by Barnett and Morse (1963) and Kraft and Kraft (1978) and recently by Shafik and Bandyopadhyay (1992) and Grossman and Kruger (1993, 1995), more attention is being given to the economic origins of environmental degradations. Thereby, researchers using different theoretical approaches introduced environmental issues such as gas emissions, deforestation, biodiversity loss and energy consumption into economic analysis.

Studies on the economic growth and energy consumption nexus represent a significant part of the existing evidences in energy economics, also characterized by a huge disparities in results and in technical approaches. For a first group of researcher, it is a causality analysis. Considering energy to be an input in production activities, the quantity of energy used reversely depends on income level.[1] For a second group, the aim in studying the link between income level and energy is not only to carry out the direction of causalities. It is also to work out the social and economic determinants of energy consumption and furthermore to question the existence of an Environmental Kuznets Curve (EKC). The existence of such an EKC suggesting that related environmental issues, gas emissions for instance, likely reverse their curses in the process of development. This perspective is animated by researchers such as Akarca et Long (1979), Gallet and List (1999), Nguyen-Van (2010), Antonakakis et al. (2016), Dogan and Turkekul (2016) among others. This literature on the linearity in energy consumption globally concluded for a positive upward trend and has worked out further determinants of energy consumption, and among these, employment, trade, population size, and urbanization.

Substantial contributions to the literature on energy and income has been focused on the spe-

[1] This literature is dominated by the contribution of Glasure and Lee (1998), Asafu-Adjaye (2000), Soytas and Sari (2003), Altinay and Karagol (2004), Lee (2005, 2006), Lee and Chang (2007) and Huang et al. (2008) among others. Extensive reviews of the causality analyses are proposed by Lee (2005), Huang et al. (2008) and Omri (2015)

cific case of African countries, where several researchers worked out the causality and long-run relationship between energy and income. The corresponding empirical evidences as expected do not contrast with the previous one in terms of disparities. At country-level for example, the results by Odhiambo (2009b) confirm the existence of a stable long-run relationship with a unilateral causality from energy to economic growth in Tanzania, while in South Africa they suggest a bidirectional causality (Odhiambo (2009a)). The evidences conclusions by Ebohon (1996), Wolde-Rufael (2009) and Esso (2010) respectively sustain this bidirectional causality in Nigeria and Tanzania, in Algeria, Benin, and South Africa and in Côte d'Ivoire. Akinlo (2008) also provided 11 country-level analyses, suggesting a bidirectional causality only in Gambia, Ghana and Senegal whilst no-causality has been observed in Cameroon, Cote D'Ivoire, Nigeria, Kenya and Togo. At a regional level and using panel data specification, Ouedraogo (2013) globally concluded for a long-run and causal relationship between energy consumption and economic growth in the 15 countries of the West African Economic Community (ECOWAS), with the causality running from GDP to energy consumption. Beside this causality analysis, researchers have also tackled different aspects of the topic. Thus, Kebede et al. (2010) worked out the regional differences in energy demand, while Grosset and Nguyen-Van (2016) concluded for a very heterogeneous relationship between income and energy use in Sub-Saharan African countries. For their part, Wesseh and Lin (2016) pointed out that capital, labor, renewable and nonrenewable energy are significant drivers for income level in African countries and questioned further the future of renewable energy use in African development processes. As being low-income countries and hence at a pre-industrial phase of their development process, questions regarding the future of renewable energy and primary energy use in Africa seems very pertinent.

Considering primary energy use as an indicator for energy consumption,[2] this paper aims to investigate its link to income per capita in Sub-Saharan Africa accounting for spatial interactions. Thereby, we argue that primary energies being essentially crude oil, coal and natural gas, thus natural resources, endowments in energy and primary energy use are both likely subject to geographical externalities among neighbouring countries. Therefore, this investigation controls for the spatial aspect and innovates in proposing a spatial study of the energy-income

[2]Biomass energies representing almost 80% of energy use in Africa (see Kebede et al. 2010 pp. 533). Hence, using primary energy use as proxies for total energy consumption in Africa also seems reliable

nexus. To our knowledge, there were few studies analysing the link of energy to economic growth using spatial methods and we intend to fill that gap. Furthermore in recent years, Sub-Saharan African countries are being classified among the fastest growing economies, denoting the take-off of economic activities and consequently an increase of energies consumption in countries such as South Africa, Gabon, Tanzania and Cameroon. This suggests a concentration of energy use in countries with relatively high income level and raises several questions regarding regional competition in resources exploitation, future demand for energy and its renewable structure and also about the existence of regional spillovers in energy use.

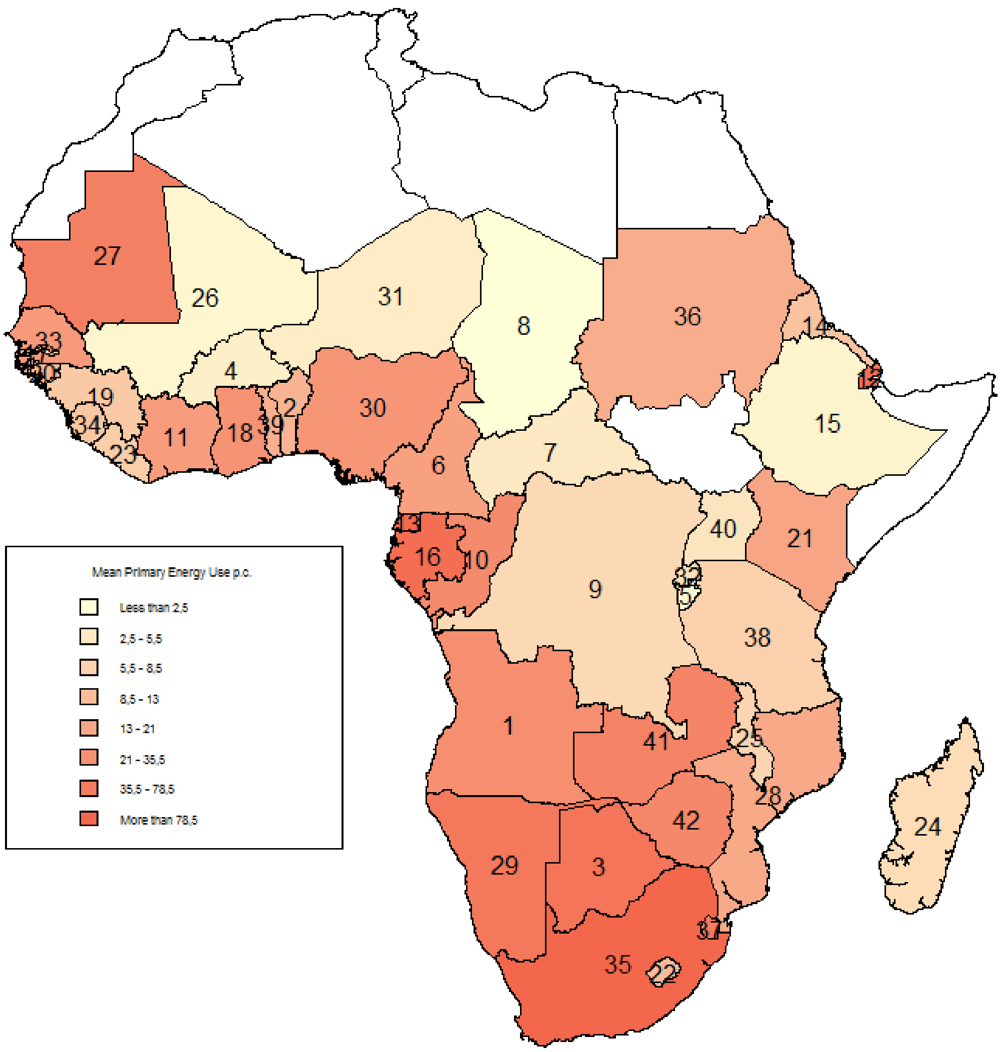

Figure 1: Map of mean primary energy use per capita, in thousandth of Kilojoule

Looking at the map[3] from the south to the north, it globally appears that countries with the

