Econometrics and Management Science

GDP and Energy Mix

Specialization Quantitative Finance

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Introduction

Understanding the relations between energy and economic output is important because of the crucial role of energy in industry and production. Energy price shocks posses the power to push entire regions into recession. Furthermore energy mix, defined as the total of all sources, processing and end use, and energy quality are in the center of attention of the climate debate. The world's energy demand has been soaring as can be seen from the energy consumption timeseries graph in Figure 1. From 1973 to 2011, so in less than 40 years the worlds energy usage has about doubled. This only increases the importance of decisions regarding energy policy and the focus on choosing an economically efficient mix.

The focus of this thesis is on the mixture aspect of the energy. By that the composition of all sources (Fossil, Renewable), carriers (Oil, Electricity) and uses (Industrial, Domestic) is intended. This thesis digs deeper into the relation between energy and economic growth by specifically taking the composition of the energy flows employed by a country into account as opposed to just the level of final consumption.

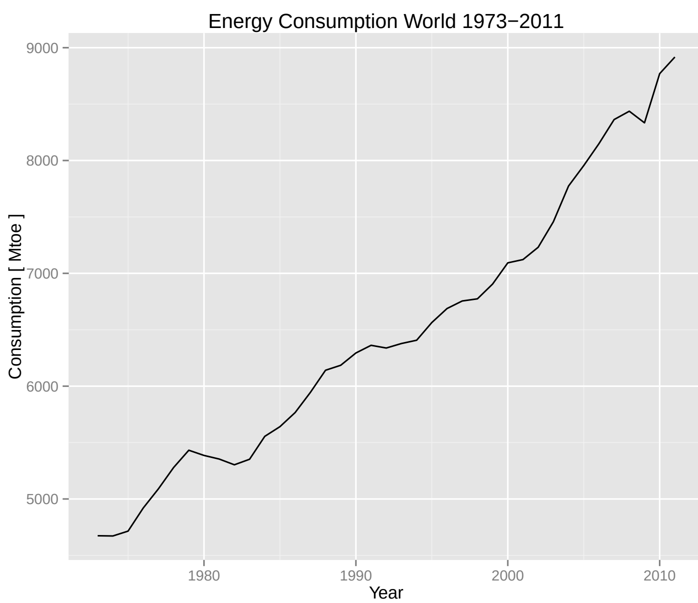

Figure 1: Timeseries plot of the world's energy consumption from 1973-2011 in mega tonnes of oil equivalent (Mtoe). The consumption almost doubles in this period. Data: IEA, Graph: author.

Research Question *What are the relations between energy mix and economic growth?*
It could be the case that some energy sources have a stronger link to Gross Domestic Product (GDP) than others. For example perhaps electricity is relatively more important as most technology requires this power source. On the other hand it also could be the case that the end use has an influence on the wealth growth. One could imagine that energy delivered to industry is more productive in the economic sense than energy used in domestic heating.

Data The International Energy Agency (IEA) and the World Bank have recently (2010) started releasing[1] a wealth of macro economic development related data via the Open Data Initiative. The IEA collects annual data on the energy mix for 156 countries/regions and publishes it online. The sample includes about 40 years of annual energy balances. This data is very granular and contains information on the nature of the energy primary as well as conversions, utilisation and export. To get an idea of the energy mix data, the final consumption of the world region subset is plotted in Figure 2 splitted into components. The left image shows all major energy carriers that compose the final usage, and the right image shows the final destination.

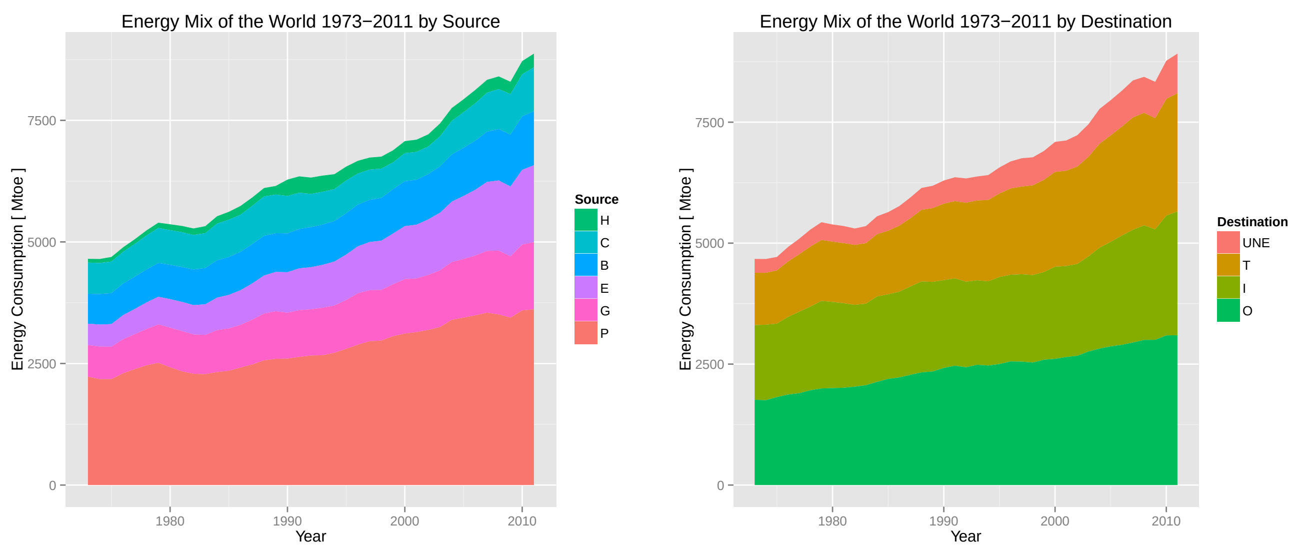

Figure 2: Timeseries area plot of the world's energy consumption from 1973-2011 in mega tonnes of oil equivalent (Mtoe). Split by energy source (left) and by final destination (right). Key Source: H: Heat, C: Coal, B: Biofuel, E: Electricity, G: Natural Gas, P: Petroleum products. Key Destination: UNE: Non-Energy Use, T: Transportation, I: Industry, O: Other uses. Data: IEA, Graph: author.

Methods overview In this thesis we quantitatively explore the relation between energy mix and Gross Domestic Product (GDP). We employ a *panel modelling approach* where we attempt to explain GDP growth patterns by a set of energy mix summary variables. These energy mix summaries are designed to proxy for four categories of effects: the aggregate energy consumption, technology level, international trade position of the country, and final utilization category of the energy such as domestic or industrial.

The model we employ extends the modelling approach of Mankiw, Romer, and Weil (1992) [30] by employing the same physical capital, human capital and labor variables in the production function. We add energy mix variables and estimate the model in 5 and 10 year block returns instead of total sample period returns. The Mankiw-Romer-Weil model is considered as a baseline model. It is frequently used in literature (e.g. [18, 4]) to test additional effects due to its extendibility and it in turn builds on the milestone capital-labor Solow-Swan model [39, 40].

There is a large literature on co-integration and causation effects between total energy consumption and GDP growth (e.g. the metastudy in [10] and the regional analyses of [26, 27, 28, 31]) but this literature is still inconclusive. Typical is to estimate dynamic Vector Auto-Regressive (VAR) models or Granger causality, but short time series and slow dynamics result in low reliability. This is the reason we will not follow this approach. Economically the processes governing energy and wealth are more easily connected:

[1] http://www.iea.org/sankey/ visited: feb-2014

Energy usage and wealth growth tend to go hand in hand. Energy used in production processes tends to increase wealth and the other way around wealth allows countries to produce and purchase more energy. This entanglement rises concerns for endogeneity of the energy mix variables. To control for this effect we develop a carefully constructed temperature instrument. The reasoning behind this choice is the idea that temperature variations influence the energy usage much stronger than the GDP growth. Thus the path from energy to GDP can be separated by the path from GDP to energy, by considering the part of the energy that is related to temperature variations. The temperature data is collected from meteorological measurement stations all over the world and the constructed variable has worldwide coverage. With this temperature variable we re-estimate the model for the endogeneous energy mix variables with *instrumental variable regressions*.

Summary of Results To our knowledge this is the first analysis of energy mix describing variables in their relation to economic growth. It is also the first study to use a temperature range instrument to counteract suspected endogeneity issues in using energy to explain wealth.

The panel analysis that is performed has resulted in several discovery of several statistically significant energy mix variables. Adding one of these variables improves the explanation of wealth patterns compared to a model that is only controlling for physical and human capital and labor factors. Increases in aggregate consumption of energy is positive for growth levels. Oil refinery capacity is strongly related to more wealth while large import streams and large trade dependence are negative for growth. All main final utilization channels are constructive for wealth but the sensitivity (magnitude of wealth added) is highest for energy utilization in domestic environments. This sensitivity is about double the effect of energy use in industry on wealth.

Overview of Thesis We start by reviewing the modern history of GDP that applies to our problem in Chapter 1. In Chapter 2 we discuss the modeling methodology we employ and collect the control variables. Then in the next chapter (Chapter 3) we present the energy dataset we will be analysing thoroughly, codify it and construct energy mix summary variables. In Chapter 4 we define and construct a annual temperature instrument with worldwide country coverage from raw geographic temperature data. Then all prerequisites have been met and in Chapter 5 we perform our regression analysis putting from techniques in panel data econometrics and instrumental variable estimation.

Chapter 1

GDP Modeling Literature

Introduction In this chapter a general review of the literature and history of GDP modeling is presented. The focus is on aspects of GDP modeling that are directly or indirectly related to our investigation of the energy mix effects on GDP. First we discuss several stylized facts of the GDP per capita in Section 1.1, then in Section 1.2 we introduce the concept of production functions and the modeling of GDP by these relations. In Section 1.3 we discuss the improvements made by the attempts to endogenize technological change. Finally in Section 1.4 we point to the search for other control variables and the issue of potential heterogeneity for the GDP generating process of countries.

1.1 Stylized facts GDP

In literature several stylized facts of GDP per capita (or per worker) are recognized. The important and related facts are repeated here from [14, 34, 15] and if possible shown for a sample analog to the energy dataset introduced in the introduction. The discussed facts are:

1. Multi modality
2. Persistence
3. β and σ convergence

The multi modality of the distribution of GDP per worker across countries is visible in the left plot in Figure 1.1. There are two or three distinct peaks in the distribution showing a clustering of production levels around the 1K, the 10K and ≈50K US $ mark. Recently attempts are made in literature to model the shape and dynamics of this distribution. The two temporal subsets (pre and post 1980) show no clear changes in this multi modality. The overall distribution does seem to shift to the right.

The high persistence results from the fact that poor countries tend to stay poor for stretched periods of time and rich countries tend to stay rich. To present this stylized fact visually the GDP at two periods in time separated by multiple decades are plotted in a scatter diagram. The right plot in Figure 1.1 shows a scatter plot of log GDP observations of the first year and the last year of the energy mix dataset. The relation is clearly very strong, the adjusted $\bar{R}^2$ is 85.5% and the slope is estimated as 0.95. A Wald restriction test cannot reject a slope of 1 which could reveal a unit root or a integrated timeseries. This persistence indicates that about all of the final wealth level is explained by the initial wealth. We know that this cannot be an infinite situation otherwise the wealth ranking of countries would not be able to change, which it does, but very slowly. We are interested in the driving forces of these, compared to the influence of initial wealth small but over the long term crucial effects.

Unconditional convergence is the convergence of GDP per capita not considering the difference in situation or state of a country. According to this type of convergence all countries converge to a shared/identical income level. This effect has been regarded as absent or at least not visible in data.

The concepts of β- and σ-convergence refer to the convergence of income conditional on several controls, and the convergence of the deviation of the distribution of income respectively. So β-convergence is convergence of GDP when other effects are filtered such as labor participation for example. The β in the name refers to the regression estimates for the included factors. With σ-convergence the width of the distribution of for example the right plot Figure 1.1 is intended. The σ refers to a measure of dispersion as the standard deviation of a distribution. The existence of actual realization of both concepts is still not agreed on.

σ-convergence, that is convergence in between country wealth differences without considering their differences, is visually not present in the distribution plot in Figure 1.1. The width of the distribution does not seem to contract over time.

Conditional convergence, or β-convergence, is what is used to construct the dynamic equilibrium model of Mankiw, Romer, and Weil which we will use later on. These models imply that countries converge to their own steady state production which depends on their individual production factors. This concept is economically defensible, income stems from generated production and not every country has the same access to factors of production.

Conditional convergence has implications on the choice to estimate in levels or in growth rates. A stable equilibrium model can be estimated in levels. If countries tend to converge, modeling in levels would show these different target wealth levels. But the convergence speeds implied by these models, and the very high persistence of income, shows that this convergence process, if it exists, is very slow. Investigating growth in changes reveals more of the driving forces behind it but masks the different levels domestic production could be converging to. Therefore estimation is performed in growth rates.

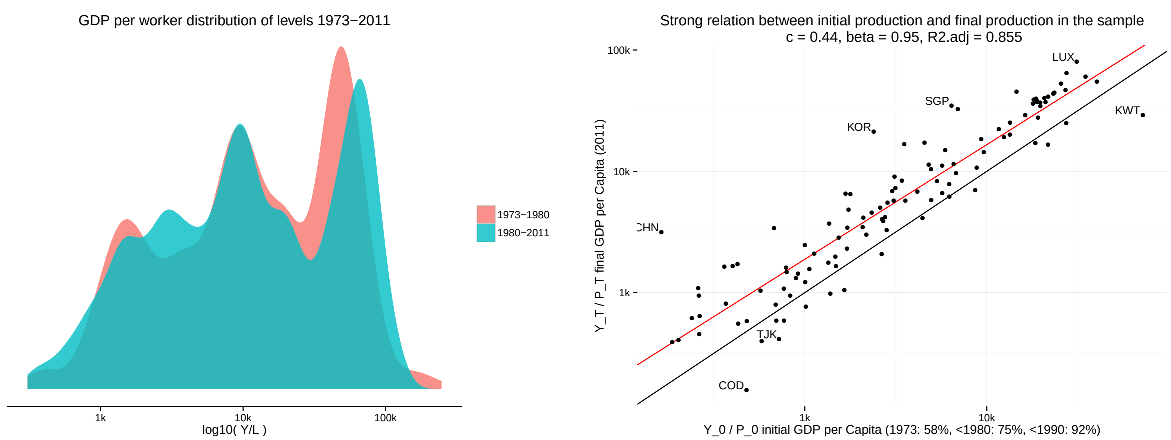

Figure 1.1: Distribution of GDP pre and post 1980 in 2005 US \$. And right the strong relation between initial production and final production in the ≈ 38 years in the sample. The start year of the sample differs, which is indicated below the scatter plot. The red line indicates the linear fit. The regression slope is 0.95 and the $\bar{R}^2 = 0.86$. Data: UN, Graph: author.

1.2 Production functions

Analytical growth modelling literature starts with the Neoclassical growth model (See Parkin (2012) [33] pp. 147–151). The name indicates that before analytical growth modelling GDP modeling was mainly qualitative in nature. Traditionally growth theory was focussed on production functions. In the 50s Solow and Swan created one of the first quantitative models for long term growth with capital and labor factors. This Solow-Swan Model [39, 40] is an evolution on the Harrod-Domar model [20, 12] which only includes capital, but splits this in a direct effect and a productivity effect. The Solow-Swan Model is nowadays most popular version to present the Neoclassical growth model. This model is shown mathematically in Equation 1.1.

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha} \tag{1.1}$$

Where Y is economic output, K is capital invested, L is labor and A is a factor capturing the efficiency of labor. The subscript t is a time variable. α is the elasticity of income due to changes in physical capital. The observation that this ratio of capital and labor proportions in income were constant in the the United States GDP data is what has inspired the development of this model. The alpha was expected by the creators of the model to be around 1/3. In estimating the Solow-Swan model it is common to aggregate the temporal dimension to one observation of the difference from start to end of the sample and thus estimate the model in a cross section. The Solow-Swan model, with its dynamics that are presented in more detail in Section 2.1, implies a convergence to a steady state income-labor ratio, which is country specific. It shows us that *solely capital (savings) and labor are not enough to fuel perpetual economic growth.*

1.3 Endogenising Technology

Unsatisfied by the exogenous factors and the implied convergence that contrasts with the persistent growth observed, Romer (1986) [37] and Lucas Jr (1988) [29] started endogenising knowledge factors in what they call a competitive equilibrium model with endogenous technological change. They depart from diminishing returns to scale by releasing the technology factor from this restriction. This implies that perpetual growth is possible and there is no explicit tendency to converge. Knowledge and technology cannot be perfectly protected and eventually become public. This process drives the global productivity growth.

Mankiw, Romer, and Weil (1992) [30] re-estimate the classic Solow-Swan model and add a proxy for changes and cross country differences in knowledge by adding a ”Human Capital” variable (H_t) to the Solow-Swan model to give Equation 1.2.[1]

$$Y_t = K_t^{\alpha} H_t^{\beta}(A_t L_t)^{1-\alpha-\beta} \tag{1.2}$$

This model (which is eventually estimated in logs) explained a large part of the variance. The $\bar{R}^2 = 0.78$ and the parameters have a intuitive interpretation as elasticities income on physical and human capital. The specifics of this particular modal are also discussed in Section 2.1.

1.4 Additional Control Variables and Heterogeneity

Since this production function format is easily expandable, a wide variety of extensions is proposed in literature. Sala-i-Martin (1997) [38] performed a large number of linear growth regressions to identify additional explanatory variables from a pool of 62 variables used in other studies. Initial physical capital (1960 GDP) and initial human capital (1960 life expectancy and primary schooling) are added in all regressions together with 4 others from the pool. From the distribution of slope estimates variables with relative robust explanatory power are identified. Several variables surface as significant. For example (Equipment) Investments, Cultural, Regional and Political dummy variables. Others, for example Government Spending and Inflation do not explain *growth rate* in this context.

Adding dummy variables essentially allows for a heterogeneous intercept term based on the membership of the dummy subgroup, such as sub-Saharan-Africa for example. Baştürk, Paap, and Van Dijk (2012) [7] go one step further. They allow for heterogeneity in all estimated parameters across *endogenously determined clusters* of countries. They find two clusters with different marginal effects in ”investment”, ”openness” and ”government share of GDP”. These clusters are not similar to conventional geographical clusters as

[1] The term endogenizing is here used in the classic macroeconomics sense as by the authors indicating addition to the model. The econometric concept where a regressor is determined by the independent variable is not intended.

for example ”Latin-America” or ”Asia”. This is evidence against treating such groups as fundamentally different. Hence no regional dummies are included in the modeling later.

With related methods as Sala-i-Martin has used to find significant additions to the GDP per capita production function we will search for the effects of the energy mix variables. Instead of adding multiple controls to a fixed set and seeking for robustness, we will add one energy mixture control to a fixed set and look for statistical significance. The modeling approach and the control variables we have collected are presented in the next chapter which is on our methodology: Chapter 2.

Chapter 2

Methodology

Introduction In this chapter we present our methodology to search for the effects of energy mix on GDP. The methodology builds on the production function GDP modeling methods of Mankiw-Romer-Weil which in turn have extended their model from the classical Solow-Swan model. We add a single constructed energy mix summary variable to a production function model with the same factors as the Mankiw-Romer-Weil model. Then we perform inference on the marginal effects of this energy mix summary variable. In this chapter we present both the Solow-Swan model as the Mankiw-Romer-Weil model in detail and introduce our modeling methodology in more detail. The second part of this chapter deals with selecting the control variables that proxy for capital and labor and selecting sources for this data.

2.1 Methodology

In this section first the Solow-Swan model, than the Mankiw-Romer-Weil model and finally our model with the energy mix-summary added is discussed. These three models follow logically from each other as they extend the predecessor with an additional control.

Solow-Swan model The Solow-Swan Model [39, 40] is nowadays most popular version to present the Neoclassical growth model. This model is shown mathematically in Equation 2.1.

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha} \tag{2.1}$$

Where Y is economic output, K is capital employed, L is labor and A is a factor capturing the efficiency of labor. The subscript t is a time variable. The Solow-Swan model has constant returns to scaling capital and efficient labor[1]. Constant returns to scale is a deviation from perfect competition: in perfect competition there is no scale advantage. The factors α and $1-\alpha$ can be interpreted as the capital and labor shares of income, which during the creation of this model were observed and considered constant among developed economies. The dynamics are fixed in the following format:

$$\begin{aligned} L_t &= L_0 e^{nt} \\ A_t &= A_0 e^{gt} \\ \frac{dK}{dt} &= s \cdot Y_t - d \cdot K_t \end{aligned} \tag{2.2}$$

Where n is labor force growth, proxied by a long term average. Labor efficiency growth rate g is fixed, or in the context of this literature called "exogenous", capital savings fraction s is derived from the investments and depreciation d is fixed. Introducing capital per effective labor $k \triangleq K/(AL)$ allows to solve

[1]proof: $(xK_t)^{\alpha}(xA_tL_t)^{1-\alpha} = x^{\alpha+1-\alpha}(K_t)^{\alpha}(A_tL_t)^{1-\alpha} = xY_t$

for steady-state k^* when $dk/dt = 0$. The steady state effective capital allows to solve for the steady state income.

$$k^* = \left(\frac{s}{n+g+d}\right)^{\frac{1}{1-\alpha}} \tag{2.3}$$

The steady state solution for k^* of Equation 2.3 is substituted into Equation 2.1, and the model is estimated in logs (see Equation 2.4) to create a linear estimation.

$$\log\left(\frac{Y_t}{L_t}\right) = \log A_0 + gt + \frac{\alpha}{1-\alpha}\log s - \frac{\alpha}{1-\alpha}\log(n+g+d) \tag{2.4}$$

The "exogenous" parameters g and d are assumed fixed and constant across countries. The term "exogenous" indicates *not modelled in the context of this model* in this macro economic literature. In [30] the sum[2] of labor efficiency growth and depreciation, $g+d$, is assumed fixed at 0.05. α, the elasticity of capital (see Equation 2.1), is expected to be around 1/3 as the capital:labor ratio in national income is about 1:2 according to Solow.

Mankiw-Romer-Weil model Mankiw, Romer, and Weil (1992) [30] re-estimate the classic Solow-Swan model and show that it results in a higher than expected elasticity of capital α. For a sample of 98 non-oil countries the implied alpha from Equation 2.4 is found to be 0.6 where about 1/3 is expected. However a high fraction of the variance is explained, the adjusted $\bar{R}^2 = 0.59$. Then they add a proxy for changes and cross country differences in knowledge by adding a "Human Capital" variable (H_t) to the Solow-Swan model as given in Equation 2.1:

$$Y_t = K_t^\alpha H_t^\beta (A_t L_t)^{1-\alpha-\beta} \tag{2.5}$$

The dynamics are identical to Equation 2.2 with the savings s subdivided in a physical capital fraction s_K and a human capital fraction s_H and a human capital dynamics equation added:

$$\begin{aligned} L_t &= L_0 e^{nt} \\ A_t &= A_0 e^{gt} \\ \frac{dK}{dt} &= s_K \cdot Y_t - d \cdot K_t \\ \frac{dH}{dt} &= s_H \cdot Y_t - d \cdot H_t \end{aligned} \tag{2.6}$$

The sum of the fixed, exogenous labor and efficiency growth parameters $g+d$ is again assumed 0.05. Introducing physical and human capital per effective unit of labor as $k_t \triangleq K_t/(A_t L_t)$ and $h_t \triangleq H_t/(A_t L_t)$ and assuming diminishing returns to all capital ($\alpha + \beta < 1$) implies existence of a steady state (k^*, h^*) and allows to solve for it. Diminishing returns to capital follows from constant returns to scale of the entire production function, which is the limiting case for stability. Increasing returns to scale would not result in a steady state efficient capital (k^*, h^*) and accompanying equilibrium income. k^* and h^* are found by:

$$\begin{aligned} k^* &= \left(\frac{s_K^{1-\beta} s_H^\beta}{n+g+d}\right)^{\frac{1}{1-\alpha-\beta}} \\ h^* &= \left(\frac{s_K^\alpha s_H^{1-\alpha}}{n+g+d}\right)^{\frac{1}{1-\alpha-\beta}} \end{aligned} \tag{2.7}$$

[2] Depreciation d is set to 0.03 after relating the Capital Consumption Allowance, the proportion of GDP that is due to depreciation, with the assumed capital-output ratio of 3. g is assumed 0.02 to resemble the long term growth that was observed[30]

Having the steady state capital ratios allows estimation of the equilibrium production function similar to Equation 2.4 in Equation 2.8. With the steady state human capital per effective worker inserted from Equation 2.7.[3]

$$\begin{aligned}\log\left(\frac{Y_t}{L_t}\right) &= \log A_0 + gt + \frac{\alpha}{1-\alpha-\beta}\log s_K + \frac{\beta}{1-\alpha-\beta}\log s_H - \frac{\alpha+\beta}{1-\alpha-\beta}\log(n+g+d) \\ &= \log A_0 + gt + \frac{\alpha}{1-\alpha}\log s_K + \frac{\beta}{1-\alpha}\log h^* - \frac{\alpha}{1-\alpha}\log(n+g+d)\end{aligned} \tag{2.8}$$

When estimated for the 98 non oil countries, this model has $\bar{R}^2 = 0.78$. The parameter restrictions cannot be rejected, and imply a physical capital elasticity α of 0.31 and a human capital elasticity β of 0.28. The implied α now is in the order of the expected value from the capital fraction in income.

Mankiw, Romer, and Weil also perform a regression in log difference GDP per working person as opposed to levels. Decreasing deviations from an expected equilibrium indicate the existence of such an equilibrium. This regression in differences is used to test the conditional convergence. If the steady state level of income per effective worker is y^*. Then a linear approximation of convergence from perturbations from this steady state is found by:

$$\begin{aligned}\frac{d\log y_t}{dt} &= \lambda\big(\log y^* - \log y_t\big) \\ \log y_t - \log y_0 &= (1-e^{-\lambda t})\log y^* - (1-e^{-\lambda t})\log y_0\end{aligned} \tag{2.9}$$

With $\lambda = (n+g+d)(1-\alpha-\beta)$ as the convergence rate. The expected value for $\alpha = \beta = 1/3$ (from [39]) and $n+d+g = 0.06$ is $\lambda = 0.02$ and the time move 50% to the equilibrium (half-time) is $-\log(0.5)/0.02 = 35$ year. The initial value of the GDP (y_0) is added to the regressors. When this is estimated for unconditional convergence (no y^* term) a $\bar{R}^2$ practically zero is found. If the Solow-Swan model is used, the $\bar{R}^2 = 0.38$ and the coefficient of $\log y_0$ is negative as expected, but the convergence rate is unrealistically slow (≈ 114 year). The addition of the human capital factor results in $\bar{R}^2 = 0.46$ and $\lambda = 0.0142$ (48 year), which is a good fit.

Fixed set + energy model In this paragraph we present our approach to study the effects of the energy mix variables. The general approach is discussed here but details with regards to for example specification tests are combined with the results chapter Chapter 5 to keep this section compact.

To investigate the energy mix variables the Mankiw-Romer-Weil model (in logs) is extended by a energy mix variable E. There are 35 of these mix variables constructed that proxy for various qualitative aspects of the energy mix. The capital and labor factors are collected into a fixed set which is added to all models. The model is estimated in block-returns with block of 5 and 10 years. These blocks form a panel of countries and block-returns. The dependent variable in the equations is the *annualized difference of logs* which behaves similar to a growth rate. A differenced context is chosen as the convergence rate is, if present, very low. See Section 1.1.

$$d\mathrm{YP} \triangleq \left(\log_{10}\frac{\mathrm{Y}_{t+\tau}}{\mathrm{P}_{t+\tau}} - \log_{10}\frac{\mathrm{Y}_t}{\mathrm{P}_t}\right)/\tau$$

Where P is the population and Y is the GDP. This panel dataformat allows to estimate the model with the within-country transformation, or analogous with the inclusion of fixed effect dummies per country. The fixed effects (FE) model is given by:

$$d\mathrm{YP}_{it} = \alpha_i + \psi^\top \mathbf{S}_{it} + \beta E_{it} + \varepsilon_{it} \qquad \text{"FE-model"} \tag{2.10}$$

[3] $h^* = \left(\frac{s_K^\alpha s_H^{1-\alpha}}{n+g+d}\right)^{\frac{1}{1-\alpha-\beta}} \rightarrow s_H = s_K^{\left(\frac{-\alpha}{1-\alpha}\right)} h^{*\left(\frac{1-\alpha-\beta}{1-\alpha}\right)} (n+g+d)^{\left(\frac{1}{1-\alpha}\right)}$

Additionally there is a pooled OLS model estimated with the initial production $\log_{10}(Y_{i0}/P_{i0})$ (or YP0) included in the regressors.

$$d\mathrm{YP}_{it} = \alpha + \gamma \log_{10}(Y_{i0}/P_{i0}) + \psi^\top \mathbf{S}_{it} + \beta E_{it} + \eta_{it} \qquad \text{"YP0-model"} \tag{2.11}$$

In the equations E_{it} is the added energy mix variable aggregated to a 5 or 10 year panel and potentially differenced. The fixed effect/initial-production models, different block lengths and energy variable transformations result in 376 models with a single energy variable. α is the intercept, β the slope of the energy mix variable, η_{ij} and ε_{ij} are error terms and $\mathbf{S}_{it}$ and ψ are a vector of control variables and their slopes respectively. As control variables the same variables as in the Mankiw-Romer-Weil model are included, so physical and human capital and labor. As shown in Section 2.2.1 a lot of other control variables are proposed and are shown to explain GDP growth. We chose to build on the Mankiw-Romer-Weil model [30] by including the same independent variables, as this model is a general and accepted model. The collection is discussed in Section 2.2.

Conclusions with regard to the direction and strength of the proposed energy mix variables are made performing inference on β. Tests presented later in Section 5.4.1 show the need for Heteroscedasticity and Autocorrelation-Consistent (HAC) standard errors.

Energy usage and GDP are highly related but the direction of causation is probably both ways (see for example the energy causality metastudy of [10]). This entanglement rises concerns for endogeneity of the energy mix variables. To control for this effect we develop a carefully constructed temperature instrument. The reasoning behind this choice is the idea that temperature variations influence the energy usage much stronger than the GDP growth. Thus the path from energy to GDP can be separated by the path from GDP to energy, by considering the part of the energy that is related to temperature variations. To counteract this suspected endogeneity issues in some of the energy-mix variables these models are re-estimated using instrumental variable estimation.

2.2 Collecting control variables

2.2.1 Overview of classes of explanatory variables

The explanatory variables used in cross country growth and wealth explanation that were encountered during literature search are divided into three classes: Capital, Labor and Policy & Cultural factors. Within these classes several categories exist:

- **Capital:** Investments, Capital Stock
- **Labor:** Human Capital, Demographics, Cultural
- **Policy & Cultural:** Government, Economic and Political Stability, Openness, Geography

These categories are proxied for by various variables. Their strength in explaining GDP (or growth) varies with the context in which they are employed. For example 'Openness' results in access to technology which is expected to have a positive effect on GDP, but it also increases competition (Harrison [19]). Others appear to explain a significant fraction but have a very low temporal and geographical coverage such as the proxies for Political Instability in Barro (1991) [5] collected by Banks (1979) [3]. In general these social variables are difficult to collect with consistent quality and to evaluate. Hall and Jones (1999) [18] even use several instruments from 16-19th century world history to estimate the effects of social infrastructure. Governmental administration agencies between countries tend to differ in methods of administration and efficiency. These capabilities tend to be related with their development level. Harder, as in more quantitative, variables as Capital and Labor are quite successfully used in various influential contributions to the cross country growth/wealth literature [39, 40, 5, 30].

2.2.2 Dimensionality of Variables

The control variables can be categorised into individual (i), time-series (t) and panel data (it). The individual dependent variables have one value per country over the entire range, and the time dependent variables have a single time-series for all the countries.

Individual variables, such as the initial level or a long period average, are mainly used in cross-sectional regressions that drop the time-series aspect as in Barro [5]. The main shortcoming with individual variables is that they ignore important changes that occur during the sample period.

For the time-series class the differences between countries is unobserved which also could result in bias. Both of these issues are prevented by using panel data (it), however both availability and quality severely restrict the choice of variables in this case. Additionally production function models do not explain the observed cyclical nature of economies. Periods of recession and expansion are not modelled. Aggregating observations in blocks of several years or decades or over the total time series, filter out the business cycle effects. So each variable dimensionality has its benefits and restrictions. However panel data allows contracting the time or individual dimension, hence offers the most versatility.

2.2.3 Variables in GDP - Energy-Mix model

Building on the work of Mankiw, Romer, and Weil [30] we decided to use capital investment data, labor data and a human capital variable. As the human capital variable provides information about the efficiency of labor, addition of energy-mix derived variables could provide information about the physical capital efficiency. As we would like to estimate, or at least have the possibility to estimate the model in a panel context, we have selected sources for country panel data with high coverage relative to the energy variable and a high quality standard:

- United Nations (UN) is an intergovernmental organization created promote international co-operation. The United Nations Statistics Division (UNSD) constructs the National Accounts Main Aggregates database presents a series of analytical national accounts tables from 1970 onwards for more than 200 countries.[4]
- World Bank (WB) is an international network of nations giving financial and technical assistance to developing countries around the world. The World Bank Open Data initiative provides free and open access to data about development in over 200 countries around the globe.[5]
- Penn World Table Version 8.0 (PWT) is a database with information on relative levels of income, output, inputs and productivity, covering 167 countries between 1950 and 2011 [16, 17] to measure real GDP across countries and over time.[6]

The five variables that proxy for wealth, physical capital, labor and human capital are given in the list in Table 2.1. The main data source for our investigation is the energy mix dataset from the International Energy Agency (IEA), which is discussed and transformed to mix variables in Chapter 3. The coverage is relative to this energy-mix dataset, which contains 4865 Country-Years. It is expressed in the % of energy mix data Country-Years that is included in the variable as well.

[4] National Accounts Main Aggregates data access: `unstats.un.org/unsd/snaama`

[5] World Bank Open Data access: `data.worldbank.org`

[6] Penn World Table data access: `www.ggdc.net/pwt`

Table 2.1: Selected variables. Wealth and Physical and Human Capital proxies.

code	name	source and coverage	description
Y	GDP	(UN, coverage 98.5%)	GDP in constant 2005 prices in US Dollar.[7]
P	Population	(WB: `SP.POP.TOTL`, 99.2%)	Population (Total).[8]
C	Capital	(WB: `NE.GDI.TOTL.ZS`, 90.3%)	Gross capital formation (% of GDP).
L	Labor	(PWT: `emp`, 91.3%)	Number of persons engaged (in millions).
H	Human capital	(PWT: `hc`, 85%)	Education based index per person.

The coverage after sequentially merging the energy data with Y, P, C, L and H reduces according to 100%(All) → 98.5%(Y) → 98.5%(P) → 90.2%(C) → 84.7%(L) → 78.6%(H). So about 4/5 of the energy-mix data is matched with explanatory and control variables. The coverage is plotted in Figure A.3 in the appendix.[9][10][11]

Of the total population, which grew from 3.9 billion to 6.9 billion between 1973 and 2011, on average 86.1% lives in the covered countries. Of the world GDP (summed UN data), which grew from 17 to 53 trillion 2005 dollar, on average 97.1% is produced by the covered countries. So there seems to be a "rich" country bias, probably due to the increased accounting capabilities of developed countries.[12] But from fact that the two coverage percentages are in the same order, this bias seems not critical and is not further investigated.

2.2.4 GDP, Labor and Physical and Human Capital

GDP data (Y) The proxy for wealth that is selected, is the output of a country, measured by it's GDP. While not covering all aspects of well being, GDP per capita varies tremendous from country to country[13] and shows an enormous diversity of living standards. See Figure 2.1. The factors that drive its growth are likely analogous for wealth in a broader sense, hence studying GDP is accepted in practice.[29]

The data based on national accounts is inherently sensitive to the capacities of the collecting agencies. However because the setting of this thesis is directed towards the patterns valid for a broad selection of countries, the individual reporting errors are less relevant. What is relevant for our attempt to relate energy usage to cross country GDP differences, is the choice for the flavour of GDP data.

GDP is collected as a nominal amount in national (local) currency. This amount can than be transformed in several ways in order to make it comparable across time and across countries. The temporal dimension is disturbed by changes in price level (inflation). To overcome this the GDP is converted from its nominal value to a real value using a price deflator. This price level series is derived from the production quantity changes or the price level of a bucket of representative goods.[14] This allows comparing history in fixed 2005 domestic prices.

[7] GDP is included in the PWT however these values are derived from UN data and are identical upon a scale factor (max 6 ×) See http://www.rug.nl/research/ggdc/data/pwt/v80/comparing_pwt80_with_pwt71.pdf (p. 3)

[8] KWT (Kuwait) in 1992-1994 is missing from WB data, this is linearly offset from PWT population data.

[9] Angola (AGO), United Arab Emirates (ARE), Azerbaijan (AZE), Bosnia and Herzegovina (BIH), Belarus (BLR), Cuba (CUB), Algeria (DZA), Eritrea (ERI), Ethiopia (ETH), Georgia (GEO), Haiti (HTI), Kosovo (KSV), Lebanon (LBN) and Libya (LBY) are missing completely after this merger. This is a moderate miss, as there are interesting countries now excluded. But the loss is diversified geographically and development level wise thus the broad patterns are still identifiable.