[3]Due to missing values, countries in gray have been excluded from the sample. For identification:Angola 1, Benin 2, Botswana 3, Burkina Faso 4, Burundi 5, Cameroon 6, Central African Republic 7, Chad 8, Congo,

lowest intensity in energy use per capita such as Chad, Democratic Republic of the Congo, Mali, and Ethiopia are surrounded by countries with a higher level of primary energy use and inversely for countries with a high level in Energy use. If geographical spillovers there are, the positive or negative nature of such spillovers seems as well to be important. Exploiting spatial regression techniques, this paper intends to test the existence of spatial effects and to help predict the near future of primary energy use in Sub Saharan Africa countries, when urbanization, industrialization processes, and sustained growth will really take off.

The remaining of this paper is organized as follows. In Section 2, we present the data we use in the empirical analysis. Section 3 describes comprehensively the main econometric approach in estimating regression models relating energy consumption to income per capita. Section 4 exposes and summarizes the results of our empirical analysis and in Section 5 and 6, we respectively check our results for robustness and draw some conclusions.

2. Data and descriptive statistics

The series on economic production, on trade, on populations dynamics and on institutional framework we intend to use in this analysis have been essentially gathered from the World Development Indicator and from Aggregate Governance Indicators of the World Bank, while the data on primary energy consumption are from the U.S. Energy Information Administration (u.s. EIA). Due to the unavailability of economic data for Somalia and South-Sudan[4], the sample is reduced to 42 Sub-Saharan African countries, observed between 1990 and 2013. The main economic indicators are GDP per capita evaluated in PPP (constant 2011 international USD), the share of trade, agriculture and industry sectors in GDP, and the rents of natural resources exploitation. As indicator of energy use, we consider the total primary energy consumption expressed in kilojoule per capita.

It is to admit that such a synthetic measure of energy consumption, corresponding to the quantity of row energy used, does not provide any information concerning its composition

Dem. Rep. 9, Congo, Rep. 10, Cote d'Ivoire 11, Djibouti 12, Equatorial Guinea 13, Eritrea 14, Ethiopia 15, Gabon 16, Gambia 17, Ghana 18, Guinea 19, Guinea-Bissau 20,Kenya 21, Lesotho 22,Liberia 23, Madagascar 24, Malawi 25, Mali 26, Mauritania 27, Mozambique 28, Namibia 29, Nigeria 30, Niger 31, Rwanda 32, Senegal 33, Sierra Leone 34, South Africa 35, Swaziland 36, Tanzania 37, Togo 38, Uganda 39, Zambia 40, Zimbabwe 41, Sudan 42.

[4] Although we have the data on primary energy use, economic series are not available for the period.

neither on its renewable structure.[5] Figure 1 helps identify Gabon, South-Africa, Nigeria, and Djibouti as countries with the highest intensities in primary energy use per capita and respectively Chad, Mali and Ethiopia as presenting the lowest levels. Table 1 reports descriptive statistics of our main series. Considering income per capita, the highest values are observed in Equatorial Guinea, Gabon, South Africa and in Botswana, which also show a high level in energy consumption. To capture the effects of economic sectors in energy consumption, we intend to introduce into the model control variables such as the added values of agriculture and of industry and series on exportations and trade. The latter represents the sum of exportations and importations of goods and services and it is expressed as a GDP share. Population dynamics are captured by the share of urban population and population density. The highest levels in population density, 449.05 and 189.747/km^2, are observed in Rwanda and Nigeria and the highest population growth rates are observed in Rwanda and in Liberia (in 1998).

Table 1: **Descriptive Statistics of the main variables**

Variables	Units	Mean	S.D	Min	Max	N. Obs.
GDP p.c. PPP 2011	USD	3362.15	5431.03	246.67	50640.18	1008
log GDP p.c	USD	7.60	0.89	5.51	10.83	1008
log Energy use p.c.	Kjoule	15.35	1.20	12.61	18.62	1008
FDI, net Inflows	% GDP	4.25	10.58	-82.89	161.82	1008
Agriculture, A.V.	% GDP	28.06	17.02	0.89	78.65	1008
Industry, A.V.	% GDP	27.26	15.80	3.33	84.28	1008
Trade	% GDP	75.08	49.57	11.09	531.70	1008
Exports	% GDP	30.83	19.73	3.33	124.40	1008
Urban Pop	% of Pop	34.89	16.14	5.42	86.66	1008
Pop Density	Count/km^2	57.26	70.44	1.72	449.10	1008
Rents of nat. res.	% GDP	14.96	14.56	.37	89.00	1008
Forest rents	% GDP	7.81	8.63	.27	74.73	1008
Institutions	index	-0.73	.57	-2.20	.84	1008

Note: The entire sample includes $N = 42$ Sub-Sahara countries observed between 1990-2013, $T = 24$ periods, thus 1008 observations.

Table 1 also includes series on natural resources and forest rents evaluated in GDP share and further series on institutions. The series on institutions are actually the arithmetic mean of the six Worldwide Governance Indicators[6] and are between -2.5 and 2.5, high values corresponding to good institutions.

[5]Nevertheless series on the share of renewable energy in total energy consumption provide some information about the regional distribution in renewable energy use: the highest share (98.34%) and lowest share (15.92%) being respectively observed in democratic republic Congo and South Africa

[6]See Kaufmann and Kraay (2009), for further description. Series downloaded on March 12, 2017

In addition to Table 1, we plot the variable primary energy against income per capita, in order to have a first look at its behaviour to changes in income per capita. The plot broadly shows a relatively clear and positive link between income per capita and primary energy consumption although for countries with a log-GDP per capita below 7 USD a fair positive relationship between income per capita and energy use is not easily perceptible.

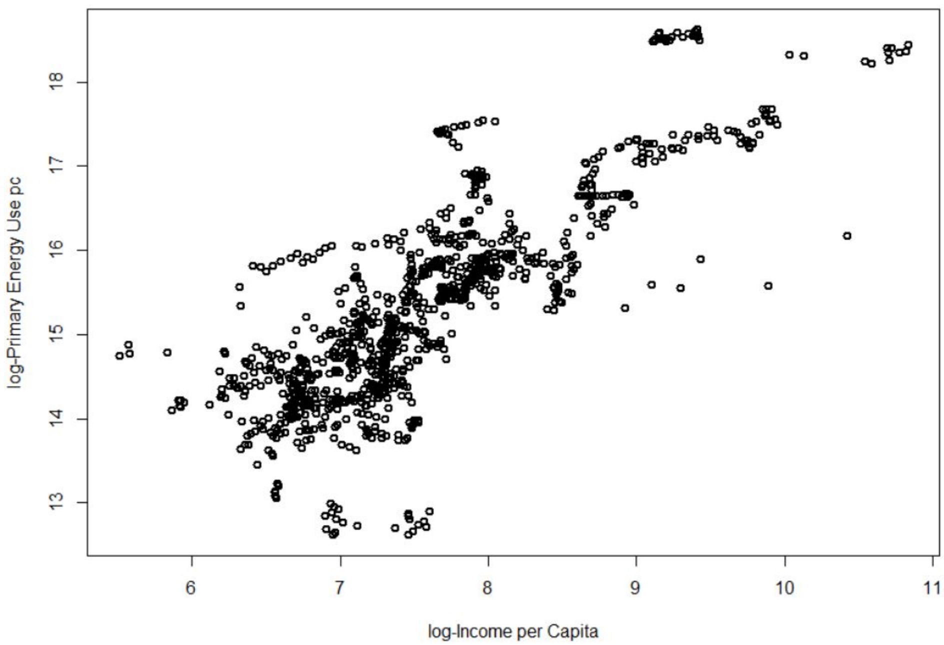

Figure 2: Scatter plot of the link between energy consumption and income per capita