[10] The new states of Germany are added to Germany for the entire sample 1973-2011.

[11] Energy data on the Sovjet Union and its former members (pre 1990) is not available. This is a loss as this is influences a significant part of the world population.

[12] Note that the total world real GDP grew about twice as much as the total population grew in the 1973-2011 period.

[13] Bottom and top GDP/capita in 2011 in US $: COD (Dem. Rep. of the Congo) 158 $, NPL (Nepal) 392 $, TGO (Togo) 399 $ and QAT (Qatar) 60 000 $, NOR (Norway) 65 000 $, LUX (Luxembourg) 80 000 $ differ by about a factor 150×

[14] GDP data: http://unstats.un.org/unsd/snaama/glossary.asp

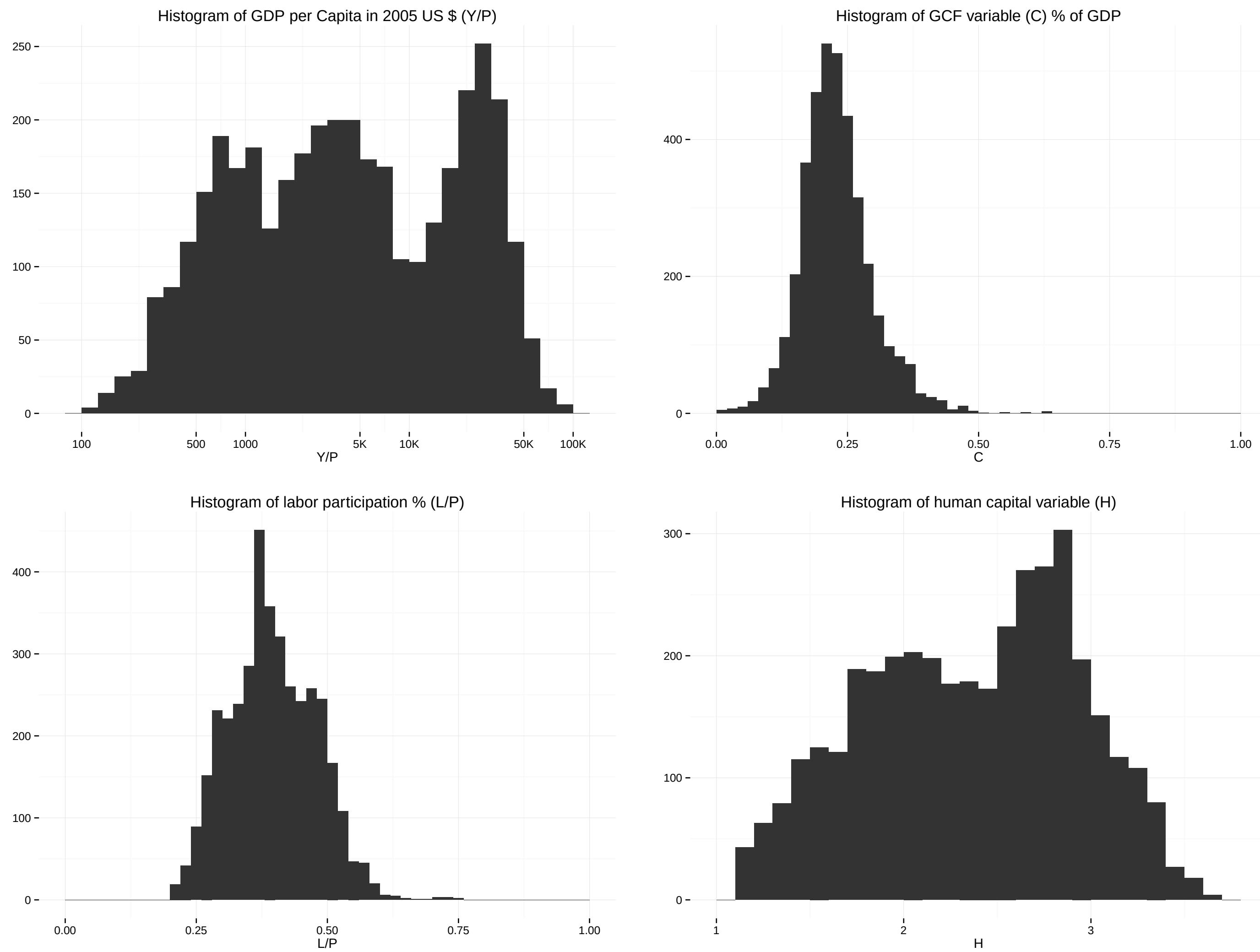

Figure 2.1: Distribution plots of the data on: GDP per capita (Y/P), Gross Capital Formation GCF (C), labor force participation (L/P) and human capital (H). Across all countries and years in the merged dataset. Graphs: author.

One of the difficulties with fixed price data is that the desired composition of the basket changes over time. The longer the periods are apart, the less comparable these are. To compare values internationally the GDP can be transformed into US $ using the average exchange rate in the fix year or with a Purchasing Power Parity (PPP) index. The value in US $ compares output as if the countries are open and in competition, under PPP we compare relative living standards in a more internationally-isolated scope. PPP-dollars are a fictitious currency and you cannot earn them in one country and spend them in another. We are more interested in the former in this context, hence we've selected GDP in fixed 2005 US $ as our dependent variable.

Population (P) and Employment (L) data The population data is collected by the WB and is unrounded. The labor force data is collected in the PWT in millions of people participating. The average participation L/P is about 40% with a variance of about 8%. See Figure 2.1.

Physical Capital data (C) Gross Captial Formation (GCF) which was formerly known as Gross Domestic Investment (GDI)[15] consists of additions to the fixed assets and inventory changes. It is expressed as a % of the GDP. This variable is used in the Solow-Swan type production functions used in [39, 30] to proxy the savings. Using a infinite inventory method, the capital stock is the initial capital plus all changes (the savings/investments) minus depreciation.

Human Capital data (H) The human capital variable from PWT is an index of human capital per person. This index is based on the years of schooling dataset by Barro and Lee (2013) [6] and the global constant returns to education duration Psacharopoulos (1994) [36]. This is a rather limited view on human capital. The labor force is only educated in school and this schooling system is equally efficient anywhere in the world. However this variable has enough variation and is a helpful proxy. The overall tendency that more education results in a more effective labor force is most likely captured, but the international comparability is limited.

[15] Collected from World Bank (WB), which in turn collected the data from World Bank National Accounts data and OECD National Accounts data. http://data.worldbank.org/indicator/NE.GDI.TOTL.ZS

Chapter 3

Energy Data

Introduction In this chapter the energy mix dataset is presented, codified and transformed into mix summary variables. In Section 3.1 the sample is described and all energy variables are given a short code in capital letters. In Section 3.2 several flow diagrams, called Sankey diagrams are shown for the per capita energy streams. Observing these diagrams together with some economic reasoning helps us define a range of energy mix variables in Section 3.3. These mix variables capture qualitative properties of the energy mix in summary flows or in ratios and can later be analysed for their relation with the GDP.

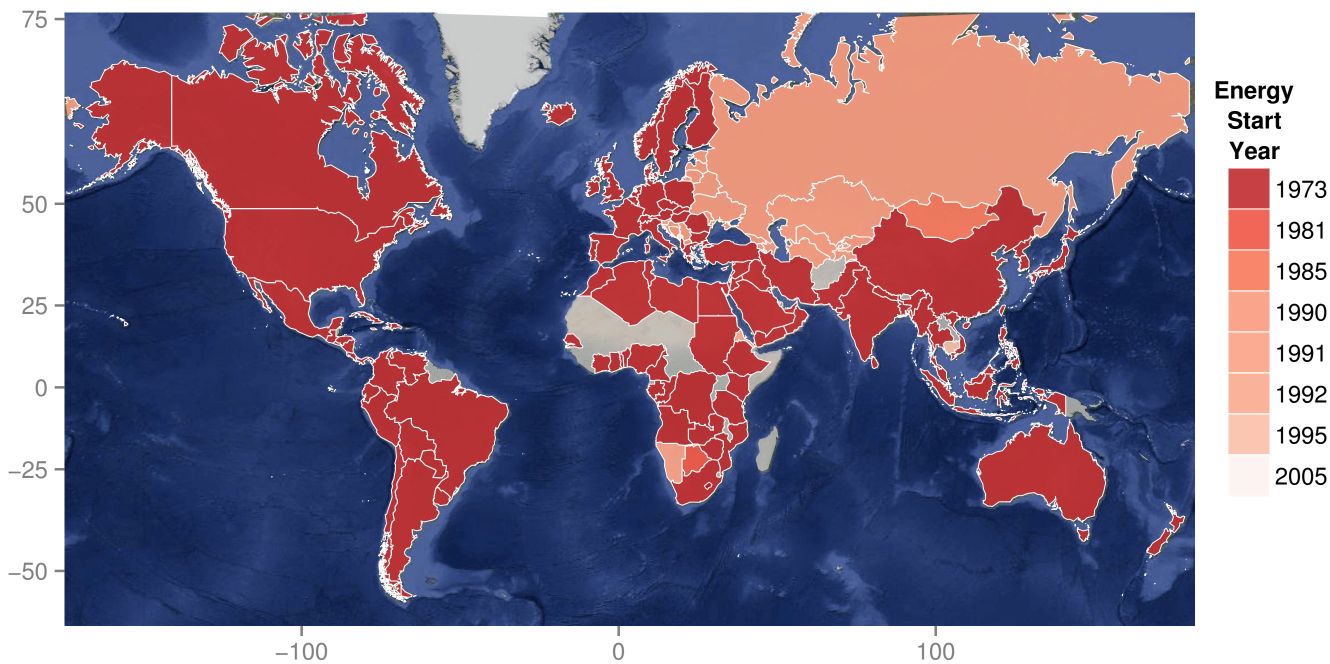

Figure 3.1: IEA energy mix data availability start date plotted on a choropleth map. The data extends annually to 2012. It can be seen that a very large part of the world is covered. Missing countries are inicated in grey. Data: IEA, Graph: author.

3.1 Energy Data

The energy mix data is recorded annually and runs for the majority of the countries from 1973 to 2012. It is visible from the map in Figure 3.1 that a very large part of the world is covered by the dataset. In total 138 countries and 3 regions (World, OECD and Middle East) of the dataset are considered. All of Europe, and the Americas is covered, a very large part of Asia and a large part of Africa. The data includes several countries which are considered cautious with information exchange with the western world such as the majority of Arabic countries, Myanmar and North Korea. Energy wise, mostly with regard to oil production, the most interesting of the missing countries are probably Afganistan and some central African countries such as the Central African Republic, the Republic of Niger, Chad and Somalia.

The energy mix data consists of yearly energy balances for all countries included. The balance is visualized schematically in Figure 3.2. The dataset contains information on the energy carriers employed by the countries such as Oil (O), natural Gas (G) or Biofuels such as wood (B)[21]. For all the codes that are assigned see Table 3.1. For each of the energy carriers several specific items are recorded (Table 3.2) regarding their origin, processing and final utilisation. Origin items such as Imports (M) or Production (P) are included. Regarding their processing items such as To Oil Refineries (TOR), To Power Stations (TPS) for electricity generation or To Other Transformation (TOT), which includes for example coking coal to coke.

The final utilisation is split up into several items such as Industry (I) use, Transport (T), exports (X) and Other (O) which for example includes domestic uses. To International (Marine/Aviation) Bunkers (TIB) are quantities delivered to ships/planes in international navigation and is split according to port of departure and arrival, not according to flag.

Finally there are items for the countries annual Stock Build and Draw (SB/SD) of the energy carrier and an item that accounts for the statistical Differences (DP/DM) between the microdata collected and recorded, and the total consumption reported by the country due to differences in data sources and specific inclusion rules. In Table 3.2 the 112[1] included carrier-item pairs are shown.

For all balances the input-output or in terms of Figure 3.2 Origin-Processing-Destination balance is kept. In symbols this balance is shown in Equation 3.1 and this relation is satisfied for all 11 energy carriers (see Table 3.1) and for all 4982 Country-Years that are included in the energy data set.

$$\begin{aligned}\overbrace{\mathrm{P}+(\mathrm{SD}-\mathrm{SB})+(\mathrm{DP}-\mathrm{DM})+\mathrm{M}}^{\textit{Origin}}+\overbrace{(\mathrm{FOT}-\mathrm{TOT})+(\mathrm{FOR}-\mathrm{TOR})+(\mathrm{FPS}-\mathrm{TPS}-\mathrm{LOSS})+\mathrm{FH}}^{\textit{Processing}}\\ =\underbrace{\mathrm{I}+\mathrm{T}+\mathrm{O}+\mathrm{U}+\mathrm{UNE}+\mathrm{TIB}+\mathrm{LOSS}+\mathrm{X}}_{\textit{Destination}}\end{aligned} \tag{3.1}$$

3.2 Energy Flows

The energy flows are visualized in so called Sankey diagrams[2]. In these plots from left to right the flows go from Origin (nodes on the left), potentially through Processing, to their Destination (nodes on the right). The color of the flows indicates the type of carrier (eg. Oil is red) and the linewidth of the flow is proportional to the share in total energy through the linked node. There are 6 snapshots created and shown in the appendix Figures A.6.1-A.6.6. When inspecting the flows visually it is clear that they differ a lot. For Ukraine and Guatamala a different year is selected that shows a more extreme mix than 2011. First in magnitude, the flows in Guatamala are in the order of hundreds of kilogrammes of oil equivalent (KGOE) where as the flows of Netherlands (Figure A.6.2) are in the thousands. The carriers and quantity of produced energy and exported: Iceland (Figure A.6.3) produces all electricity from geothermal energy and hydropower, imports all petroleum and exports no energy. The Netherlands seems to trade (import and export) a lot of petroleum products and gas, whereas China (Figure A.6.6) produces a lot of its energy, and an increasing share, from coal.

Guatamala, which is considered as a developing country, relies primary on biofuels (e.g. wood) and uses and produced only 133 KGOE of electricity per inhabitant in 2005. The USA (Figure A.6.5) produces energy from a wide variety of, mainly fossil, carriers and used 2943 KGOE of electricity per capita in the most recent measurement.

[1] ODM is split into ODM and ODMFOT

[2] Named after Matthew Henry Phineas Riall Sankey (1853-1926)

Table 3.1: All codes used to describe the energy mix data.

Energy Carriers		Recorded Items			
Code	Name	Code	Name	Code	Name
B	Biofuels and waste	P	Production	I	To Industry
C	Coal	M	Import	T	To Transport
E	Electricity	FOT	From Other Transformation	O	To Other
G	Natural Gas	TOT	To Other Transformation	U	Own Use
H	Heat	FOR	From Oil Refineries	UNE	Non-energy Use
N	Nuclear	TOR	To Oil Refineries	X	Exports
O	Oil	FPS	From Power Stations	SB	Stock Build
P	Oil products	TPS	To Power Stations	SD	Stock Draw
S	Solar/tide/wind	FH	From heat	DP	Difference statistical [+]
T	Geothermal			DM	Difference statistical [-]
W	Hydro			LOSS	Losses
				TIB	To International Bunkers

Table 3.2: All 112 Carrier-Items pairs considered in the energy mix data across all countries in the set. The codes are constructed according to Table 3.1.

	P	M	FOT	TOT	FOR	TOR	FPS	TPS	FH	I	T	O	U	UNE	X	SB	SD	DP	DM	LOSS	TIB
B	BP	BM	BFOT	BTOT				BTPS		BI	BT	BO	BU		BX	BSB	BSD	BDP	BDM		
C	CP	CM	CFOT	CTOT				CTPS		CI	CT	CO	CU	CUNE	CX	CSB	CSD	CDP	CDM		
E		EM					EFPS		EFH	EI	ET	EO	EU		EX			EDP	EDM	ELOSS	
G	GP	GM	GFOT	GTOT		GTOR		GTPS		GI	GT	GO	GU	GUNE	GX	GSB	GSD	GDP	GDM		
H	HP	HM					HFPS			HI		HO	HU					HDP	HDM		
N	NP							NTPS													
O	OP	OM	OFOT	OTOT	OFOR	OTOR		OTPS		OI	OT	OO	OU	OUNE	OX	OSB	OSD	ODP	ODM		
P		PM			PFOR			PTPS		PI	PT	PO	PU	PUNE	PX	PSB	PSD	PDP	PDM		PTIB
S	SP							STPS		SI		SO	SU					SDP	SDM		
T	TP							TTPS		TI		TO						TDP	TDM		
W	WP							WTPS													

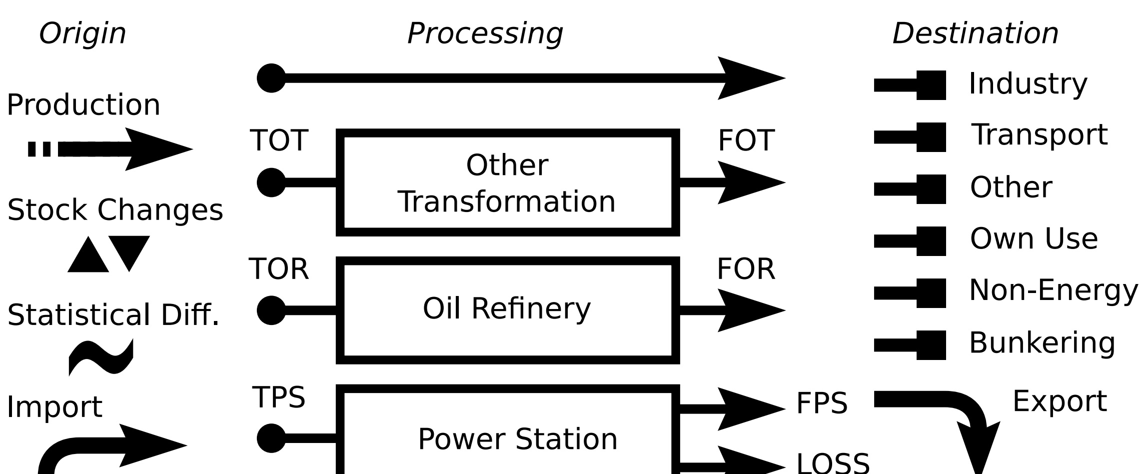

Figure 3.2: The energy balance flows visualized schematically. Graphic: author.

Ukraine (Figure A.6.4) produces a large part of its energy from imported (Russian) gas, which makes the country dependent on international trade for its energy need. Such foreign dependence makes a country's economy manipulable by others which could be used against them. In the same category we see that Guatamala (Figure A.6.1) has no oil refinery and is completely surrendered to other countries for its petroleum product demand. In fact it does produce oil, but practically all oil is exported. Does such a dependent positioning influence the developed welfare?