3. Econometric model

Panel data models relating a measure of environmental quality to economic and social indicators generally start from the following form, where the error terms (ε_{it}) are assumed to be independent of the vector of regressors (x_{it}) and y_{it} being the environmental indicator.

$$y_{it} = x_{it}\beta + \mu_i + \varepsilon_{it}, \quad E(\varepsilon|X) = 0 \tag{1}$$

In the presence of spatial dependences or spatial effects, the assumptions made on the disturbance ε_{it} are not fulfilled, leading to biased estimators. Econometric texts, such Anselin (2013), Anselin and Arribas-Bel (2013), Arbia (2006, 2014), Baltagi (2003), and LeSage and Pace (2009) to cite few, argue for the use of spatial regression methods, as the latter exploit the set of information relative to the location where the facts are observed as well as the possible links of proximity between observations. Working with series on primary energy use,[7] thus essentially raw energies, we assert that the observations are processes with possible geographical characteristics and spillovers. This motivates the use of spatial regression techniques, controlling for time-invariant and specific spatial spillovers, whose omission could bias the estimates.

Considering $W_{n\times n}$ to be a *connectivity matrix (row-standardized weights matrix)*, the most general form of the spatial panel data model corresponding to (1) is:

$$y_{it} = \mu_i + \rho W y_{it} + W x_{it}\beta_w + x_{it}\beta + \varepsilon_{it}, \qquad |\rho| < 1 \tag{2}$$

$$\varepsilon_{it} = \delta W \varepsilon_{it} + \epsilon_{it} \quad and \;\; E(\epsilon|x) = 0, \qquad |\delta| < 1 \tag{3}$$

with ρ, δ, β_w and β being the parameters to be estimated.[8] In this formulation, the term Wy stands for the spatial endogenous effects and technically represents in our context the average primary energy use in the neighbouring countries while $W\varepsilon$ and Wx respectively stand for the residuals spatial heterogeneity and the spatial lag of the vector of regressors.

In the latter model, the interpretable spatial parameter ρ technically captures the strength of spatial dependence of neighbouring countries, if spatial effects there are in primary energy use. When models comparison tests (F-test or Wald-test) suggest excluding the regressors' spatial lag, Wx, (2) becomes a model combining only a spatial autoregressive model (SAR) with spatially autocorrelated disturbances (SEM).[9] In that case and assuming $A = (I - \rho W)$ and $B = (I - \delta W)$ to be invertible, (2) and (3) can be rewritten as:

$$y_{it} = A^{-1}\mu_i + A^{-1}x_{it}\beta + A^{-1}\varepsilon_{it} \;\text{ and }\; \varepsilon_{it} = B^{-1}\epsilon_{it} \;\text{ with }\; E(\epsilon|x) = 0 \tag{4}$$

The regression model (4) is the specification we use estimating a model relating energy use to income per capita and several other regressors. Estimating ρ, δ, and the vector of parameters β, in fixed and random-effects SARAR(1,1) model, researchers such as Elhorst (2003, 2009), Baltagi et al. (2003, 2007), Kelejian and Prucha (1999) and Kapoor et al. (2007) propose a maximum likelihood (ML) procedure based on several estimation steps and a generalized moment method.[10] Discussing these estimation strategies, Yu et al. (2008) and Debarsy and

[7]"Energy that have not been subject to any conversion process", Glossary of Environment Statistics

[8]This is the general form of SARAR model (see Arbia, 2014, pp.55) and specification tests help find the appropriate form of the model to be estimated. (2) and (3) also consider fixed effects for individuals and assume spatial autocorrelation only in the idiosyncratic term. A model where both the error terms and individual effects are spatially correlated is also feasible, see Kapoor et al. (2007).

[9]In that case, the equations (2) take the form: $y_{it} = \mu_i + \rho W y_{it} + x_{it}\beta + \varepsilon_{it}$ and (3) remains unchanged.

[10]A very comprehensive presentation of this procedure is resented by Milo and Piras (2012).

Ertur (2010), noticed that they provide consistent estimates of the parameters but not of the variance of the disturbance for small T and large N. Nevertheless, in our case with $N = 42$ and $T = 24$, we rely on these ML estimation procedures.

4. Estimation and Results

Before applying spatial data analysis methods to our panel data, some prior tests helping correctly specify the SARAR(1,1)-model are important. This is firstly testing whether a random-effects modelling matches the observations better than fixed-effects and secondly checking the presence of spatial effects among our data. Performing the latter tests and the spatial regressions which stem from them, it is important to note that in all this Section we use a common borders-based spatial matrix, WII (see Table B-1, in Appendix B).

4.1. Testing and modelling standard fixed effects

Considering a panel regression model, $y_{it} = X_{it}\beta + \mu_i + \varepsilon_{it}$ with $\varepsilon|X \sim N(0, \sigma^2 I)$, a random effects modelling assumes the individual unobserved heterogeneity μ_i, to be independent on the regressors, X, $(E(\mu_i|X) = 0)$, while the fixed-effects model assumes the exact opposite. Econometric texts suggest the Hausman-test to deal with this choice issue and we perform the latter using four different standard fixed and random-effects specifications. The test results (Table A-1, in Appendix A) point to the alternative hypothesis, indicating that a fixed-effects model-ling should consistently match the data.

Using then a standard fixed-effects modelling, we naively analyse the economic determinants of primary energy use in Sub-Saharan Africa, regressing models explaining primary energy use by income per capita. Thus, starting from a simple specification (model I), we consecutively introduce control variables into the model. Table A-2 (in Appendix A) summarizes the results of this primer regression analysis. Observing these results, it appears that income per capita positively affects primary energy use, confirming our guess based on figure 2. In addition, the GDP share of industry, urban population, and exportations positively affect energy use. A negative link appears between primary energy and population density which at a first look seems counter-intuitive. More concretely, it indicates that in presence of human pressure or of population growth less primary energies are used in per capita (and not globally). Possibly, alternative energies are consumed to compensate increases in demand for energy.

This primer econometric analysis albeit full of insights likely suffers from several statistical problems, from endogeneity at least. Furthermore, it does not account for possible spatial correlations. As we argue that environmental phenomenon, including primary energy consumption, have spatial aspects, we test the existence of spatial effects and re-estimate the parameters of the models, also solving for endogeneity in GDP per capita.

4.2. Testing the presence of spatial effects in fixed-effects models

Testing for spatial dependence in energy use and for spatial error dependence is an important step in applying spatial regression methods. Thus, to learn more on the data generating process and to avoid model misspecification, we first consider and perform tests for spatial effects in the 24 yearly waves of our panel dataset. Doing that, the standard approach (Anselin (2013), Arbia (2014)) starts by testing spatial lag dependence in the endogenous variable and also for spatial effects in residuals. We follow this approach for each yearly wave, testing for the presence of spatial lag dependence in primary energy use.