From these Sankey diagrams it is not possible to assess the variability over time of the mixture composition. Variation over time is required to estimate the effect of energy use and policy changes. The balances are rendered for all years, and chronologically inspected for changes. And separate energy items are plotted in a time series plot. Both are excluded from this thesis. The temporal changes are plenty, thus estimation with country fixed effects (the within transformation) is possible. The observed variations and their historical context are used to inspire the energy mix summaries that are constructed from the flow items.

3.3 Energy Mix Variables

3.3.1 Energy Mix Variables from Flows

The raw energy data consists of the 112 carrier-item pairs given in Table 3.2 for all 4865 country-years. It is uninformative to link the raw carrier-item flows or random combinations of the flows to the GDP. To quantitatively capture certain aspects and qualities of the energy mix, the recorded flows (See Figure 3.2 and Table 3.1) are summarized in several mix variables. Four categories of mix variables are defined: Aggregates, Technology Proxies, International Positioning and Utilization. All constructed variables are named, described and defined in Table 3.3. In the following paragraphs we will discuss these defined energy mix variables by category.

A. Aggregates The Aggregates are the total energy on the consumption side (FIN), on the primary supply side (TPES) and the domestic production (PROD). The items in FIN are generally forms with a direct consumer use such as petroleum products to use as car fuel or electricity, whereas the TPES items also consist of (crude) oil and nuclear energy.

B. Technology Proxies The Technology Proxies are streams and ratios that can be argued to have a relation with technological progress. Such as the fraction of the energy from wood (biofuels B.F) and the electricity consumption/fraction E/E.F or nuclear power supply fraction N.F. Broader choices such as percentage of the energy that is supplied as fossil fuels (FOSSIL.F) and renewables (RENEW.F). The efficiency of power stations (PSEFF) and the capacity of the oil refineries (OR.CAP).

C. International Positioning International Positioning mix variables attempt to capture trade and trade dependence for energy (TRADE.DEP). It expresses the net trade position in a fraction (multiplier) of the total primary energy supply of a country. The concentration (inversely related to variety) of energy carriers is described from the supply (CONCSQ.TPES) and production (CONCSQ.PROD). The concentration is measured in two methods: the maximum fraction (a supremum function over the carriers), and the sum of the squared fractions. OR.INDEP shows the capability to refine sufficient petroleum products from crude oil to satisfy or exceed the domestic demand. In the same theme the OILEX.PETRIM capture the net oil export position ratio to the net petroleum products import position. As oil is practically useless without turning it into products, this variable could show weak trade position for countries with large supplies but underdeveloped technology.

D. Utilization The Utilization variables show to what final destination or purpose the energy is directed. Utilizations such as industry usage (IND.F), other uses (primarily domestic) (OTHER.F) and transportation

(TRANSP). But also less common entries such as the fraction used in international bunkering (INTBUNKER.F) or the fraction of alternative fuel used in the transportation sector: TRANSP.ALT.

3.3.2 Summary statistics

Several summary statistics of the energy mix variables are given in Table 3.4. Several observations can be made from this table. All variables measured in equivalent heating value (Mtoe) are highly positively skewed due to the overweighting of small countries as every country has the same weight.

The average country supplies in its primary energy need with 70% fossil fuels, 24% biofuels and wood and for the remaining 6% with renewables and alternatives. The assigned uses are on average 45% to other uses (domestic etc), 26% to industry, 23% to transportation and 6% to non energy uses.

On average the power stations are 48% efficient with their input energy (PSEFF) and the electricity fraction in final consumption is on average only 13% (E.F). The fraction of transportation not running on petroleum products is only 3%. The majority of countries is not dependent for other countries for their oil refineries as OR.INDEP > 1 but there are 202 country-years in the dataset that are fully dependent on import for their petroleum products.

The products that countries produce are quite concentrated as the mean of CONCMX.PROD is 72%. The concentrations in the total primary energy supply CONCMX.TPES and CONCSQ.TPES can be higher than 1. The individual carrier contributions to the TPES can be negative for example if a country imports a lot of oil and exports lots of petroleum products, the TPES does not need to be large as the import and export cancel in the TPES but carrier concentration of oil is high.

The trade positions averaged of all countries are practically zero, as they should be cancelling each other. The average country independent for their energy supply and exports can range up to 155$\times$ their own primary supply. OILEX.PETRIM shows that the average trade ratio oil for petroleum is about 3½ : 1. The trade position variables all have very high values for kurtosis while their interpretation and interesting points are most valuable around 0 and 1. This is the point where the dependence switches from completely self sufficient to completely trade dependent. This suggest applying a transformation.

The dependent variable in our models defined in Chapter 2.1, Equations 2.10 and 2.11, is transformed by the logarithm. This suggest transforming all the level variables by the logarithm too. This is what we will do when constructing the 5 and 10 year blocks from these mix variables in Section 5.2.3.

Table 3.3: Energy Mix Variables. Code, Discription, Units/Range and Construction. Source data from IEA energy balances. See Table 3.1. 'items' are the recorded flows e.g. Production [P]. 'carriers' are for example Oil [O] or Biofuel [B]. 'carrier-items' are a flow of a specific type such as Oil Production [OP] or Petroleum Products to Transportation [PT]. 'mixvars' refer to other energy mix variables. If no carriers are specified, all carriers are included. $Mtoe$ are millions of tonnes of oil equivalent (generally ≥ 0 unless $\pm$ is added) and % is a fraction (0..1). The ratios have no units, their range is denoted.

Mix Variable	Discription	Unit	Definition
A. Aggregates			
FIN	Final consumption	$Mtoe$	'items'[I T O UNE]
TPES	Total Primary Energy Supply	$Mtoe$	'items'[P M-X SD-SB DP-DM -TIB]
PROD	Production capacity	$Mtoe$	'item'[P]
B. Technology Proxies			
E	Electricity consumption[3]	$Mtoe$	'carrier'[E] 'items'[I T O UNE]
E.F	Electricity consumption fraction	%	'mixvar'[E/FIN]
B	Biofuel (wood) primary supply	$Mtoe$	'carrier'[B] 'items'[P M-X SD-SB DP-DM -TIB]
B.F	Biofuel (wood) primary fraction	%	'mixvar'[B/TPES]
N.F	Nuclear production fraction	%	'carrier-item'[NP]/'mixvar'[PROD]
FOSSIL	Fossil fuel primary supply[4]	$Mtoe$	'carriers'[O,P,G,C] 'items'[P M-X SD-SB DP-DM -TIB]
FOSSIL.F	Fossil fuel primary fraction	%	'mixvar'[FOSSIL/TPES]
RENEW.F	Renewables primary fraction	%	'carriers'[S,T,W] 'items'[P M-X SD-SB DP-DM -TIB]/'mixvar'[TPES]
PSEFF	Power station efficiency[5]	%	1 – 'carrier-item'[ELOSS] / 'item'[TPS]
OR.CAP	Oil refinery production capacity[6]	$Mtoe$	'carrier-item'[PFOR]
C. International Positioning			
TRADE.POS	Net trade position[7]	$\pm Mtoe$	'item'[M] – 'item'[X]
TRADE.POS.FOSSIL	Net trade position for fossil fuels	$\pm Mtoe$	'item'[M] – 'item'[X] 'carriers'[O,P,G,C]
TRADE.VOL	Trade volume	$Mtoe$	'item'[M] + 'item'[X]
TRADE.DEP	Dependence on foreign trade, trade position[8]	$-\infty..\infty$	'mixvar'[TRADE.POS/TPES]
TRADE.DEP.FOSSIL	Dependence on foreign trade for fossil fuels	$-\infty..\infty$	'mixvar'[TRADE.POS.FOSSIL/FOSSIL]
OR.INDEP	Oil refinery Petr. Prod home produced[9]	$\approx 0..\infty$	'items'[(FOR SD-SB DP-DM) / (I T O UNE)] 'carrier'[P]
OILEX.PETRIM	Ratio net Oil export to net Petr. Prod. import[10]	$-\infty..\infty$	'carrier-items' [(OX-OM) / (PI-PX)]
CONCMX.TPES	Primary supply carrier concentration[11]	0..1	$\sup_x$('carrier'[x]/'mixvar'[TPES]) with x $\in$ all 'carriers'
CONCSQ.TPES	Primary supply carrier concentration[12]	$1/x..1$	$\sum_x$('carrier'[x]/'mixvar'[TPES])^2 with x $\in$ all 'carriers'
CONCMX.PROD	Production carrier concentration	0..1	$\sup_x$('carrier-item'[xP]/'mixvar'[PROD]) with x $\in$ all 'carriers'
CONCSQ.PROD	Production carrier concentration	$1/x..1$	$\sum_x$('carrier-item'[xP]/'mixvar'[PROD])^2 with x $\in$ all 'carriers'
D. Utilization			
IND	Industry	$Mtoe$	'item'[I]
IND.F	Industry consumption fraction	%	'mixvar'[IND/FIN]
OTHER	Other uses (mainly domestic)	$Mtoe$	'item'[O]
OTHER.F	Other uses consumption fraction	%	'mixvar'[OTHER/FIN]
NONENERGY	Non Energy Use	$Mtoe$	'item'[UNE]
NONENERGY.F	Non Energy Use consumption fraction	%	'mixvar'[NONENERGY/FIN]
INTBUNKER	International Bunkering Use	$Mtoe$	'item'[TIB]
INTBUNKER.F	International Bunkering supply multiplier[13]	$0..\infty$	'mixvar'[INTBUNKER/TPES]
TRANSP	Transportation	$Mtoe$	'item'[T]
TRANSP.F	Transportation consumption fraction	%	'mixvar'[TRANSP/FIN]
TRANSP.ALT	Electricity (alt. Fuel) in Transportation	%	'carriers'[not-P] 'item'[T]/'mixvar'[TRANSP]

[3] Consumption indicates same items as 'mixvar'[FIN], and supply indicates same items as 'mixvar'[TPES]

[4] Fossil fuels: Oil, Petroleum Products, Gas and Coal, Renewable fuels: Solar/tide/wind, Geothermal and Hydro

[5] Specification allows for wasted heat HFPS utilization, but not fair for different carrier thermodynamic transition efficiencies.

[6] Petroleum Products (diesel, fuel, etc)

[7] TRADE.POS and TRADE.POS.FOSSILare nett trade positions and can be < 0 so log not simply applicable

[8] Relative trade dependence, 1 for all supply from import, 0 for independence and < 0 for net exporters.

[9] 1 (or > 1) is everything could be home produced, < 1 indicates import dependence. Net of stock and statistical changes. Can become negative only du to difference minus [DM] and stock build [SB] which are typically relatively small.

[10] Ratio > 0 if country is a net trader, < 0 if a net exporter or importer.
High magnitude $\rightarrow$ high quantity of oil traded for relatively low amount of petrol.

[11] Supremum $\sup_x f(x)$ gives the maximum value of the argument among the candidates x

[12] Specification similar to the Herfindahl index used in a.o. Competition/monopoly economics.

Table 3.4: Summary statistics of constructed energy mix variables. Sample moments: Mean, Standard deviation, Skewness and Kurtosis. The range (min. . . max) and the number of missing, zero and nonzero values.

	m	s	S	K	range	unit	NA	0	≠0
A. Aggregates									
FIN	46.87	153.26	7.20	61.20	(0.08 . . . 1635)	$Mtoe$			4865
TPES	65.33	219.27	7.40	65.30	(0.09 . . . 2583)	$Mtoe$			4865
PROD	67.75	201.55	6.30	48.30	(0 . . . 2432)	$Mtoe$		30	4835
B. Technology Proxies									
E	6.94	26.03	8.60	88.90	(0 . . . 332)	$Mtoe$		2	4863
E.F	0.13	0.09	1.40	6.70	(0 . . . 0.65)	%		2	4863
B	7.07	23.25	6.20	45.40	(0 . . . 216)	$Mtoe$		496	4369
B.F	0.24	0.30	1.10	2.70	(0 . . . 0.98)	%		496	4369
N.F	0.06	0.18	3.20	12.30	(0 . . . 0.92)	%		3854	1011
FOSSIL	53.46	190.52	7.70	68.30	(0.06 . . . 2289)	$Mtoe$			4865
FOSSIL.F	0.70	0.30	-0.80	2.20	(0.02 . . . 1.1)	%			4865
RENEW.F	0.06	0.12	4.90	32.80	(0 . . . 1.23)	%		764	4101
PSEFF	0.48	0.20	1.00	3.50	(0 . . . 1)	%		6	4859
OR.CAP	24.55	77.21	7.90	76.60	(0 . . . 865)	$Mtoe$		795	4070
C. International Positioning									
TRADE.POS	0.50	84.11	1.00	23.20	(−579.1 . . . 736)	$Mtoe$			4865
TRADE.POS.FOSSIL	0.49	83.96	0.90	23.10	(−577.6 . . . 734)	$Mtoe$			4865
TRADE.VOL	49.11	96.57	4.10	25.90	(0.03 . . . 969)	$Mtoe$			4865
TRADE.DEP	-0.70	4.57	-13.90	340.70	(−154.67 . . . 3.7)	×			4865
TRADE.DEP.FOSSIL	-1.05	6.56	-9.50	146.10	(−154.67 . . . 3.67)	×			4865
OR.INDEP	1.66	4.19	14.70	326.90	(−0.43 . . . 126.48)	×		202	4663
OILEX.PETRIM	3.46	164.33	11.40	422.20	(−2386 . . . 5684)	×	750		4115
CONCMX.TPES	0.72	0.52	6.30	58.40	(0.22 . . . 7.63)	%			4865
CONCSQ.TPES	1.16	4.70	12.90	199.30	(0.18 . . . 102.21)	%			4865
CONCMX.PROD	0.72	0.20	-0.30	1.90	(0.22 . . . 1)	%	30		4835
CONCSQ.PROD	0.63	0.23	0.10	1.80	(0.18 . . . 1)	%	30		4835
D. Utilization									
IND	13.80	46.00	7.90	84.60	(0 . . . 783)	$Mtoe$		24	4841
IND.F	0.26	0.14	0.70	4.10	(0 . . . 0.87)	%		24	4841
OTHER	18.04	54.40	6.10	44.80	(0.03 . . . 513)	$Mtoe$			4865
OTHER.F	0.45	0.20	0.50	2.70	(0.03 . . . 0.99)	%			4865
NONENERGY	3.90	13.52	7.40	68.40	(0 . . . 166)	$Mtoe$		348	4517
NONENERGY.F	0.06	0.08	3.70	22.80	(0 . . . 0.74)	%		348	4517
INTBUNKER	1.71	4.58	6.10	50.80	(0 . . . 54)	$Mtoe$		227	4638
INTBUNKER.F	0.07	0.28	26.60	1,119.90	(0 . . . 13.22)	×		227	4638
TRANSP	11.12	47.77	9.90	109.10	(0.01 . . . 629)	$Mtoe$			4865
TRANSP.F	0.23	0.12	0.60	3.70	(0 . . . 0.81)	%			4865
TRANSP.ALT	0.03	0.08	4.20	24.50	(0 . . . 0.78)	%		2480	2385

[13] [TIB] is excluded from TPES so this variable indicates how many times the primary supply is used in bunkering.

Chapter 4

Temperature Instrument

In this section the construction of a annual temperature instrument per country is discussed. As energy and growth are both unable to influence annual temperature anomalies, it is exogenous[1] and is likely to influence energy and production. The motivation for using temperature as an instrument for energy is the mechanism where temperature fluctuations influence energy usage directly, opposed to influencing productivity primarily *through* this energy usage. Off course there is a direct path from temperature to production where no energy is in the loop. But this direct path is assumed small compared to the energy influenced path as this direct path uses less technology and thus has a smaller share in the total production.[2] The construction approach uses a discretized grid of $5° \times 5°$ cells in a Mercator (longitude-latitude) plot, as this is the format of the raw temperature data. The resulting instrument is 100% complete relative to the energy mix data.

4.1 Overview of construction

`Panel 1`

Weather Station Temperature Data

↳ Monthly Anomaly Grid Data $\xrightarrow{[\ TPS\ ]}$ Monthly Full World Coverage

$\downarrow$ [$12M$ *AGGREGATE*]

Annual-Grid Temperature Variable

Country Polygon Data $\xrightarrow{[\ CLIP\ ]}$ **Country-Grid Cell Area Data**

—————————————— $\times$

Annual-Country Temperature Instrument

Construction of the temperature instrument is visualised schematically in Panel 1 above. The trajectory consists of a temperature track, a polygon track and the join. The center and right column in the panel shows the actions the author has performed, the left are data and methods of other parties. The temperature track starts with a incomplete monthly temperature anomaly grid, and results in a grid of temperature anomalies covering all landmass on earth. The anomalies are temperature changes relative to a base period.

[1] The global warming literature, if considered valid, proposes a energy-use→climate-change relation. However this is a long term (much slower than annual) shifting

[2] Instrumental Variables approaches always require such an intuition/assumption from the underling mechanism which makes them difficult to generalize. The strength of their application depends on the strength of these assumptions.

The data is interpolated by a Thin Plate Spline (TPS) and aggregated by several simple metrics. This entire process is discussed in Section 4.2.

The polygon track starts with country polygons for all countries and construct from these, by clipping, the relative land area in the grid cells. The methods to do this were created by the author, however to keep focus on the main topic this presentation is moved into the appendix: Section A.4. The Annual-Grid Temperature Variable and the Country-Grid Cell Area Data are combined in Section 4.3. The temperature variable is weighted by the area data and the result is a annual-per-country temperature variable.

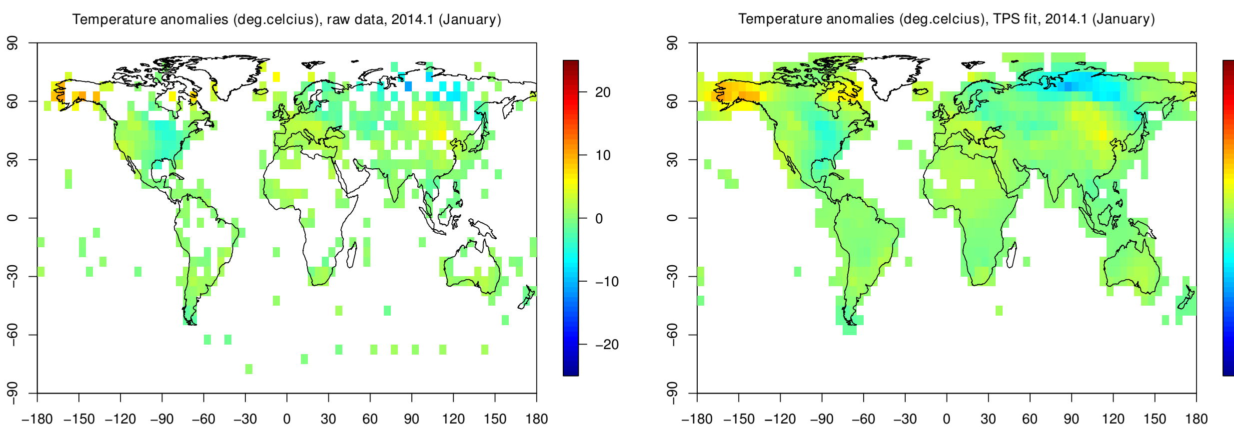

Figure 4.1: Snapshot of raw and TPS fitted temperature $5^\circ \times 5^\circ$ grid data. For the TPS fit the subset for countries with energy mix data is shown. The fit is exact in observed data, and seems very reasonable elsewhere. Data: GHCN, Fit and Graphs: author.

4.2 Temperature data

Origin & description Originally the temperature data is collected by national and regional climate agencies from 7 280 weather stations. This data is then transformed into anomalies relative to a base period, gridded and made available by the Global Historical Climatology Network (GHCN). The gridded temperature anomaly data has a sample of 1880.1 - 2014.2 (1610 months) for 72 longitude and 36 latitude cell indices (2592 cells). The index codes employed are of the form $\{i,\, j\}$ and indicate the top left corner of the specified grid cell. To find the latitude and longitude use:

$$\begin{aligned} \text{latitude} &= \quad 90 \quad - 5\,(i-1) \\ \text{longitude} &= -180 + 5\,(j-1) \end{aligned} \tag{4.1}$$

So the top left cell is $\{1,\, 1\} \to (90^\circ N,\, -180^\circ W)$ and the bottom right cell is $\{36,\, 72\} \to (-85^\circ S,\, 175^\circ E)$.

The months and cells combined give $1610 \cdot 2592 = 4\,173\,120$ data points. Of the approximately 4.2 million values, 630 377 are nonmissing, or about 15%. All measurements are land measurements.[3] The source of the temperature data is the Global Historical Climatology Network-Monthly (GHCN-M) version 3.2.1 and is constructed from intra daily temperature observations from weather stations situated around the globe [35, 25].[4] The plain temperature data is transformed by deviations from a long term average with a base period to construct a time series of "temperature anomalies". For the GHCN-M data, this base period is 1981-2010. In other words the data is translated in such a way that the average for 1981-2010 is zero. The weather station data is adjusted for spatial outliers and requires at least 20 years of data

[3] Only cell $\{14,\, 67\}$, with top-right latitude 25° and longitude 150° -a block between Japan and Papua New Guinea- has temperature measurements but no land in the polygon dataset. Satellite images show no land here.

[4] http://www.ncdc.noaa.gov/temp-and-precip/ghcn-gridded-products.php, visited Jan-2014

in the 1961–1990 period. [5,6] The calculation of the deviation from the base period is performed at meteorological measurement station level. This allows stations to become more comparable, take for example stations situated at different altitudes having different mean temperatures, but if geographically close their anomalies are more similar.

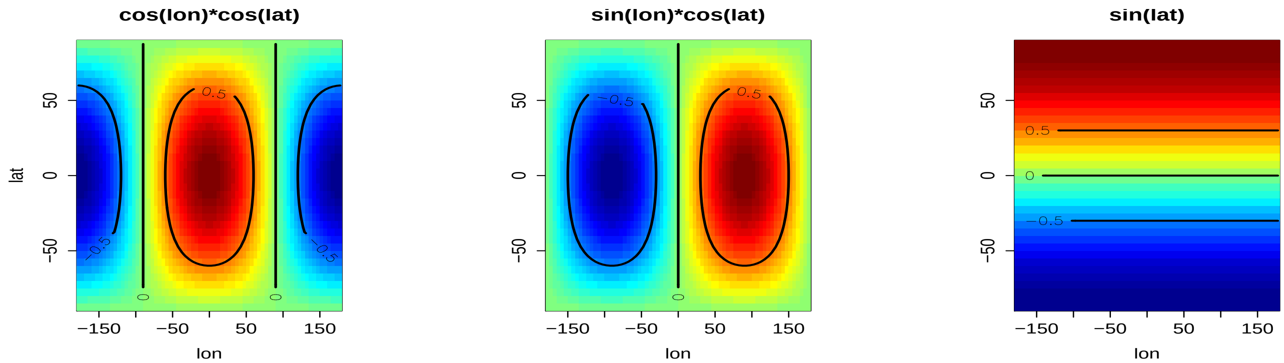

Figure 4.2: Three dimensional coordinate transformation from latitude and longitude. Used to estimate the spatial temperature model. The coordinates map to the unit sphere. Graphics: author.

TPS fit There are 1429 cells with land (Section A.4), out of the total of $72 \cdot 36 = 2592$. So about 55% of the all cells have landmass. Of the total of 2 300 690 landmass temperature observations, 629 568 are non missing or 27%. For the post 1970 set the measurement landmass coverage improved to 269 539 out of 757 370, or about 35% non missing. The coverage for 2010- is still about 35% of landmass.

The subset of cells with land belonging to the 137 countries that are included in the energy mix dataset, consists of 938 cells, or about 66% of all the cells with land. Conditional on this subset the total length of the dataset the coverage is 587 534 out of 1 510 180 observations or 39%. For post 1970 this is 245 592/497 140 or 49% and 2010- about 48%. So for the period we're investigating, on average about half of the land (cells) we are interested in has temperature anomaly observations.

From investigating the raw temperature anomaly data visually in a spatial plot, see Figure 4.1 (left), and from the fact that about one half of the region of interest is measured, estimating the other half of the cells appears tractable. The spatial dataset for every month in the dataset from 1970 onwards is fit with a TPS with the `fields` [R] package.[32] The model that is estimated predicts the temperature by:

$$\hat{f}(\mathbf{x}) = \sum_j \phi_j(\mathbf{x}) \cdot d_j + \sum_k \psi_k(\mathbf{x}) \cdot c_k \tag{4.2}$$

$\mathbf{x}$ are the independent variables, in our case the location, and $\hat{f}$ is the prediction function. The two parts in the constructive side are a low order polynomial model ϕ_j, also referred to as spatial drift which is linear in our case ($j \in 0, 1$), and ψ_k are the covariance functions for all knots. In our case the functions are radial basis functions and the knots are all grid cells with temperature data. For $\mathbf{x}$ the latitude and longitude are transformed to points in 3 dimensions on the unit sphere by the functions plotted in Figure 4.2. The resulting TPS fit is shown for one month in Figure 4.1 (right) and looks very reasonable.

[5] The original base period for anomaly calculation was 1961-1990, but this period has been readjusted to 1981-2010.

[6] The foresight that is introduced in the data by adjusting for (so knowing the) the 1981-2010 average is presumed to have negligible predictive power for the cross country wealth and energy variations. Additionally the constructed temperature instrument is dependent on the scale of temperature anomalies, not the level.

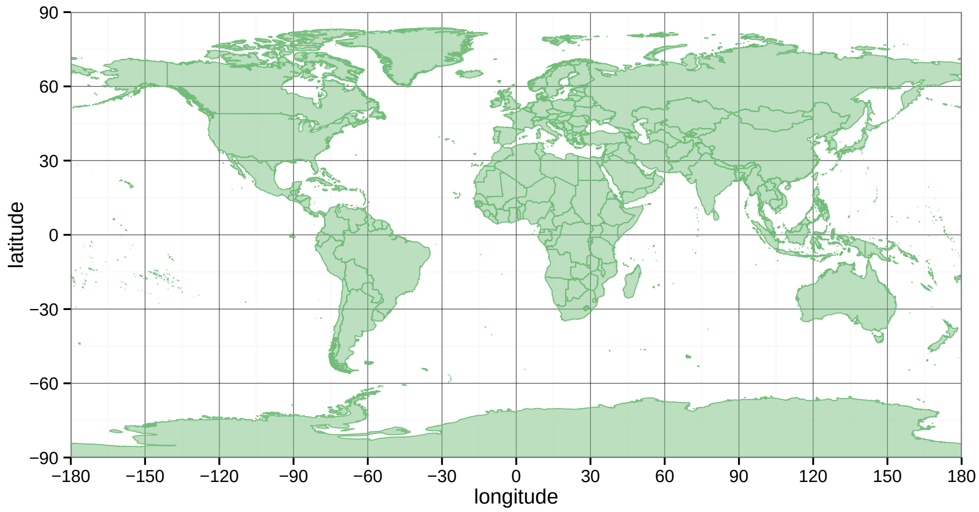

Figure 4.3: Plot of all of the 239 country polygon sets (green) in the Eurostat statistical boundary data. These polygons are gridded to a $5° \times 5°$ grid. The plot with ISO3 labels is given in Figure A.1. Data: Eurostat, Graph: author.

4.3 Joining to Temperature Instrument

Now the temperature data covers all landmass due to the TPS fit. From the polygon gridding and clipping routine described in appendix Section A.4 and all country area weights are calculated. These area weights and temperature data can be combined to construct the temperature anomalies for each country. To do this, for each month in the temperature data the temperature of grid cell $\{i, j\}$ (See Equation 4.1) denoted by $\mathrm{Temp}_{ij}(Year, Month)$ is multiplied with counties that have nonzero weight in the country-area grid. This weight, the relative contribution to the total area of this country (`perckm` in Panel 3), is denoted by $\mathrm{W}_{ij}(ISO3)$. Now the temperature anomaly for this country in this month is found by summing over all cells:

$$\mathrm{Temp}(ISO3, Year, Month) = \sum_{ij} \mathrm{Temp}_{ij}(Year, Month) \cdot \mathrm{W}_{ij}(ISO3) \tag{4.3}$$

Spatial subset After the contraction sequence over all cells in Equation 4.3 we now have a monthly time series of temperature anomalies for all 241 countries. However only the 137 countries for which IEA energy mix data is available (See Panel 2) are required in the desired temperature instrument. All grid cells with nonzero landmass and the subset of cells when only the countries with energy data are plotted in Figure 4.4.

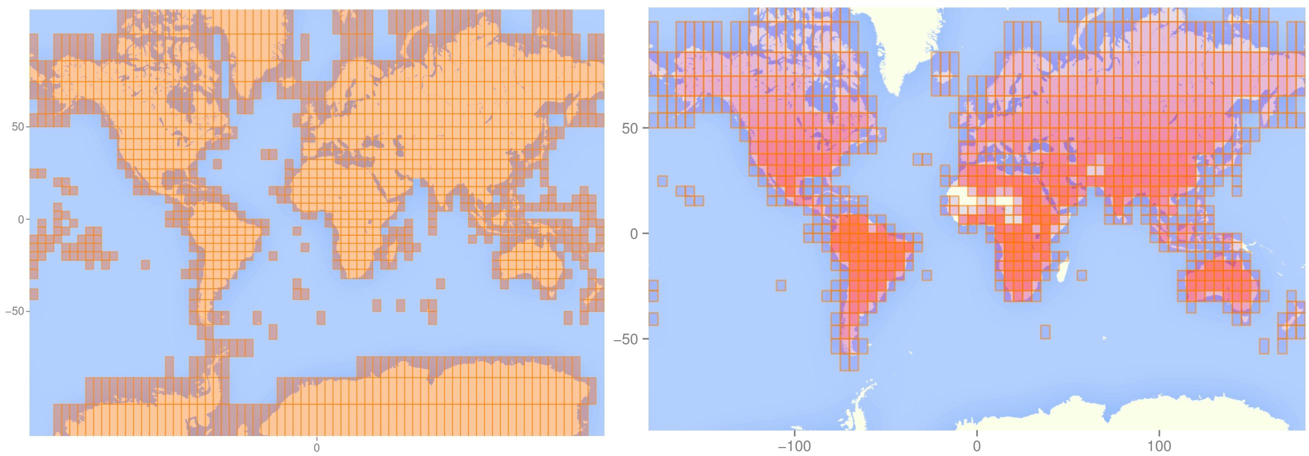

Figure 4.4: Grid cells with nonzero landmass. Left: for all land in country polygon dataset (1429 cells), Right: for the subset of countries for which energy mix data is available (938 cells), colored by area in km^2. Graph: author.

Temporal aggregation Now to construct an annual instrument T from the monthly observations of temperature anomalies, the 12 months in each year of data must be aggregated. This is done by calculating the range by $\mathrm{Range}_{it} = \max \mathrm{T}_{iy} - \min \mathrm{T}_{iy}$, with T_{iy} the vector containing the temperature anomaly observations for country i in year y. The range is selected for multiple reasons:

it solves the issue of the fact that the base period that is selected to construct the temperature anomalies is not the oldest part of the temperature data.

Also the temperature range is a measure for extremity, if a year was very hot in the summer, the range will by high and if it was a harsh winter too. The range is low for countries where it is always hot. It is likely that this influences the labor productivity directly, but we want the indirect path Temperature→Energy→GDP. Permanent climate differences are most likely solved by technology, not by increased energy hence less related to the level of the temperature.

Finally it solves for the trend that is present in the raw temperature data due to global warming. For an observable energy usage that is linked to temperature, faster (in the order below a few years) variations are needed. An overall permanent increase in temperature is likely not solved by increasing overall energy usage but rather by technologically innovating. E.g. improved isolation as opposed to cranking up the air-conditioning power.

A histogram of the constructed annual temperature range is plotted in Figure 4.5 on a logarithmic scale as the range is by construction positive and had high positive skewness. The resulting temperature range variable is 100% complete for all countries and years in the energy mix dataset.

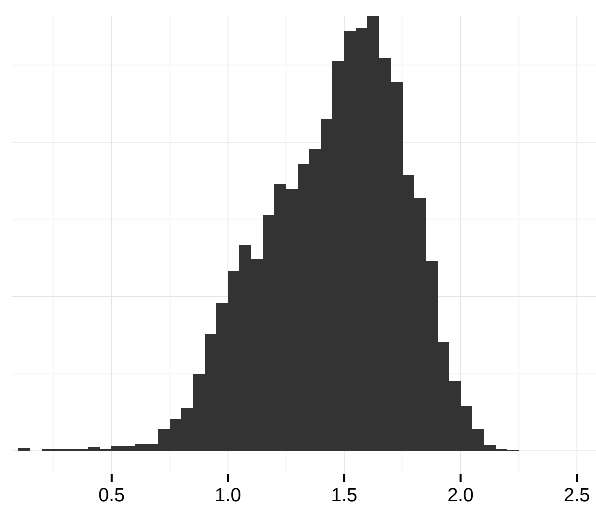

Figure 4.5: Distribution plot for the temperature range on a logarithmic axis for all ISO3-Years. Graph: author.

Chapter 5

EnergyMix-GDP Regressions

Introduction In this chapter the constructed energy mix variables of Chapter 3 Table 3.3 are used in a regression framework to estimate their marginal effect on per capita domestic production. Estimates for the sensitivities on these energy factors are interesting to reveal their relative influence and directionality which can both be used to construct energy related policies. Note that these policies do not require a a priory direction of causation between energy and GDP. Example policies could be: If high growth is observed, anticipate a higher energy demand. Or the lack of oil refineries throttles growth, this bottleneck must be mitigated.

This chapter alternates between results and methods. To simplify grasping the scope of the analyses that are performed, a brief summary of the methods of this chapter is given here. In general the text after the preliminary unconditional regression can be split up into two parts. Both parts consider panel models with human/physical capital labor and energy. In the fist part the majority of energy mix variables are added one by one to the baseline model, and the model is tested for joint significance, heteroskedasticity, autocorrelation, pooled-OLS versus fixed effects and random versus fixed effects. Then the estimates for the mix variables are investigated and inference is performed on them with Heteroscedasticity and Autocorrelation-Consistent (HAC) standard errors. Then in the second part the models with energy mix variables that are suspected of endogeneity are re-estimated with instrumental variables by the temperature variable and these results are then again interpreted and compared to the Ordinary Least Squares (OLS) estimates.

Overview by section First a preliminary unconditional annual regression is performed in Section 5.1. Then the mix variables are gathered together with the selected traditional control variables from Chapter 1 that proxy for physical and human capital savings and labor and aggregated into blocks of 5 and 10 years in Section 5.2. Theory form growth literature together with systematic model selection gives us a base regression to which the mix variables can be added in Section 5.3. In Section 5.4 the results of this analysis are presented and analysed. Finally in Section 5.5 a couple of results that could suffer from endogeneity in the mix variable are analysed with instrumental variables.

5.1 Final Energy Consumption - Wealth regression

To get a rough idea of the relation between the energy and the wealth of all the countries included in the energy mix data sample, a simple model is constructed. First the final consumption FIN_{it} of energy is formed (Equation 5.1 and Table 3.3) as the sum of all energy used in Industry, Transport, Other and Non-energy destinations, for country i in year t.

$$\text{FIN}_{it} \triangleq \sum_{c} \left(\text{I}_{it} + \text{T}_{it} + \text{O}_{it} + \text{UNE}_{it}\right), \quad \text{with } c \in \{\text{B},\text{C},\text{E},\text{G},\text{H},\text{N},\text{O},\text{P},\text{S},\text{T},\text{W}\} \tag{5.1}$$

The goal of this comparison is to get an idea of the influence and direction of changes of energy consumption on wealth. The independent variable FIN_{it} is transformed into its (base 10) logarithm $\log_{10}\text{FIN}_{it}$ and its first time difference is taken (Equation 5.2).

$$\text{dlog}_{10}\text{FIN}_{it} \triangleq \log_{10}(\text{FIN}_{it}) - \log_{10}(\text{FIN}_{it-1}) \tag{5.2}$$

The data on GDP for constant USD is used and this data is also log-differenced to construct $\text{dlog}_{10}\text{GDP}_{it}$. And is matched to the countries and years in the energy dataset. This results in 3710 observations of $\text{dlog}_{10}\text{GDP}_{it}$ and $\text{dlog}_{10}\text{FIN}_{it}$. This data is plotted in Figure 5.1 together with a model fit. The linear model is estimated as:

$$\begin{aligned} \text{dlog}_{10}\text{GDP}_{it} &= \alpha \qquad + \beta\, \text{dlog}_{10}\text{FIN}_{it} + \varepsilon_{it} \\ &\approx \underset{(0.000)}{0.011} \; + \underset{(0.010)}{0.335}\, \text{dlog}_{10}\text{FIN}_{it} \end{aligned}$$

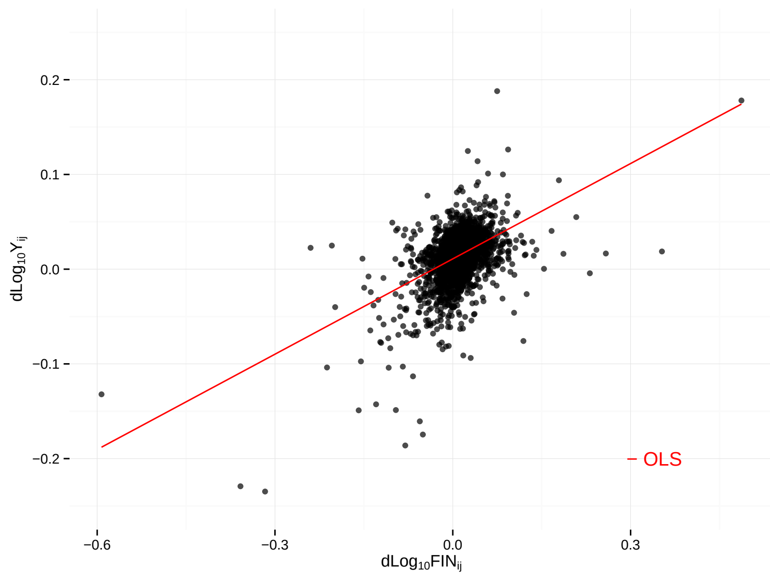

Figure 5.1: Scatterplot of difference in logs of final consumption FIN against GDP with an OLS fit. The relationship seems positive. Graph: author.