The test results for spatial lag in the 24 waves (in Appendix B-3) show some evidences of spatial lag dependence, suggesting that using primary energy as dependent variable in a regression model, a spatial lag term could be included among the regressors. Beside this cross-sectional spatial tests, we re-investigate the presence of spatial effects considering the panel aspect of the dataset. Thus, we applied the Lagrange Multiplier (LM) test proposed by Baltagi et al. (2003, 2007) and by Anselin et al. (2013) to our panel dataset which helps find out, modelling spatial fixed-effects, the type of spatial model that suits the data. More compactly, this Lagrange Multiplier (LM) approach permits to test for both spatial lag and spatial error dependence in panel data models. Doing this, we use the same models I-IV as in Table A-2 and test for both spatial effects. The results of theses tests are presented in Table 2. Analysing the latter, it clearly appears that the panel data based LM-tests for spatial dependences confirm the indications of the cross-country or wave tests, suggesting a spatial lag modelling. Furthermore, the tests for different models strongly suggest to account for spatial heterogeneity in residuals (see Table 2^b).

4.3. Spatial Hausman and Wald-tests

The tests performed previously suggest a fixed-effects modelling and moreover indicate the presence of spatial lag in primary energy use and of spatial heterogeneity in residuals. Now that we account for both spatial effects, we conduct a spatial Hausman test and then inspect whether the model should contain the spatial lag of the regressors, Wx. The results of the former tests sustain the fixed effects modelling (see Table 2^c), as the reported p-values for model I-IV all reject the null-hypothesis.

In Table 2^d, we report tests comparing a FE-SARAR models to so-called augmented models, which include the spatial lag of regressors, Wx. Thereby, we precisely test the joint significance of the regressors' spatial lag introduced into the models I-IV. The test statistics for the four different models suggest a non-rejection of the null-hypothesis, indicating that the spatial lag of the regressors does not significantly contribute to the goodness of fit. Estimating finally the spatial models relating primary energy use to income per capita and further regressors, we apply Maximum Likelihood (LM) techniques to the specification presented in (4).

4.4. Estimating spatial fixed-effects models for energy use

Table 2^a presents the results of estimating the FE-SARAR models for primary energy use, combining maximum likelihood techniques with instrumental variable methods. For this, we use for the first stage the one period lagged-GDP per-capita as instrument for GDP per-capita.[11] At the second stage, a two-step ML approach following Baltagi et al. (2007) and Millo and Piras (2012) helps estimate the parameters of the models.

The spatial lag of the dependent variable Wy reflects spatial interactions and more precisely spillovers from the neighbouring countries in primary energy use. Relatively to the spatial error term $W\varepsilon$, its parameter depending on the nature of the weight matrix is easily interpretable. Analysing the estimated parameters, $\hat{\rho}$ and $\hat{\delta}$, it seems that the specification suggested by the LM-tests holds, as both spatial effects are statistically significant. Nevertheless, it is important to point out that as spatial analyses highly depend on the type of connectivity, interpreting the results should be carefully done, as it depends on the type of weighing matrix used.

The connectivity matrix we use for this spatial regression analysis (Appendix B, Tables B-2), is a simple border-based weight matrix and it indicates whether countries share a common boundary or not. Its main advantage remains in easing results interpretation. In our cases, the spatial parameter depicts how primary energy use in the neighbouring countries meanly affects a country's own level of energy use. Moreover in Table 2, the sign of $\hat{\rho}$ implies the existence of

[11] The lagged GDP per capita, with a correlation coefficient around 0.96, seems to be a very good instrument.

positive externalities in primary energy use in Sub-Saharan Africa. Such a result suggests that on average a country i's own level of primary energy use positively depends on those in the neighbouring countries. More precisely, it suggests that a 1% increase in energy use per-capita in the neighbouring countries increases a country i's level in energy consumption by 0.17%. This apparently surprising result can be defended by observing in Figure 1 that each energy poor economy is surrounded by more energy intense ones than inversely.

Apart from the spatial effects, the estimated parameters of the vector of regressors delivers very interesting results. The literature on energy use and economic growth, despite the non-unanimity regarding the direction of the causality, has shaded light on the existence of a significant link between economic activities and energy use. The results of our standard FE models and those of the FE-SARAR models support this commonly-known energy-income link, in addition to carry out the existence of spatial effects in energy use.

Demographic dynamics captured by population density and by the share of urban population produce divergent results. The former is negatively related to primary energy consumption while the latter is positively linked to it. This negative link to primary energy use per capita, previously suggested by the standard fixed-effects models, seems understandable, as in contrary to changes in urban population, increases in total population, as well as in population density, should be diluting energy consumption measured in per capita. Indeed, increases in total population, thus in population density, lead to increases in demand for energy and possibly to alternative energies use. This logically reduces primary energy use per-capita, but not necessarily if deemed globally at country-level.

Further control variables have been introduced into the models and among these, the GDP shares of agriculture and industry. The estimated parameters hint that production in the industry sector significantly consumes primary energies. Regarding trade and exportations shares in GDP, the former negatively affects energy use but seems less instructive as the series on trade are concretely the sum of a country's exportations and importations of goods and services over GDP. The export parameters clarify things by showing a steady positive and significant link to primary energy use. The rents of natural resources present a similar positive results whilst the indicator of institutional quality and the rents of natural resources negatively affect energy use.

Table 2: Maximum Likelihood estimation of FE SARAR-models for primary energy use[a]

Covariates	Model (I)	Model(II)	Model (III)	Model (IV)
Spa. Effects in En. use $\hat{\rho}$	.169* (.071)	.126* (.072)	.179** (.068)	.158* (.073)
Spa. Effects in Resid. $\hat{\delta}$	−.155* (.089)	−.121 (.037)	−.190* (.087)	−.206* (.073)
log-GDP per capita	.778*** (.032)	.793*** (.032)	.695*** (.038)	.765*** (.040)
Population Density	−.003*** (.000)	−.003*** (.000)	−.002*** (.000)	−.003*** (.000)
Agriculture, value added		−.001 (.002)	−.002 (.002)	−.001 (.002)
Industry, value added		.006*** (.002)	.007*** (.001)	.010*** (.002)
Foreign direct investments			−.002 (.001)	.001 (.001)
Trade, GDP share			−.003*** (.000)	−.003*** (.000)
Export, GDP share			.003* (.002)	.007*** (.001)
Forest rents				.019*** (.003)
Natural resources rents				−.016*** (.001)
Urban pop. share				.010** (.003)
Institution				−.104* (.044)
Number of Obs.	1008	1008	1008	1008
AIC Criterion	3529.006	3508.764	3462.196	3377.232
Log Likelihood	-1717.503	-1705.382	-1679.098	-1632.616

	Fixed Effects Spatial dependence tests[b]			
SARAR:	(I)	(II)	(III)	(IV)
Test for spatial lag dep.	6.39 (0.01)	3.29 (.06)	8.56 (.00)	4.78 (.02)
Test for spatial error dep.	2.76 (.09)	1.13 (.28)	4.68 (.03)	3.51 (.06)

	Spatial Hausman Test[c]			
FE vs. RE SARAR:	(I)	(II)	(III)	(IV)
χ^2	15.50	16.12	28.80	21.92
p-value	.00	.00	.00	0.03

	SARAR vs. SARAR augmented models: A Wald test[d]			
FE models:	(I)	(II)	(III)	(IV)
χ^2	0.37	3.89	11.53	15.27
p-value	.83	.42	.11	0.17

Note: [a] Dependent variable is log-primary energy use per capita. In bracket are standard errors derived from numerical Hessians estimation strategy. n=42 and T=24. $\hat{\rho}$ and $\hat{\delta}$ respectively stand for the spatial effects in energy use and in residuals. *, ** and *** respectively indicate significance at 10% 5% and 1% levels.
[b] Based on the results of standard Hausman tests, we perform Locally Robust LM Tests for spatial lag and spatial error dependences. The statistics are the LM-Stat and in brackets are the corresponding p-values.
[c] Based on the the spatial LM-test results, we perform Hausman test comparing FE vs. RE SARAR-models.
[d] The augmented FE-SARAR-model includes in addition to the regressors, their corresponding spatial lag. Wald-tests compares both models and help clarify whether spatial lag of regressors should be introduced into the models.