The two regression coefficients are highly significant as seen by the standard errors in parenthesis. But their validity is arguable. They could be interpreted as the average GDP growth of a country is 1% and for every 3% increase in final energy consumption the GDP rises 1%.

This simple model and the conclusions we can form after inspection are very limited. It does not include the traditional production factors capital and labor, and it is unlikely that energy without these factors can be used to result in production. Secondly the model is estimated annually, which focusses on short term deviations, whereas the larger long term results in wealth are more interesting. Apart from these facts there is probably a hoist of other factors that are omitted and bias the results.

Due to the limited specification no conclusions on direction or nature of a relation can be made, but the simple model does show us that there exists some relation between energy and wealth worth investigating. The specification of the base regression framework in Section 5.3.1 solves several of these issues and results in more reliable results.

5.2 Panel formation

5.2.1 Multi year blocks

As was shown in the section on stylized facts of the log real GDP per capita section (see Section 1.1), the GDP timeseries is either highly persistent or integrated. Considering this and the fact that we will not include any business cycle related variables suggest aggregating into block differences of multiple years. Aggregation into a total difference from start to end of the sample transforms the model into a cross country growth regression, which is commonly used in GDP growth literature.

However as we are interested in effects of structural changes regarding energy mix we keep some of the time dimension to retain the possibility to observe such dynamics. Therefore the annual raw panel dataset, consisting of control variables and energy mix variables, is aggregated into two panels. One with 5 year and one with 10 year blocks, both with the most recent block complete. For the 10 year series this is the block (2001, 2011], indicating the growth from the end of 2001 to the end of 2011 [1] resulting in 4 observations per country for the countries that have data starting from 1973. The 5 year blocks run up to (2006, 2011] and thus result in 8 observations.[2]

5.2.2 Temporal Aggregation functions and transformations

There are several possibilities to aggregate and transform the included variables into a panel. As dependent variable in all panels the real 2005 US $ GDP annual time series is divided by the population size (per capita transformation) and aggregated using *annualized difference of logs* which behaves similar to a growth rate:

$$d\mathrm{YP} \triangleq \left(\log_{10}\frac{\mathrm{Y}_{t+\tau}}{\mathrm{P}_{t+\tau}} - \log_{10}\frac{\mathrm{Y}_t}{\mathrm{P}_t}\right)/\tau \tag{5.3}$$

With $\mathrm{Y}_t/\mathrm{P}_t$ the GDP per capita at the start of the block, τ the block length (either 5 or 10 years). Blocks are allowed to be incomplete, as this and following block aggregating definitions are all transformed to annualized effects. The annualized mean of a block of factor X is defined excluding the first observation to prevent double inclusion:

$$\mathrm{X.m} \triangleq \sum_{\theta=t+1}^{t+\tau} \mathrm{X}_\theta/(\tau-1) \tag{5.4}$$

Which can then be transformed to the log of the annualized mean by $\mathrm{X.lm} \triangleq \log_{10}\mathrm{X.m}$

Log-like transformations Several mix variables, especially ratios such as the TRADE.DEP that measures the trade dependence by dividing the net import position by the total primary energy supply, can become very high in magnitude. But the most interesting is the region between for example -1 and 1 as this is where the country switches from dependent to independent. To reduce the influence of observations far out, log-like transformations which accept negative numbers are used.

To facilitate a transformation that is analogous to the logarithm, in the sense that it puts more emphasis on lower values and reduces the overweighting of very extreme values but also available for negative numbers we define the following transformation function:

$$f(x) \triangleq \mathrm{sign}(x)\log_{10}(|x|+1) \tag{5.5}$$

with sign(x) the sign of x and $|x|$ the absolute value. This function is inverting symmetric and crosses the origin with a unit slope[3]. Applying this function to the annualized mean is denoted by X.fm and

[1] (2001, 2011] indicates from 2001 up to and including 2011, not including 2001, hence the parenthesis-bracket '(Year$_t$, Year$_{t+\tau}$]' notation.

[2] The temporal unbalancedness of the data results in very short timeseries for several countries. In an attempt to include their dynamics the 5 year block length is retained.

[3] Inverting symmetric in the sense that $-f(x) = f(-x)$, continuous $\forall x \in \mathbb{R}$ crosses the origin $f(0) = 0$ and has a unity slope there $df/dx(0) = 1$.

constructing an annualized difference from $f(\mathrm{X})$ is denoted by X.df. Additionally for variables that can become negative the transformation is performed conditional on the sign, which creates missing values (e.g. X = 0 is dropped):

$$\begin{aligned} \mathrm{X.lm+} &\triangleq \log_{10} \mathrm{X.m} && \text{for X} > 0 \\ \mathrm{X.lm-} &\triangleq -\log_{10}(-\mathrm{X.m}) && \text{for X} < 0 \end{aligned} \tag{5.6}$$

5.2.3 Aggregating the Energy Mix Variables

The variables defined in Table 3.3 are aggregated to the 5 and 10 year blocks by the functions defined in the previous paragraph giving 94 transformed mix variables per panel. There are a couple of rules that are applied to transform the energy mix variables and create multi year blocks from the annual data. These rules are based on the units and range of these energy summaries. In general if the units are a physical energy level, the value is taken per capita and a logarithm (like) transformation is applied. If it is a bounded ratio, it is not transformed by the log. Furthermore all variables are tested in a block averaged form as in a block differenced (return like) form.

- **Mtoe → /cap** All variables that are measured in mega tonnes of oil equivalent (MTOE) are transformed into their per capita equivalents dividing by the population size. (FIN, TPES, PROD, E, B, N.F, OR.CAP, TRADE.POS, TRADE.POS.FOSSIL, TRADE.VOL, IND, OTHER, NONENERGY, INTBUNKER, TRANSP)
- **Mtoe > 0 → .dl and .lm** The variables that are measured in MTOE that are > 0 are transformed to annualized difference of logs and log annualized mean. This is the majority of level variables that are defined.
- **Mtoe < 0 → .d, .m and log-likes** E.TRADE.POS and E.TRADE.POS.FOSSIL can be negative so the log transformation is not applicable. As alternatives the function $f(x)$ from Equation 5.5 and the sign split from Equation 5.6.
- **% and ratios → .d and .m** All variables that are in % and all unit-less ratios are transformed into an annualized difference and into an annualized average (.d and .m). (E.F, B.F, N.F, FOSSIL.F, RENEW.F, PSEFF, TRADE.DEP, TRADE.DEP.FOSSIL, OR.INDEP, OILEX.PETRIM, CONCMX.TPES, CONCSQ.TPES, CONCMX.PROD, CONCSQ.PROD, IND.F, OTHER.F, NONENERGY.F, INTBUNKER.F, TRANSP.F, TRANSP.ALT)
- **±∞ → log-likes** The ratios that can become very extreme in value but are generally relatively centred around 0 or between 0 and 1 are also transformed using the log-like functions. (E.TRADE.DEP, E.TRADE.DEP.FOSSIL, E.OR.INDEP, E.OILEX.PETRIM)

5.3 Base Regression Framework

5.3.1 Framework

To test and compare influence of the energy mix variables a fixed regression framework is used. This framework includes a constant set of control variables, and transformations thereof, inspired by the literature described in Chapter 1.

The dependent variable is $\left(\log_{10}\frac{\mathrm{Y}_{t+\tau}}{\mathrm{P}_{t+\tau}} - \log_{10}\frac{\mathrm{Y}_t}{\mathrm{P}_t}\right)/\tau$, which can be described as the *annualized block difference in log per capita production*, is written using the transformations from Section 5.2 as $d\mathrm{YP}_{it}$ or according to the defined post script notation by Y_P.dl. The panel is created in a 5 and a 10 year form and in two specifications: One true panel model with fixed effects (individual intercepts) and one with the initial capital for each country added. The fixed effects panel model is sometimes referred to as the 'within' transformation, as the intercepts α_i capture all (unobserved) variance between individuals and the the focus is on the time dimension. The initial production per capita is a proxy for initial capital, and is the first observation of Y/P for each country[4]. The estimate for this factor is often linked to conditional convergence. If it is negative this is taken as evidence for convergence as lower initial incomes then grow faster. This variable is added as the initial production values show high correlation with the estimates for the fixed effects α_i. The fixed effects (FE) model is given by:

$$d\mathrm{YP}_{it} = \alpha_i + \psi^\top \mathbf{S}_{it} + \beta E_{it} + \varepsilon_{it} \qquad \text{"FE-model"} \tag{5.7}$$

And the model with initial production $\log_{10}(Y_{i0}/P_{i0})$ or YP0:

$$d\mathrm{YP}_{it} = \alpha + \gamma \log_{10}(Y_{i0}/P_{i0}) + \psi^\top \mathbf{S}_{it} + \beta E_{it} + \eta_{it} \qquad \text{"YP0-model"} \tag{5.8}$$

Where E_{it} is the added energy mix variable transformed to a 5 or 10 year panel. α is the intercept, β the slope of the energy mix variable, η_{ij} and ε_{ij} are error terms and $\mathbf{S}_{it}$ and ψ are a vector of control variables and their slopes respectively.

5.3.2 Fixed Regressor Set

The controls added in $\mathbf{S}_{it}$ are identical for all regressions and proxy for the traditional production factors: Labor and physical capital from the Solow-Swan model and human capital from Mankiw, Romer, and Weil. To decide which transformations of the collected control variables GCF [C], Human capital index [H], Labor size [L] (Section 2.2) and the temperature instrument [T] to use, systematic model selection is employed. The controls are transformed according to the annualized difference/return (of logs) and averaging methods given in Section 5.2. Additionally the labor participation [L/P] is calculated and added to the initial, unrestricted, model[5]. Than a systematic model size reduction based on the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC), sequentially removing the variable with the highest p-value, retaining at least one variable to proxy for all the traditional production factors. This defines the six variables that form the fixed set $\mathbf{S}_{it}$:

$$\mathbf{S}_{it} \triangleq [\text{C.lm, C.dl, H.lm, P.r, L\_P.dl, T.n}]_{it} \tag{5.9}$$

The six variables of the fixed set are: the log annualized mean of GCF C.lm, the annualized difference of logs of capital C.dl, the log annualized mean of the human capital index H.lm, the growth rate of the population P.r, the annualized difference of logs of labor participation L_P.dl and the block temperature range T.n.

5.3.3 Correlation matrix

In Figure 5.2 the correlation matrix of the variables in the model is shown. The dependent variable, the annualized difference of log production Y_P.dl is shown together with the fixed regressor set S (see Equation 5.9). Also the initial capital YP0 and final energy consumption per capita FIN[6] are included. The right plot shows the coefficients of first 3 principal components (Varimax rotated[7]).

[4] For the construction of YP0 the first available year for each country is used, not the first available (complete or incomplete) block. So no degrees of freedom are lost.

[5] Y_P.dl regressed on the nonsingular subset of C.m, C.lm, C.d, C.dl, H.m, H.lm, H.d, H.dl, L.r, L.dl, L.m, L.lm, P.r, P.dl, P.m, P.lm, L_P.r, L_P.dl, L_P.m, L_P.lm, T.n, T.m and a constant. The T values are newly (T.n) constructed temperature range and block mean temperature range

[6] FIN_P.lm and FIN_P.dl: annualized log-of-mean and diff-of-logs

[7] The **RC** (Kaiser (1956) [23] of the principal component matrix **PC** (eigenvectors of correlation matrix) are found by the rotation matrix R that maximizes the variance of the sum of the squared loadings: $R^* = \arg\max_R \sum_{ij} \mathrm{Var}(R \cdot \mathbf{PC})_{ij}$ so that $\mathbf{RC} = R^* \cdot \mathbf{PC}$

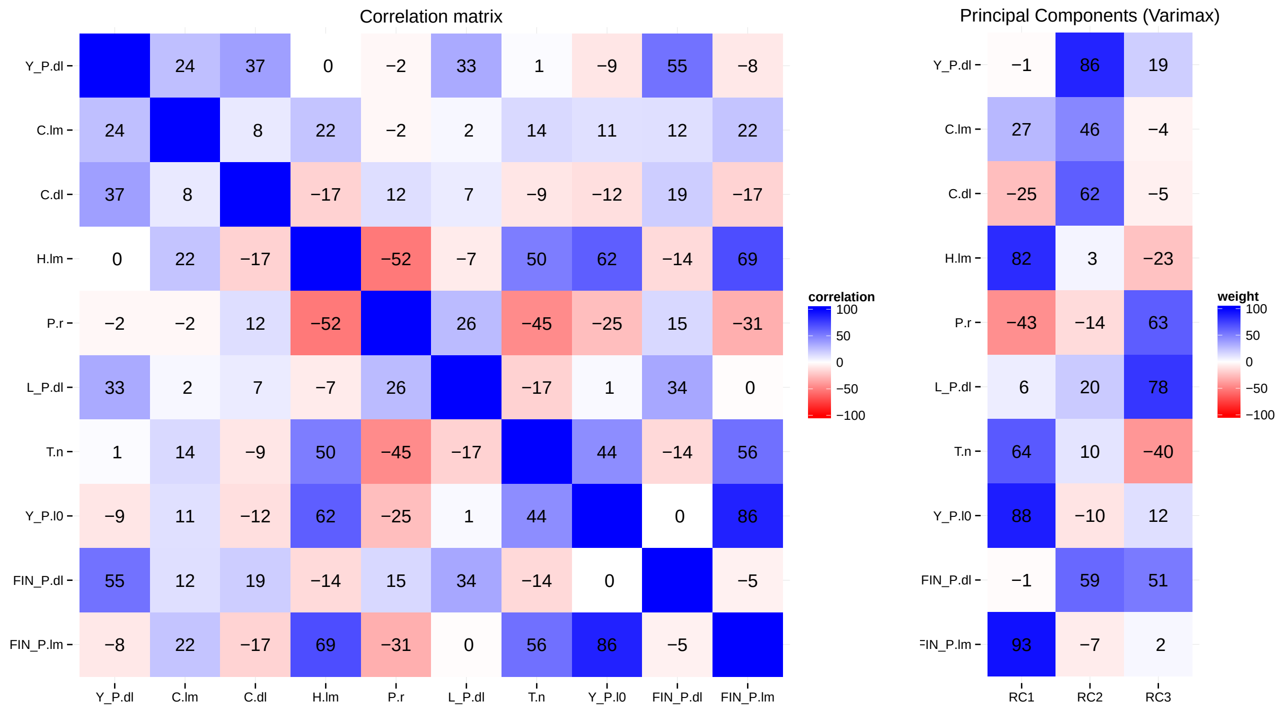

Figure 5.2: Correlation matrix of dependent and independent variables. (Correlation $\times$ 100) Included are Y_P.dl, the fixed regressor set S (see Equation 5.9) initial capital YP0 and annualized log-of-mean and difference-of-logs of final energy consumption per capita FIN_P.lm and FIN_P.dl The right plot are the coefficients of first 3 principal components of this correlation matrix (after orthogonal Varimax rotation). Cumulative variance proportion explained for RC1, RC2, RC3 is 0.31, 0.49 and 0.65.

The correlation between the growth and capital savings (level and changes) C.lm and C.dl, and labor participation is positive which is as expected by the Solow-Swan [39, 40] production function model. The index of human capital H.lm is negatively related with the growth rate of the population P.r. This is due to the fact that poor countries tend to have larger population growth and worse education. This can be seen by the negative relation between initial wealth Y_P.l0 and population growth P.r, and the positive relation between initial wealth and human capital. The correlation between final energy consumption changes FIN_P.dl and GDP growth rates is high, and so is the correlation between final energy consumption level FIN_P.lm and initial wealth Y_P.l0. The causality direction in this relation is still in debate [10]. Most likely both the production effect where energy is used in industry which adds value, as the wealth effect where richer countries consume more energy in affluence and abundance coexist.

The correlation between temperature range T.n and (initial) wealth level related variables is high. A high wealth level is associated with: a high initial wealth level Y_P.l0, low population growth, high level of human capital and high energy consumption. These correlations are partly due to the fact that the temperature range is a positive function of geographic latitude, and wealthy countries tend to have be further away from the equator. The temperature range has a low direct effect on GDP growth Y_P.dl, which is as desired. Remember we want to use the temperature as an instrument to measure the effect of energy, so we want the indirect path: the path from temperature range to energy to growth. The temperature range does have a high correlation with final energy consumption which is also desirable for and instrument.

The largest proportion of variance is explained by the process described by the first principal component RC1: the co-movement of human capital, temperature range, initial production and energy consumption level together with the contra-movement of population growth. This factor groups initial wealthy and educated, energy consuming, high temperature range climate[8] and slow population growth countries together[9]. Note that this factor is not correlated to the dependent variable. This factor is best summarized as the *initial development conditions* factor.

The second principal component RC2 captures the co-movement of the growth, capital savings and final energy consumption. It can be described as the *technology augmented classical Solow capital* factor. The third principal component RC3 consists of participation rate changes L_P.dl, population growth P.r, energy consumption, lack of human capital per person and low temperature range. This factor can be summarized as the *Mankiw, Romer, and Weil efficient labor force* factor.

Table 5.1: Base regression framework for four base regressions without energy mix variable. Two block lengths, 5 and 10 years, and two model forms, fixed effects (FE) and initial production per captita (YP0). Fitted without adding energy variables. Estmates for the physical and human capital savings (C and H), population P, labor L, temperature T and initial production per capita variables. *dt* is the block length for the panel. HAC standard errors are in parenthesis. α is the intercept, mean α_i is the average fixed effect dummy. These four base models will be extended by the defined energy mix summaries to create the extended model to determine the energy mix effects.

	dt	α	mean α_i	C.lm	C.dl	H.lm	P.r	L_P.dl	T.n	YP0	$\bar{R}^2$
FE	5		0.018	0.018 (0.006)	0.148 (0.016)	0.002 (0.012)	-0.324 (0.064)	0.607 (0.087)	0.001 (0.001)		0.40
FE	10		0.008	0.027 (0.008)	0.208 (0.027)	0.008 (0.015)	-0.224 (0.072)	0.736 (0.154)	0.003 (0.001)		0.48
YP0	5	0.041 (0.005)		0.027 (0.004)	0.147 (0.016)	0.003 (0.007)	-0.226 (0.043)	0.710 (0.082)	-0.000 (0.000)	-0.004 (0.001)	0.24
YP0	10	0.037 (0.006)		0.028 (0.006)	0.212 (0.026)	0.005 (0.009)	-0.144 (0.047)	1.123 (0.134)	0.000 (0.000)	-0.004 (0.001)	0.30

5.3.4 Models without energy

In Table 5.1 models Equation 5.7 and 5.8 are estimated for the panels of lengths 5 and 10 years. The parameters have economical interpretations as elasticities. The GDP per capita increments change 1% for evergy 5-6% of additional capital savings. The labor participation has a very strong effect of adding 1% GDP per capita increments each year for every 0.6-1.1% additional labor participation. This postive effect of labor participation rate is in line with earlier findings in literature. The labor participation L/P has the nominator effect when a larger proportion of the population is participating, and the denominator effect when the population is shrinking that both contribute to increasing the growth rate. The second effect is controlled for, at least the linear approximation, by adding the population growth separately, which is estimated to have an effect of -1% of annualized difference in GDP for every 5% of population growth. The estimates for the intercept are all in the order of a couple (1-4) of % GDP increment per year. The estimates for the level of capital savings is also significant and positive but not very high. The estimates for human capital are insignificant but all positive, as expected. The estimates for the temperature range are very low in magnitude.

Overall the fit of the models is pretty good. The fixed effects models do have a adjusted $\bar{R}^2$: 40 and 48% for the 5 and the 10 year panel respectively, and the $\bar{R}^2$ for the models with initial capital stock: 24 and 30% for 5 and 10 years. The $\bar{R}^2$ cannot be compared between the 5 and the 10 year block model as the dependent variable differs, but they can be compared between the fixed effects and the initial wealth model. The fixed effects do capture a big part of additional variance as adding them improves the $\bar{R}^2$ considerably.

The estimate of the log initial capital stock (YP0) is negative. The negative coefficient indicates that higher initial capital stocks result in lower growth rates. This is an argument in favour of the conditional convergence (β-convergence) theory, but the estimate is small in magnitude indicating a very slow convergence. The fixed effect estimates α_i are plotted against the initial capital stock in Figure 5.3.

[8] Temperature range is related to the distance from the equator.

[9] C.lm and C.dl are in contramovement in this factor showing that high capital savings rate is related to low additional capital savings rate increments. Which is a result from the fact that these two factors are related by construction.

Visually they seem highly related, and the regression fit gives a significant negative relation with a $\bar{\mathrm{R}}^2$ of 0.17. Outliers such as over performer Qatar (QAT) and under performer Moldova (MDA) aside, a large part of the unexplained heterogeneity in the fixed effects model is due to the initial capital stock. This explains our choice to include the models with initial capital in stead of fixed effects to the base models Equation 5.7 and 5.8. Geographically (also in Figure 5.3) the large dummy variables, thus the over performers relative to the models prediction, are found in eastern Africa, Asia and Brazil. The under performers are in the former Soviet Union, Europe and North America. This list and the map do seem to imply there is some geographical clustering in the fixed effects estimates.

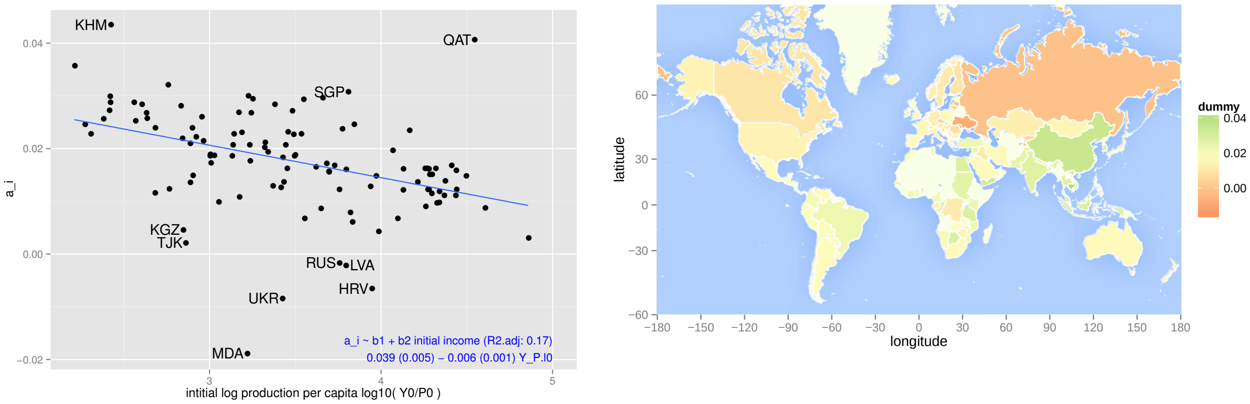

Figure 5.3: Fixed effects dummies versus initial income and fixed effects geographical distribution. The strong relation shows that a large part of the heterogeneity captured by the fixed effects can be explained by the initial GDP per capita YP0. The outliers have thier ISO3 code attached. Right: geographical view on fixed effects. α_i. Graph: author.

5.4 Results from Base Regression

The model framework described in Section 5.3.1 in Equations 5.7 and 5.8 (Fixed Effects and Initial Production) is estimated by OLS for all energy mix variables in Table 3.3 transformed into 5 and 10 year blocks by the methods given in Section 5.2.3. That is the regressions defined by:

$$\begin{aligned} d\mathrm{YP}_{it} &= \alpha_i + \psi^\top \mathbf{S}_{it} + \beta E_{it} + \varepsilon_{it} && \text{"FE-models"} \\ &= \alpha_i + \psi^\top [\text{C.lm} \;\; \text{C.dl} \;\; \text{H.lm} \;\; \text{P.r} \;\; \text{L\_P.dl} \;\; \text{T.n}]_{it}^\top + \beta E_{it} + \varepsilon_{it} && \text{"FE-models"} \quad (5.10) \\ d\mathrm{YP}_{it} &= \alpha + \gamma \log_{10}(Y_{i0}/P_{i0}) + \psi^\top [\text{C.lm} \;\; \text{C.dl} \;\; \text{H.lm} \;\; \text{P.r} \;\; \text{L\_P.dl} \;\; \text{T.n}]_{it}^\top + \beta E_{it} + \eta_{it} && \text{"YP0-models"} \end{aligned}$$

Here α is the intercept and α_i are the fixed effects. The six shared regressors are in the constant set $\mathbf{S}_{it}$ defined in Section 5.3.2. YP0 is the initial production per capita at the start of the dataset for each country and E_{it} is one of the list of list of energy mix variables, transformed to blocks by various averaging or differencing transformations. This is giving a total of 94 transformed energy mix variables, that are tested in 2 model forms for 2 block lengths, so $94 \cdot 2 \cdot 2 = 376$ regressions.

If 5% significance is taken as significance level then we expect to find about 19 significant energy variables out of the 376 tries. We control for the fact that we try so many energy related variables by investigating the p-values of the estimated mix-variable coefficients. In the results later it is visible that quite a few of the tried energy mix variables are significant on much lower levels such as 0.1%.

5.4.1 Tests for Heteroskedasticity and Autocorrelation

To determine whether we should use Heteroscedasticity-Consistent (HC) or even Heteroscedasticity and Autocorrelation-Consistent (HAC) standard errors instead of standard errors based on Independent and

Identically Distributed (IID) errors we performed two tests on the residuals from the models estimated in Equation 5.10. A Breusch-Pagan (BP) test [9] for homoskedasticity, and a Durbin-Watson (DW) test [13] for absence of (first order) serial correlation.

The BP test is a Lagrange Multiplier (LM) test with an auxiliary regression on the squared residuals of the estimated model:

$$\hat{u}^2 = \alpha + \phi^\top \left[\text{C.lm} \quad \text{C.dl} \quad \text{H.lm} \quad \text{P.r} \quad \text{L\_P.dl} \quad \text{T.n}\right]^\top (+\ \text{YP0}) + \eta_{it} \tag{5.11}$$

Where the last regressor YP0 is only added in the model with initial production, not in the fixed effects model (see Equation 5.10). The coefficient of determination R^2 of this regression gives the statistic by:

$$BP = n\mathrm{R}^2 = \sum_{i=1}^{N} (\tau_i) \cdot \mathrm{R}^2 \tag{5.12}$$

Where n is the number of observations which in our case is the sum of N countries with (varying) number of blocks τ_i. BP is distributed asymptotically and under the null hypothesis of homoscedasticity as $\chi^2(p)$ where p is the number of regressors except the constant α fitted to the squared residuals. We employed Koenker (1981) [24] and Studentized the BP test to reduce dependency on normality assumption.

The DW test statistic responds to first order autocorrelation. DW_i calculated for timeseries of residuals for individual (country) i is given by Equation 5.13 and its value ranges from 0 to 4. Values below 2 indicate that the errors of successive events are on average closer together and thus signs a positive autocorrelation.

$$\text{DW}_i = \frac{\sum_{t=2}^{T} (\hat{u}_{it} - \hat{u}_{it-1})^2}{\sum_{t=1}^{T} \hat{u}_{it}^2} \tag{5.13}$$

Bhargava, Franzini, and Narendranathan (1982) [8] proposed a panel generalization of DW using the per individual (country) demeaned residuals $\tilde{u}_{it}$[10] which is given in Equation 5.14.

$$\text{DW}_P = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} (\tilde{u}_{it} - \tilde{u}_{it-1})^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{u}_{it}^2} \tag{5.14}$$

The critical values for the panel DW stat are tabulated in [8] and depend on the time series length[11] T the number of individuals N and the number of regressors used in the primary regression not including fixed effects p.

The test statistics for the BP and DW tests are plotted in the histograms in Figure 5.4. A large majority of the BP statistics are above the 5% critical value[12] thus we reject the null hypothesis of homoskedasticity of the residuals. In the second plot we see that the majority of panel DW statistics is below the 5% critical value[13]. This leads to the conclusion that the residuals show significant positive autocorrelation. The approximate relation between the DW statistic and the first order autocorrelation process in the residuals is $DW = 2(1 - \rho_1)$. As the average DW value is 1.6 for all regressions, the fist order autocorrelation ρ_1 is about 0.2. One of the reasons for creating multiple year blocks was reducing the effect of strong persistence in the model, the average DW_P values for the 5 and 10 year blocks are compared. The implied ρ_1 for the 5 year blocks is 0.218 and for the 10 year blocks is 0.214, thus the residual persistence is not a strong function of block length.

The results from the Breusch-Pagan and Durbin-Watson tests show that the homoskedasticity and IID assumptions of the standard OLS model are violated. Hence we decided to use Heteroscedasticity and

[10] Per individual demeaned indicates $\sum_{t=1}^{\tau_i} \tilde{u}_{it} = 0 \; \forall \; i \in N$ with N countries with length τ_i

[11] For T the average time series length among individuals is used as [8] uses balanced panels to calculate the p-values. However even if the lowest tabulated critical value is used nearly all panel DW statistics are lower.

[12] The x value where the cumulative $\chi^2 \bar{p}$ distribution is 0.95. Where $\bar{p}$ is the average number non fixed effect coefficients (6.5). $x_{cv} = 13.3$. Only 6/376 BP tests do not reject homoskedasticity.

[13] As the panel Durbin-Watson p-values depend on number of included regressors, time series length the exact critical value can differ from one regression to another. But only 3/376 regressions had insignificant positive autocorrelation.

Autocorrelation-Consistent (HAC) standard errors for inference on the estimates of the mix variables. We used the methods for panel models described by Arellano (2003) [1], which are discussed in more detail in the appendix.

The fact that we must correct for the autocorrelation is no surprise, the stylized facts in Section 1.1 showed the high persistence. Apparently differencing over the blocks did not remove all of this effect. Also the residual heteroskedasticity was expected as the dependent variable showed a complex multi modality, and the explanatory variables in the base regression did not convincingly showed this shape their histogram plots in Figure 2.1. Also there are a lot of cultural and historical factors and business cyclical related effects unmodeled.

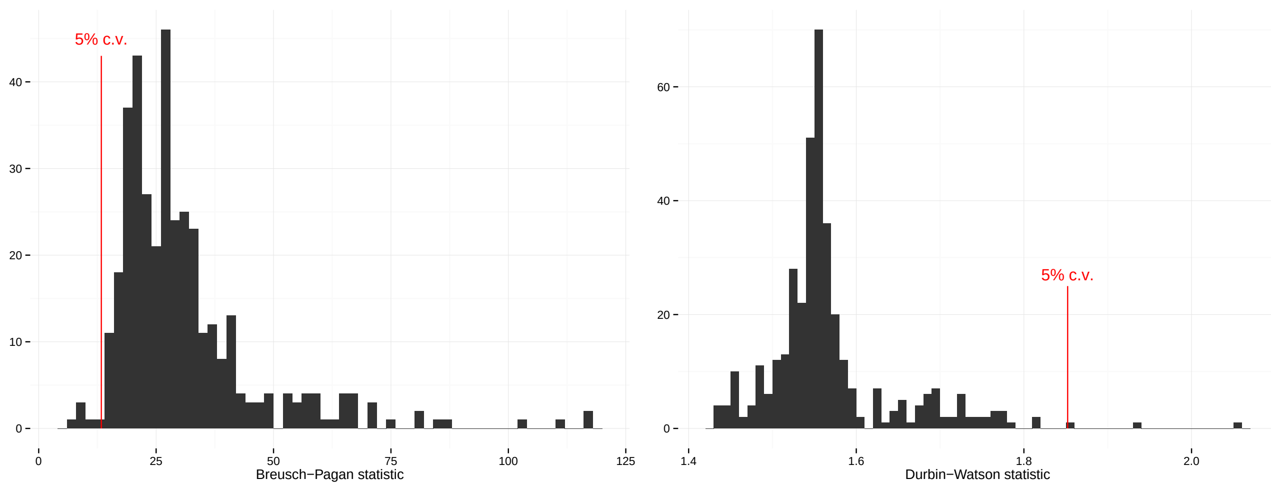

Figure 5.4: Breusch-Pagan and Durbin-Watson test statistics for all energy mixvar augmented base models defined by Equation 5.10. 5% critical value denoted by red line. Critical region is right in BP test and left in positive autocorrelation DW test. Both homoskedasticity and indipendence are rejected.

5.4.2 Panel model Specification Tests

Joint Significance F-test As a general misspecification check, a joint significance on the non intercept regressors is performed for every energy regression. This F-test rejects the null of joint insignificance on the 0.1% level for 374 and on 1% for the remaining 2 regressions.

Hausman Random/Fixed Effects If the country specific intercepts are drawn from a shared and independent process, we can omit the country intercepts of the fixed effects specification to obtain a random effects model. However if the random effects assumptions do not hold, the model is inconsistent. The Hausman test compares the estimates of the two methods knowing that one is consistent. If their difference is high compared to the efficiency of estimation, one model is inconsistent:

$$HM = (\beta_{RE} - \beta_{FE})^\top \left(\widehat{\mathrm{Var}}(\beta_{RE}) - \widehat{\mathrm{Var}}(\beta_{FE})\right)^{-1} (\beta_{RE} - \beta_{FE}) \tag{5.15}$$

Where β is the vector of parameter estimates, and $\widehat{\mathrm{Var}}(\beta)$ is the estimated covariance matrix of the parameter estimates. Under the null of two consistent estimates, the statistic HM is distributed (asymptotically) as $\chi^2(p)$ with p the number of estimated parameters. For the 188 regressions with fixed effects (second equation in 5.10) 180 Hausman tests rejected consistency the random effects model on 5% significance, in 144 cases even on 0.1% significance level.

Pooled OLS F-test For the fixed effects models, that is the models without initial production YP0, the joint significance of all country intercepts is tested with an F-Test. The alternative of this regression, if the country fixed effects are insignificant, is a pooled OLS model. Insignificance of the α_i parameters is rejected on 5% level for 180/188 panel models, on 1% level for 27 and on 0.1% level for 9 regressions. This test result also indicates that country fixed effects should be added.[14]

5.4.3 Energy Mix Variable Results

In this section the results from the regressions with the mix variables will be drawn. The tests from previous section (Section 5.4.2) have build a case for the modeling decisions that were made. And in Section 5.4.1 the necessity for Heteroscedasticity and Autocorrelation-Consistent (HAC) standard errors is shown. Now we present the estimates and implied effects of the energy mix variables and perform inference on the parameters. From these estimated parameters we attempt to draw conclusions and try to explain the observed effects economically. It is not possible to determine causality from this modeling setup, hence all statements insinuating such relations are speculative.

In Table 5.2 all estimated intercepts β from the Equations 5.7 and 5.8 are shown. For all transformations and for a panel with 5 and with 10 year blocks. The significance and strength of this significance is indicated with asterisks next to the estimates. This significance is determined with a t-test with HAC standard errors determined by the Arellano method described in the section on robust standard errors in the Appendix.

Averaged and Differenced Of the 376 estimated models there are 100 configurations in which an energy variable is 5% significant. Which is a comparatively strong result because it shows that a large part of the constructed energy mix variables can be related to our measure of wealth. The p-values in the differenced energy mix variables group seem much lower compared to the averaged mix variables. In the differenced group 42/66 5% significant variables are also significant on the 0.1% significance level. Whereas in the averaged group the majority 25/34 significant variables is only 5% significant. There are 42 of 94 mix variable transformations that have significant estimates in one of the block lengths (5/10 years) and in one of the model forms (FE/YP0). The split of these 42 between the averaged and differenced transformation equal (21:21).

Energy Mix Categories We've defined 35 energy mix variables, of which 27 have one or more 5% significant transformations. In this section we will discuss these results and their implications. We will follow the table in order and by the four categories of energy mix variables.

A. Aggregates: The energy aggregates (FIN, TPES and PROD) are statistically among the strongest results of the table. The aggregates show sign consistency and significance both in the differenced as in the averaged form. A higher consumption is related to lower growth. This can be interpreted as the tendency of mature economies to lower their energy use per capita versus emerging which are still building demand. In the differenced form, increasing energy consumption/supply/production, leads to increasing growth. The interpretation is identical and this effect is related to economic development. This interpretation makes sense and is backed by the data: low income countries with high growth rates also show a high increase in energy usage per capita, whereas developed countries show decreasing energy per capita levels (a.o. Netherlands).