5. Robustness check

To check the robustness of our whole analysis, from the spatial test up to the estimation of the final FE-SARAR models I-IV, we apply the same procedures as above but by using a different connectivity matrix. Unlike the border based matrix WII, where we only considered existing common borders between countries, this section considers a distance-based weighing matrix, which exploits the k-nearest neighbouring algorithm (with k=2). This means that even not directly contiguous countries could be considered as neighbours by the standardized matrix entries (see Table B-1, appendix B).

The results using this second matrix, in the same way as in Table 2, are summarized in Table C-1 in appendix C. Observing the LM-test statistics, one notices that the null-hypotheses regarding the absence of spatial effects in primary energy use and residuals are not supported. In accordance with our previous results, these tests stress the importance of accounting for spatial effects, when modelling primary energy use. Apart from this investigation on the presence of spatial effects, we consider spatial models and use them testing fixed-effects SARAR against random effects modelling. These spatial Hausman tests also support those reported in Table A-1, concerning the suitability of a fixed-effects modelling.

In addition to these tests, we re-estimate the econometric model presented in (4) and compare the results to those obtained in models containing the vector Wx, using a Wald-test. In this case where we use the weighting matrix WI, the p-values of the Wald-test suggest at 10% significance level and regarding models II & III that the the spatial lag of the regressors improves the quality of the FE-SARAR models. When considering a 1% decision-level, all our models I-IV all reject the inclusion of the Wx into the FE-SARAR models. Finally analysing the outputs of the two-steps maximum likelihood estimation of the spatial panel data models (with instrumental variable techniques), we notice that the estimated parameters are consistent with those reported in Table 2. The amplitude of the estimated parameters of our regressors shows values which almost equal those obtained previously. In sight to these last results, our primer interpretations strongly hold, beside the size of the spatial effects which seem higher than those obtained primarily.

This robustness analysis, using a connectivity matrix different from the one we use in the previous section, confirms the results regarding not only the preliminary spatial and Hausman tests. It also delivers estimated parameters almost equalling those obtained in Section 4.

6. Concluding remarks

A large empirical literature focuses on the energy consumption and economic growth nexus by using different proxies and regression analysis methods. The aim in this literature is not only to find out the direction of causalities but also to test the EKC-hypothesis of energy use and further to highlight possible social and economic determinants of energy use. In Sub-Saharan Africa, where population and economic activities tend to be increasing, the existing contributions have raised the question on the determinants of energy use. Moreover, it questions the future of energy demand, pointing out that investigating the link between energy and GDP is more than a causality analysis.

Observing that primary energies can be considered as natural endowment in resources, their consumption is highly related to economic production, to social changes, and to cooperation between neighbouring countries, motivating an investigation of spatial interactions in primary energy use. This study thus proposes to investigate the relationship between energy use and income per capita in Sub-Saharan Africa using spatial analysis methods, by principally targeting primary energies use. Tests of the existence of spatial interactions within our sample of 42 countries suggest that the level of primary energy use in a country i is significantly affected by the use of primary energy in the neighbouring countries. Results of estimating spatial models indicate for primary energy use that the spatial dependence is positive, while unobserved factors have negative effects. Such positive spatial effects point to the existence of positive network-effects or externalities of primary energy use among the considered countries.

Furthermore our estimations confirm the existence of a strong positive link of primary energy use to income per capita, implying that future economic performances in Sub-Saharan Africa will lead to higher demands for energies. This is currently the case in South-Africa, Gabon, Equatorial Guinea and Ghana where economic performances coincide with intensive primary energy use. As the sample is constituted by pre-industrial countries, thus low-income countries, huge demands for energy are to be expected in Sub-Saharan African countries. Finally, the control variables we introduce into the regression models permit to see that not only economic activities will lead to increases in energy demand but also demographic dynamics. As projections point to a fast population growth in the next 50 years, increases in demand for energy and a growing share of now-renewable energy use are to expect, making Sustainable Development Goals not easily reachable.

This study on primary energy use and economic growth in Sub-Saharan Africa using spatial regression methods technically relies on weight matrices we built, using the queen contiguity principle which only account for the number and the proximity of neighbouring countries. A possible very insightful extension of this paper could be re-evaluating the existence of positive spatial effects in primary energy consumption, using weight matrix based on energy trade and on economic cooperation among countries in Sub-Saharan Africa.

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Appendix A

Table A-1: Hausman-Test using standard FE and RE models

Hausman-Test Stat.	χ^2	p-value	d.f.
Model 1	6.697	0.03	964
Model 2	10.84	0.02	962
Model 3	16.59	0.02	959
Model 4	19.55	0.05	955

Note: See Table A-2 below for the variables involved in each of the models 1-4.

Table A-2: Estimation of standard fixed-effects models for primary energies use

Covariates	Model I	Model II	Model III	Model IV
log-GDP per capita	.783*** (.033)	.778*** (1.349)	.697*** (.039)	.802*** (.042)
Population Density	−.003*** (.000)	−.003*** (.000)	−.002*** (.000)	−.003*** (.000)
Agriculture, value added		−.001 (.002)	−.001 (.002)	−.001 (.001)
Industry, value added		.007*** (.002)	.008*** (.002)	.011*** (.001)
Foreign direct investments			−.001 (.001)	−.001 (.001)
Trade, GDP share			−.003*** (.000)	−.003** (.000)
Export, GDP share			.002 (.001)	.006 (.002)
Forest rents				.021*** (.003)
Natural resources rents				−.016*** (.001)
Urban pop. share				.012*** (.003)
Institution				−.114* (.046)
N (D. of freedom)	1008 (964)	1008 (962)	1008 (959)	1008 (955)
F-stat (p-value)	280.934 (.00)	148.452 (.00)	100.939 (.00)	81.822 (.00)

Note: Dependent variable is primary energies use. See Table 3 above for further details. In bracket are standard errors. n=42 and T=24. *, ** and *** respectively indicate significance at 10% 5% and 1% levels.

Appendix B

Table B-1: The connectivity matrix, WI

1.	0.00	0.000	0.17	0.000	0.00	0.000	0.000	0.000	0.167	0.000	0.17	0.00	0.000	0.00	0.00	0.167	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.17	0.000	0.000	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.17	0.00	0.00
2.	0.00	0.000	0.00	0.091	0.00	0.091	0.000	0.000	0.000	0.091	0.00	0.00	0.091	0.00	0.00	0.000	0.000	0.091	0.091	0.000	0.00	0.00	0.091	0.00	0.00	0.091	0.000	0.00	0.00	0.091	0.091	0.00	0.000	0.000	0.00	0.00	0.00	0.091	0.00	0.00	0.00	0.00
3.	0.12	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.12	0.000	0.00	0.00	0.000	0.000	0.12	0.12	0.000	0.000	0.00	0.000	0.000	0.12	0.12	0.00	0.000	0.00	0.12	0.12	0.00
4.	0.00	0.071	0.00	0.000	0.00	0.000	0.000	0.000	0.000	0.071	0.00	0.00	0.000	0.00	0.00	0.000	0.071	0.071	0.071	0.071	0.00	0.00	0.071	0.00	0.00	0.071	0.071	0.00	0.00	0.071	0.071	0.00	0.071	0.071	0.00	0.00	0.00	0.071	0.00	0.00	0.00	0.00
5.	0.00	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.14	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.14	0.00	0.000	0.00	0.14	0.000	0.000	0.00	0.00	0.000	0.000	0.14	0.000	0.000	0.00	0.00	0.14	0.000	0.14	0.14	0.00	0.00
6.	0.00	0.111	0.00	0.000	0.00	0.000	0.111	0.111	0.111	0.000	0.00	0.00	0.111	0.00	0.00	0.111	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.111	0.111	0.00	0.000	0.000	0.00	0.00	0.00	0.111	0.00	0.00	0.00	0.00
7.	0.00	0.000	0.00	0.000	0.00	0.100	0.000	0.100	0.100	0.000	0.10	0.00	0.100	0.00	0.00	0.100	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.100	0.10	0.000	0.000	0.00	0.00	0.00	0.000	0.10	0.00	0.00	0.10
8.	0.00	0.000	0.00	0.000	0.00	0.200	0.200	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.200	0.200	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.20
9.	0.14	0.000	0.00	0.000	0.00	0.143	0.143	0.000	0.000	0.000	0.14	0.00	0.143	0.00	0.00	0.143	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.143	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
10.	0.00	0.091	0.00	0.091	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.091	0.091	0.091	0.091	0.00	0.00	0.091	0.00	0.00	0.091	0.000	0.00	0.00	0.000	0.000	0.00	0.091	0.091	0.00	0.00	0.00	0.091	0.00	0.00	0.00	0.00
11.	0.11	0.000	0.00	0.000	0.11	0.000	0.111	0.000	0.111	0.000	0.00	0.00	0.000	0.00	0.00	0.111	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.11	0.000	0.000	0.00	0.00	0.11	0.000	0.11	0.11	0.00	0.00
12.	0.00	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.25	0.25	0.000	0.000	0.000	0.000	0.000	0.25	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.25
13.	0.00	0.125	0.00	0.000	0.00	0.125	0.125	0.000	0.125	0.000	0.00	0.00	0.000	0.00	0.00	0.125	0.000	0.125	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.125	0.00	0.000	0.000	0.00	0.00	0.00	0.125	0.00	0.00	0.00	0.00
14.	0.00	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.33	0.000	0.00	0.33	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.33
15.	0.00	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.20	0.000	0.20	0.00	0.000	0.000	0.000	0.000	0.000	0.20	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.20	0.00	0.00	0.20
16.	0.14	0.000	0.00	0.000	0.00	0.143	0.143	0.000	0.143	0.000	0.14	0.00	0.143	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.143	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
17.	0.00	0.000	0.00	0.111	0.00	0.000	0.000	0.000	0.000	0.111	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.111	0.111	0.00	0.00	0.111	0.00	0.00	0.111	0.111	0.00	0.00	0.000	0.000	0.00	0.111	0.111	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
18.	0.00	0.100	0.00	0.100	0.00	0.000	0.000	0.000	0.000	0.100	0.00	0.00	0.100	0.00	0.00	0.000	0.000	0.000	0.100	0.000	0.00	0.00	0.100	0.00	0.00	0.100	0.000	0.00	0.00	0.000	0.100	0.00	0.000	0.100	0.00	0.00	0.00	0.100	0.00	0.00	0.00	0.00
19.	0.00	0.083	0.00	0.083	0.00	0.000	0.000	0.000	0.000	0.083	0.00	0.00	0.000	0.00	0.00	0.000	0.083	0.083	0.000	0.083	0.00	0.00	0.083	0.00	0.00	0.083	0.083	0.00	0.00	0.000	0.000	0.00	0.083	0.083	0.00	0.00	0.00	0.083	0.00	0.00	0.00	0.00
20.	0.00	0.000	0.00	0.111	0.00	0.000	0.000	0.000	0.000	0.111	0.00	0.00	0.000	0.00	0.00	0.000	0.111	0.000	0.111	0.000	0.00	0.00	0.111	0.00	0.00	0.111	0.111	0.00	0.00	0.000	0.000	0.00	0.111	0.111	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
21.	0.00	0.000	0.00	0.000	0.17	0.000	0.000	0.000	0.000	0.000	0.00	0.17	0.000	0.00	0.17	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.17	0.000	0.000	0.00	0.00	0.17	0.000	0.17	0.00	0.00	0.00
22.	0.00	0.000	0.20	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.20	0.000	0.000	0.00	0.000	0.000	0.20	0.20	0.00	0.000	0.00	0.00	0.20	0.00
23.	0.00	0.091	0.00	0.091	0.00	0.000	0.000	0.000	0.000	0.091	0.00	0.00	0.000	0.00	0.00	0.000	0.091	0.091	0.091	0.091	0.00	0.00	0.000	0.00	0.00	0.091	0.000	0.00	0.00	0.000	0.000	0.00	0.091	0.091	0.00	0.00	0.00	0.091	0.00	0.00	0.00	0.00
24.	0.00	0.000	0.00	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.50	0.000	0.000	0.50	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
25.	0.00	0.000	0.00	0.000	0.14	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.14	0.00	0.000	0.000	0.14	0.00	0.000	0.000	0.14	0.000	0.000	0.00	0.00	0.14	0.000	0.00	0.14	0.14	0.00
26.	0.00	0.077	0.00	0.077	0.00	0.000	0.000	0.000	0.000	0.077	0.00	0.00	0.000	0.00	0.00	0.000	0.077	0.077	0.077	0.077	0.00	0.00	0.077	0.00	0.00	0.000	0.077	0.00	0.00	0.077	0.000	0.00	0.077	0.077	0.00	0.00	0.00	0.077	0.00	0.00	0.00	0.00
27.	0.00	0.000	0.00	0.143	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.143	0.000	0.143	0.143	0.00	0.00	0.000	0.00	0.00	0.143	0.000	0.00	0.00	0.000	0.000	0.00	0.143	0.143	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
28.	0.00	0.000	0.14	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.14	0.14	0.000	0.000	0.00	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.14	0.14	0.000	0.00	0.14	0.14	0.00
29.	0.17	0.000	0.17	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.17	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.00	0.000	0.000	0.17	0.00	0.00	0.000	0.00	0.17	0.17	0.00
30.	0.00	0.143	0.00	0.143	0.00	0.143	0.000	0.143	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.143	0.000	0.00	0.00	0.000	0.143	0.00	0.000	0.000	0.00	0.00	0.00	0.143	0.00	0.00	0.00	0.00
31.	0.00	0.091	0.00	0.091	0.00	0.091	0.091	0.091	0.091	0.000	0.00	0.00	0.091	0.00	0.00	0.091	0.000	0.091	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.091	0.000	0.00	0.000	0.000	0.00	0.00	0.00	0.091	0.00	0.00	0.00	0.00
32.	0.00	0.000	0.00	0.000	0.12	0.000	0.125	0.000	0.000	0.000	0.12	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.12	0.00	0.000	0.00	0.12	0.000	0.000	0.00	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.00	0.12	0.000	0.12	0.12	0.00	0.00
33.	0.00	0.000	0.00	0.111	0.00	0.000	0.000	0.000	0.000	0.111	0.00	0.00	0.000	0.00	0.00	0.000	0.111	0.000	0.111	0.111	0.00	0.00	0.111	0.00	0.00	0.111	0.111	0.00	0.00	0.000	0.000	0.00	0.000	0.111	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
34.	0.00	0.000	0.00	0.091	0.00	0.000	0.000	0.000	0.000	0.091	0.00	0.00	0.000	0.00	0.00	0.000	0.091	0.091	0.091	0.091	0.00	0.00	0.091	0.00	0.00	0.091	0.091	0.00	0.00	0.000	0.000	0.00	0.091	0.000	0.00	0.00	0.00	0.091	0.00	0.00	0.00	0.00
35.	0.00	0.000	0.20	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.20	0.000	0.00	0.00	0.000	0.000	0.00	0.20	0.000	0.000	0.00	0.000	0.000	0.00	0.20	0.00	0.000	0.00	0.00	0.20	0.00
36.	0.00	0.000	0.20	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.20	0.000	0.00	0.00	0.000	0.000	0.20	0.00	0.000	0.000	0.00	0.000	0.000	0.20	0.00	0.00	0.000	0.00	0.00	0.20	0.00
37.	0.00	0.000	0.00	0.000	0.12	0.000	0.000	0.000	0.000	0.000	0.12	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.12	0.00	0.000	0.00	0.12	0.000	0.000	0.12	0.00	0.000	0.000	0.12	0.000	0.000	0.00	0.00	0.00	0.000	0.12	0.12	0.00	0.00
38.	0.00	0.083	0.00	0.083	0.00	0.083	0.000	0.000	0.000	0.083	0.00	0.00	0.083	0.00	0.00	0.000	0.000	0.083	0.083	0.000	0.00	0.00	0.083	0.00	0.00	0.083	0.000	0.00	0.00	0.083	0.083	0.00	0.000	0.083	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00
39.	0.00	0.000	0.00	0.000	0.14	0.000	0.143	0.000	0.000	0.000	0.14	0.00	0.000	0.00	0.14	0.000	0.000	0.000	0.000	0.000	0.14	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.14	0.000	0.000	0.00	0.00	0.14	0.000	0.00	0.00	0.00	0.00
40.	0.10	0.000	0.10	0.000	0.10	0.000	0.000	0.000	0.000	0.000	0.10	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.10	0.000	0.000	0.10	0.10	0.000	0.000	0.10	0.000	0.000	0.00	0.00	0.10	0.000	0.00	0.00	0.10	0.00
41.	0.00	0.000	0.12	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.000	0.000	0.000	0.00	0.12	0.000	0.00	0.12	0.000	0.000	0.12	0.12	0.000	0.000	0.00	0.000	0.000	0.12	0.12	0.00	0.000	0.00	0.12	0.00	0.00
42.	0.00	0.000	0.00	0.000	0.00	0.000	0.200	0.200	0.000	0.000	0.00	0.20	0.000	0.20	0.20	0.000	0.000	0.000	0.000	0.000	0.00	0.00	0.000	0.00	0.00	0.000	0.000	0.00	0.00	0.000	0.000	0.00	0.000	0.000	0.00	0.00	0.00	0.000	0.00	0.00	0.00	0.00

Note: This matrix has been built considering the k-nearest neighbouring countries, with k=2. Number of countries = 42.

Number of non-zero links: 334, Percentage non-zero weights: 18.93424. Average number of links: 7.952381

Table B-2: The connectivity matrix, WII

1.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00
2.	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00
3.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.25	0.25	0.00
4.	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00
5.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00
6.	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.17	0.17	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7.	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.20	0.20	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20
8.	0.00	0.00	0.00	0.00	0.00	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25
9.	0.00	0.00	0.00	0.00	0.00	0.25	0.25	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.25	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10.	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.20	0.20	0.00	0.00	0.00	0.20	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11.	0.12	0.00	0.00	0.00	0.12	0.00	0.12	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.12	0.00	0.12	0.12	0.00	0.00
12.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13.	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.33	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33
15.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.25	0.00	0.00	0.0	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25
16.	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.33	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18.	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00
19.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.33	0.00	0.00	0.33	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.33	0.00	0.00	0.00
22.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.33	0.00	0.00
26.	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.17	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.14	0.14	0.00	0.00	0.14	0.14	0.00
29.	0.25	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.25	0.00	0.00
30.	0.00	0.20	0.00	0.20	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31.	0.00	0.25	0.00	0.00	0.00	0.25	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32.	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.25	0.00	0.00	0.00
33.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.2	0.00	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.50	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
35.	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.17	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.17	0.00
36.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
37.	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.12	0.00	0.00	0.12	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.12	0.00	0.00
38.	0.00	0.33	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
39.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00
40.	0.12	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.12	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.12	0.00
41.	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.25	0.00	0.00
42.	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.17	0.00	0.00	0.00	0.00	0.00	0.17	0.17	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: This matrix is based on common borders principle. Number of non-zero links: 167, Percentage non-zero weights: 9.46712, Average number of links: 3.97619

Table B-3: Test for spatial lag dependence in energy use for each yearly wave of the dataset

	using WI		using WII	
Wave	Moran I	p-value	Moran I	p-value
Wave 1990	0.04	0.17	-0.03	0.53
Wave 1991	0.03	0.24	-0.06	0.63
Wave 1992	0.02	0.27	-0.06	0.62
Wave 1993	0.02	0.26	-0.05	0.60
Wave 1994	0.01	0.34	-0.06	0.65
Wave 1995	0.01	0.31	-0.06	0.63
Wave 1996	0.00	0.36	-0.09	0.73
Wave 1997	0.01	0.33	-0.09	0.72
Wave 1998	0.02	0.28	-0.06	0.62
Wave 1999	0.03	0.20	-0.03	0.52
Wave 2000	0.04	0.16	0.00	0.39
Wave 2001	0.07	0.09	0.02	0.33
Wave 2002	0.04	0.16	0.09	0.14
Wave 2003	0.04	0.17	0.09	0.14
Wave 2004	0.07	0.08	0.05	0.10
Wave 2005	0.06	0.10	0.12	0.09
Wave 2006	0.07	0.09	0.12	0.09
Wave 2007	0.08	0.06	0.15	0.05
Wave 2008	0.11	0.03	0.17	0.04
Wave 2009	0.12	0.02	0.17	0.03
Wave 2010	0.13	0.01	0.19	0.02
Wave 2011	0.11	0.03	0.17	0.04
Wave 2012	0.10	0.05	0.15	0.05
Wave 2013	0.12	0.02	0.17	0.03

Note: For both Moran I test under randomisation, the null hypothesis is: no spatial dependence. The tests are performed on series on primary energy use and for each yearly wave, n=24. The weighting matrices WI and WII are respectively the k nearest neighbour (with k=2) and a common border based weighting matrices

Appendix C

Table C-1: Maximum Likelihood estimation of FE SARAR-models for primary energy use[a]

Covariates	Model (I)	Model(II)	Model (III)	Model (IV)
Spa. Effects in En. use $\hat{\rho}$	.282*** (.065)	.244*** (.069)	.284*** (.067)	.245** (.112)
Spa. Effects in Resid. $\hat{\delta}$	−.297** (.108)	−.237* (.109)	−.269* (.109)	−.226* (.099)
log-GDP per capita	.769*** (.032)	.783*** (.032)	.687*** (.038)	.767*** (.039)
Population Density	−.003*** (.000)	−.003*** (.000)	−.002*** (.000)	−.003***(.000)
Agriculture, value added		−.001 (.002)	−.000 (.002)	−.001 (.001)
Industry, value added		.006*** (.001)	−.008*** (.002)	.011*** (.001)
Foreign direct investments			−.002 (.001)	−.001 (.001)
Trade, GDP share			−.003*** (.000)	−.003*** (.000)
Export, GDP share			.003* (.001)	.007*** (.002)
Forest rents				.019*** (.002)
Natural resources rents				−.016*** (.002)
Urban pop. share				.008* (.003)
Institution				−.108* (.044)
Number of Obs.	1008	1008	1008	1008
AIC Criterion	3519.122	3500.344	3453.092	3372.662
Log Likelihood	-1712.561	-1701.172	-1674.546	-1630.331

	Fixed Effects Spatial dependence tests[b]			
SARAR:	(I)	(II)	(III)	(IV)
Test for spatial lag dep.	16.46 (.00)	11.71 (0.00)	16.76 (.00)	8.07 (.00)
Test for spatial error dep.	9.77 (.00)	6.19 (.01)	8.01 (.00)	2.69 (0.10)

	Spatial Hausman Test[c]			
FE vs. RE SARAR:	(I)	(II)	(III)	(IV)
χ^2	1.19	173.14	24.34	44.44
p-value	.75	.00	.00	0.00

	SARAR vs. SARAR augmented models: A Wald test[d]			
FE models:	(I)	(II)	(III)	(IV)
χ^2	3.84	13.04	15.69	14.74
p-value	.14	.01	.03	0.19

Note: [a] Dependent variable is log-primary energy use per capita. In bracket are standard errors derived from numerical Hessians estimation strategy. n=42 and T=24. $\hat{\rho}$ and $\hat{\delta}$ respectively stand for the spatial effects in energy use and in residuals. *, ** and *** respectively indicate significance at 10% 5% and 1% levels.

[b] Based on the results of standard Hausman tests, we perform Locally Robust LM Tests for spatial lag and spatial error dependences. The statistics are the LM-Stat and in brackets are the corresponding p-values.

[c] Based on the the spatial LM-test results, we perform Hausman test comparing FE vs. RE SARAR-models.

[d] The augmented FE-SARAR-model includes in addition to the regressors, their corresponding spatial lag. Wald-tests compares both models and help clarify whether spatial lag of regressors should be introduced into the models.

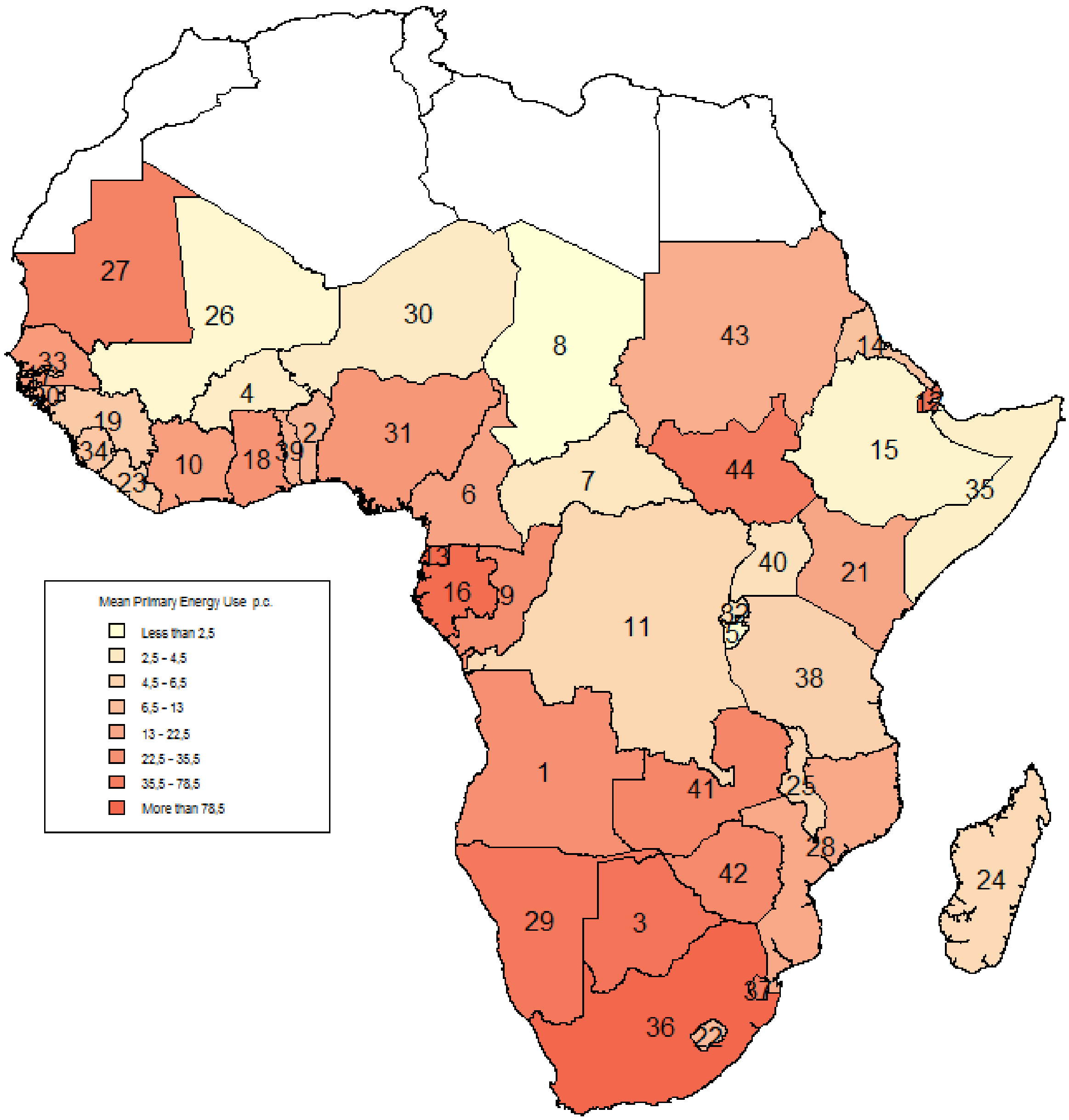

Figure 3: Map of mean primary energy use per capita, in Thousandth of Kilojoule

Angola 1,Benin 2, Botswana 3, Burkina Faso 4, Burundi 5, Cameroon 6, Central African Republic 7, Chad 8, Congo, Dem. Rep. 9, Congo, Rep. 10, Cote d'Ivoire 11, Djibouti 12, Equatorial Guinea 13, Eritrea 14, Ethiopia 15, Gabon 16, Gambia, The 17, Ghana 18, Guinea 19, Guinea-Bissau 20, Kenya 21, Lesotho 22, Liberia 23, Madagascar 24, Malawi 25, Mali 26, Mauritania 27, Mozambique 28, Namibia 29, Nigeria 30, Niger 31, Rwanda 32, Senegal 33, Sierra Leone 34, Somalia 35, South Africa 36, Swaziland 37, Tanzania 38, Togo 39, Uganda 40, Zambia 41, Zimbabwe 42, Sudan 43, South Sudan 44.