This is an interesting effect as it shows that growth rates and energy aggregates are linked and it could be the case that a throttle on energy supply works as a throttle on economic development rate. To determine the direction or at least filter the backward direction from GDP to energy, the instrumental variable approach of Section 5.5 is applied to the energy aggregates.

[14]Note that this does not compare the relative quality of models *YP0* and *FE* as these are not nested. Rather *FE* and this model without the α_i are compared.

Table 5.2: Primary results table. Inference on all energy mix variable estimates in 5 and 10 year panel regression with either fixed effects dummies or with the initial production added. The models are defined by Equation 5.10. Significance $^+$, *, **, *** indicate significance on the 10, 5, 1, and 0.1% level, and bold font indicates 5% significance.
The transformation codes are: `m` mean, `lm` log-of-mean, `fm` loglikefunction-mean, `+/-` only positive/negative, `d` difference, `dl` difference-of-logs, `df` diff-of-loglikefunction

Averaged

	/cap		Fixed Effects β_5	Fixed Effects β_{10}	Initial Production β_5	Initial Production β_{10}
FIN	×	**lm**	−0.0312**	−0.0261*	−0.0039	−0.0070
TPES	×	**lm**	−0.0314**	−0.0261*	−0.0021	−0.0056
PROD	×	lm	−0.0032	−0.0064	−0.0012	−0.0018
E	×	lm	−0.0085	−0.0068	−0.0009	−0.0030
E.F		**m**	0.0651*	0.0534	0.0097	0.0080
B	×	lm	0.0011	−0.0011	0.0003	0.0008
B.F		m	0.0093	0.0102	−0.0023	0.0010
N.F		m	0.0057	0.0035	0.0017	0.0030
FOSSIL	×	**lm**	−0.0247**	−0.0210*	0.0002	−0.0028
FOSSIL.F		m	−0.0189$^+$	−0.0158	0.0018	−0.0012
RENEW.F		m	0.0421	0.0179	−0.0018	−0.0005
PSEFF		**m**	0.0031	0.0046	−0.0073*	−0.0054
OR.CAP	×	lm	−0.0029	−0.0033	0.0027	0.0009
TRADE.POS	×	fm	−379.3	−219.9	85.95	251.3
···	×	lm+	−0.0080	−0.0046	0.0005	−0.0008
···	×	lm−	−0.0026	0.0018	−0.0022	−0.0006
···	×	m	−164.7	−95.51	37.33	109.1
TRADE.POS.FOSSIL	×	fm	−375.5	−216.9	85.94	252.1
···	×	lm+	−0.0053	−0.0031	0.0018	−0.0001
···	×	**lm−**	−0.0032	0.0007	−0.0027*	−0.0011
···	×	m	−163.1	−94.20	37.32	109.5
TRADE.VOL	×	lm	−0.0042	−0.0052	0.0002	−0.0019
TRADE.DEP		fm	−0.0061	0.0050	0.0025	0.0049*
···		lm+	0.0011	0.0037	0.0014	0.0003
···		lm−	−0.0029	0.0016	−0.0015	−0.0003
···		m	−0.0003	0.0001	0.0002	0.0005
TRADE.DEP.FOSSIL		fm	−0.0020	0.0037	0.0017	0.0032*
···		**lm+**	0.0070*	0.0075*	0.0022	0.0009
···		lm−	−0.0036	0.0016	−0.0015	−0.0003
···		m	0.0001	0.0004	0.0001	0.0002*
OR.INDEP		fm	−0.0093	−0.0149	−0.0015	−0.0030
···		lm+	0.0001	−0.0002	0.0005	0.0004
···		lm−	−0.0010	0.0007	−0.0012	−0.0001
···		m	−0.0006	−0.0008	−0.0003	−0.0005
OILEX.PETRIM		fm	0.0003	0.0006	0.0002	0.0004
···		lm+	0.0003	0.0004	0.0004	0.0004
···		lm−	−0.0019	−0.0021	−0.0003	−0.0004
···		m	−0.0000	−0.0000	0.0000	−0.0000
CONCMX.TPES		m	0.0011	0.0002	0.0001	−0.0012
CONCSQ.TPES		m	−0.0001	−0.0002	−0.0000	−0.0001
CONCMX.PROD		m	0.0033	0.0014	−0.0009	−0.0029
CONCSQ.PROD		m	0.0030	−0.0008	−0.0000	−0.0022
IND	×	**lm**	−0.0123*	−0.0091	−0.0011	−0.0032
IND.F		m	−0.0070	−0.0083	−0.0065	−0.0118
OTHER	×	**lm**	−0.0313**	−0.0289**	−0.0085*	−0.0103*
OTHER.F		**m**	−0.0167	−0.0201	−0.0117**	−0.0105$^+$
NONENERGY	×	lm	−0.0001	0.0022	0.0020$^+$	0.0028*
NONENERGY.F		**m**	0.0277	0.0364	0.0215*	0.0253*
INTBUNKER	×	**lm**	−0.0053	−0.0045	0.0024*	0.0025*
INTBUNKER.F		**m**	−0.0046	−0.0062	0.0076***	0.0085***
TRANSP	×	**lm**	−0.0118	−0.0064	0.0055*	0.0039
TRANSP.F		**m**	0.0253*	0.0284*	0.0182**	0.0186*
TRANSP.ALT		**m**	0.0156	0.0344	−0.0187*	−0.0244*

Differenced

		Fixed Effects β_5	Fixed Effects β_{10}	Initial Production β_5	Initial Production β_{10}
FIN	**dl**	0.4305***	0.3895***	0.4387***	0.4211***
TPES	**dl**	0.4779***	0.4295***	0.4895***	0.4725***
PROD	**dl**	0.0858	0.0801	0.0955$^+$	0.1124*
E	**dl**	0.2144**	0.1081	0.2348**	0.1395
E.F	**d**	−0.6776**	−0.6990$^+$	−0.6510*	−0.7140
B	**dl**	0.0260	0.0590	0.0416*	0.0555
B.F	**d**	−0.2516***	−0.0743	−0.2736***	−0.2082
N.F	d	−0.0848	−0.0612	−0.0587	−0.0184
FOSSIL	**dl**	0.3198***	0.2316**	0.3383***	0.2802**
FOSSIL.F	**d**	0.3393**	0.2028	0.3612***	0.2789$^+$
RENEW.F	d	−0.2801	−0.2738	−0.2938	−0.3046
PSEFF	d	−0.0491	−0.0419	−0.0415	−0.0206
OR.CAP	**dl**	0.1468**	0.1379$^+$	0.1517***	0.1360*
TRADE.POS	**d**	−4189***	−3819***	−3986***	−3926***
···	**df**	−9648***	−8796***	−9178***	−9040***
TRADE.POS.FOSSIL	**d**	−4181***	−3810***	−3978***	−3912***
···	**df**	−9628***	−8773***	−9161***	−9008***
TRADE.VOL	**dl**	0.1258**	0.0782*	0.1400***	0.1007*
TRADE.DEP	d	−0.0040	−0.0021	−0.0053	−0.0054
···	**df**	−0.0941$^+$	−0.0735	−0.1001*	−0.1165*
TRADE.DEP.FOSSIL	d	−0.0014	−0.0013	−0.0020	−0.0029
···	df	−0.0340	−0.0238	−0.0383	−0.0361
OR.INDEP	d	0.0047	0.0022	0.0052	0.0047
···	**df**	0.0643$^+$	0.0498*	0.0798*	0.0711*
OILEX.PETRIM	d	0.0000	−0.0000	0.0000	−0.0000
···	df	−0.0018	−0.0003	−0.0022	−0.0008
CONCMX.TPES	d	0.0142	0.0028	0.0132	0.0088
CONCSQ.TPES	d	0.0011	0.0002	0.0010	0.0005
CONCMX.PROD	d	0.0026	−0.0272	−0.0087	−0.0385
CONCSQ.PROD	d	−0.0071	−0.0294	−0.0176	−0.0443
IND	**dl**	0.1969***	0.1474**	0.1965***	0.1522**
IND.F	d	0.0965	0.0163	0.1053	−0.0113
OTHER	**dl**	0.3363***	0.3486***	0.3356***	0.3620**
OTHER.F	d	−0.0875	0.0735	−0.0708	0.1251
NONENERGY	dl	0.0310$^+$	0.0057	0.0302$^+$	0.0083
NONENERGY.F	d	−0.1002	−0.1401	−0.0956	−0.1745
INTBUNKER	**dl**	0.0891***	0.0861***	0.0973***	0.0937***
INTBUNKER.F	d	−0.0227	0.0156	0.0158	0.0828
TRANSP	**dl**	0.1825***	0.0867$^+$	0.1942***	0.1046$^+$
TRANSP.F	d	0.0434	−0.1336	−0.0036	−0.1899
TRANSP.ALT	**d**	−0.3211**	−0.1937	−0.3086*	−0.2532

A result on its own is the fact that the quantity of production PROD has a comparatively low effect on GDP growth rates. The consumption/suply effect is much larger and more significant.

B. Technology Proxies: As a group the technology proxy explanatory variables perform better in differenced form. The mix variables that are measured in energy units are highly related to the aggregates, so individually they do not show us new information. However what can be seen is that the substitution: more fossil for less electricity, renewables nuclear and biofuels in differences (primarily visible in fractions) is productive for GDP growth. Biofuels (wood etc.) are readily accessible without a lot of required technology and hence used more by rural and less developed nations. Improvements in technology open up possibilities to *'higher'* energy forms such as fossil fuels.

The averaged variable that measures the electricity fraction E.F shows one significant sensitivity in the 5 year fixed effect model, namely 6½%, and the other models show the same sign. The estimate is indicating that for every ≈5% (percent point) of electricity fraction increase, the GDP growth goes up by $\frac{1}{3}$%. Increasing electricity usage E has a significant positive estimate estimate for the short term, however for the long block length this effect is no longer visible. Power station efficiency improvements, PSEFF in differences, are not very significant but are all of negative sign pointing at a reverse relation. Oil refinery capacity mix variable OR.CAP measures the oil refining capacity of a country per person. Adding new oil refineries, thus increasing this capacity, and GDP growth rate improvements are strongly linked.

C. International Positioning: The variables related to international trade TRADE.POS(.FOSSIL), TRADE.VOL and TRADE.DEP(.FOSSIL) perform very good in their differenced form. While there are hardly any significance nor sign consistency in the averaged form. The signs of the estimates are intuitive: If a country is becoming more of an importer, their TRADE.POS and their TRADE.DEP increase. Large net import streams and large trade dependency indicate inability to be self sufficient which works as a drag on the GDP growth. Hence the significant negative signs on these energy mix variables.

The Oil refinery independence mix variable OR.INDEP is significant in the differenced form with the log-like transformation. This variable measures the fraction (or multiple) of its petroleum demand a country is able to produce. Overcapacity can be traded but lack of capacity needs to be imported. For example the Netherlands imports oil, and (net) exports petroleum products (Figure A.6.2) whereas Guatamala does not have oil refineries and is dependent on trade for their car fuel etc (Figure A.6.1). The fact that the parameters of the untransformed difference are not significant, shows that the effect is non-linear. The impact of oil refining capacity is more pronounced in the area the between full dependence and exact self sufficiency. Thereafter the petroleum products supply is no longer a bottleneck on growth.

The oil for petrol trade variable OILEX.PETRIM (net oil export divided by net petroleum product import) is harder to interpret. It is nowhere significant but nevertheless interesting to study. The sign indicates if a country is a net trader > 0 or a net importer/exporter < 0. A high magnitude value for this value indicates an unfair trade if one is treating the two carriers as equivalents as as they are both expressed in heating value MTOE. The only positive transformation lm+ has all positive estimates. Positive estimates of lm+ indicate that if the country is a net trader (importer of one good and exporter of the other) the country benefits from an higher oil for petrol ratio. The negative lm− shows us[15] that this is also the case for (oil and petroleum product) importers or exporters. The ratio is high for a large oil position which could be related to the large oil producing countries which generally have high GDP per capita.

CONCMX and CONCSQ are energy carrier concentration proxies. They measure the lack of variety in energy carriers of the produced and total supplied energy. Their estimates show that the choice/experienced variety of carriers is not related to changes in a countries domestic product. These variables show low estimates, no sign consistence and no significant t-test values.

D. Utilization: In the Utilization category there are again 5 variables that are measured in MTOE which

[15] lm− is minus the logarithm of the absolute variable. It selects only the negative part of the variable: x.lm− $= -\log_{10}(|x|)$ for $x < 0$

are highly related to the Aggregates. Their relative values are what is interesting. First the differenced utilizations are explored. The highest sensitivity is with OTHER. A 3% increment in domestic energy use is accompanied with with a 1% increment in GDP growth rate. This sensitivity is about double that of the industry usage IND and the transportation TRANSP. Changes in relative allocation of the energy uses are not significant. When the levels (block averages) are considered the estimates are much smaller and all negative similar to the supply aggregates. What does stand out is that the fixed effects tend to rule out a lot of the significant averaged utilization mix variables (and aggregation variables) in the regressions with initial capital. This could be due to some unobserved heterogeneity that is removed by the country intercepts.

A higher level of international bunkering INTBUNKER is beneficial for growth as it is related to international trade. More alternative fuel in transportation TRANSP.ALT is not. These two estimates are based on a smaller subset that use these technologies, for example Singapore has tremendous amounts of bunkering.

Overall several interesting relations are uncovered. Quite a few are robust to different block length and substitution of the fixed effects for the initial capital. The most attractive results are the aggregate energy effect, the trade variables and the utilization allocation variables. The significant positive relationship between GDP and energy aggregates, such as total consumption for example, has been known for some time in literature. This relation is re-established here. Electricity usage is not as positively related with wealth as fossil fuels. So oil and gas still have a much larger influence on well being than electrical power. This is also visible in the influence oil refineries have in the model. More oil refineries OR.CAP goes along with a higher GDP. Energy trade is also a influential factor. Nett importers and import dependent countries tend to have a lower GDP than the exporters. On the other hand high concentration on one particular type of energy carrier, which could be used for manipulation and power by other countries, does not clearly influence wealth. A surprising outcome is that the OTHER, mainly domestic, energy usage has a high effect. The positive relation with wealth is about double the strength as compared to industry and transportation usage.

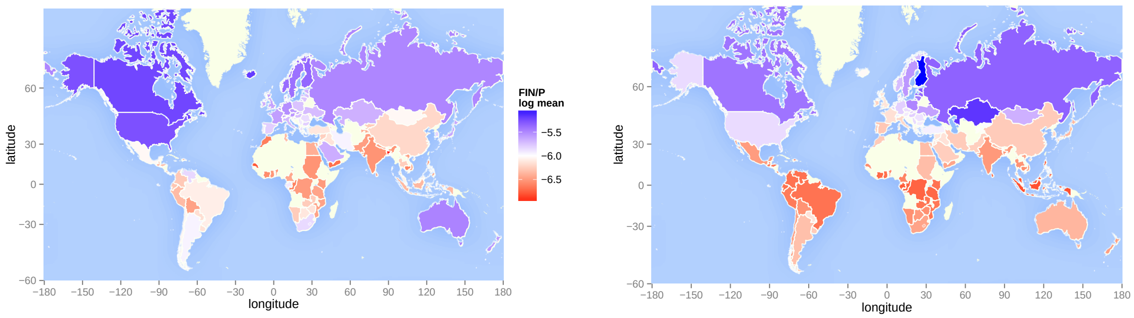

Figure 5.5: Left: Average final energergy consumption compared to average temperature range in the context of geograpy. mean(FIN) Right: mean(T.RANGE). The two maps look very similar. The distribution is also related to the latitude.

5.5 IV regression

5.5.1 Economic arguments for IV selection

A year or a block of years with more extreme temperatures requires more energy consumption. On the 'hotter than usual' side all cooling processes such as air conditioning, food conservation and running industrial furnaces require more energy and on in 'cooler than usual' periods for example domestic heating requires more energy. A measure for extremity of the temperature during a period is the temperature range (see Chapter 4). This vision is backed by the data as is visible in the similarities in Figure 5.5. The geographic distribution of average energy consumption on the left and average temperature ranges is plotted on the right. The above reasoning implies a causation from observe temperature range to energy usage. The reverse direction, from a countries high energy usage to more extreme temperatures, is discarded as being not possible. That is a individual country cannot control nor influence the temperature range it experiences.

As is shown in the regressions with the classic production factors in Table 5.1, the partial effect of temperature range on GDP growth is insignificant (and the correlation is about zero). Due to the thought train in the first paragraph, we can use the temperature range to explain energy usage differences. Than observing what effect these temperature-induced energy usages have on GDP reveals the direct effect of energy on GDP changes. The reverse and endogenous effect, GDP causing energy usage, is filtered by the fact that energy→temperature is not possible. Thus economically the usage of temperature as an Instrumental Variable (IV) to estimate the energy usage effects on domestic production is defensible.

However this reasoning that the energy usage is influenced by temperature range does not hold for most of mix variables defined in Chapter 3 Table 3.3. For example the idea that the ratio of independence from oil refineries OR.INDEP is influenced by weather is far fetched. Therefore the variables that are estimated by instrumental variables are the consumptive variables that are expressed in MTOE: Final consumption FIN, electricity consumption E, Industry utilization IND, Other uses (domestic) OTHER and Transportation utilization TRANSP. And a few production/supply mix variables that can be argued to increase with temperature range[16]: Total Primary Energy Supply TPES, Production capacity PROD, Biofuel supply B and Fossil fuel primary supply FOSSIL. This results in 9 mix variable regressions that are re-estimated using the temperature range IV: FIN, TPES, PROD, E, B, FOSSIL, IND, OTHER, TRANSP. In these re-estimations the only

[16]Either by predicting temperatures and adjusting supply accordingly or by dipping into stocks or obtainment by trade and/or lagging production adjustments.

source of endogeneity affected and reduced by the temperature instrument, is assumed to be the energy mix variable. The fixed regressor set is regarded exogeneous.

The mechanics of IV estimation are similar two stage least squares. The set of regressors X is split into two parts: the exogenous part X_{ex} and the endogenous part X_{en}. For the first stage the endogenous variables are regressed on the instruments Z_{IV} and all exogenous variables in the model:

$$X_{\text{en}} = \gamma[Z_{IV},\, X_{\text{ex}}] + \eta \tag{5.16}$$

Which gives estimates $\hat{X}_{\text{en}}$. These estimates are then used in the second stage regression to replace the endogenous regressors:

$$Y = \beta_{IV}[\hat{X}_{\text{en}},\, X_{\text{ex}}] + \varepsilon \tag{5.17}$$

5.5.2 IV Tests

Along side with the IV estimates three tests are performed: A test to assert the strength of the instruments (Weak Instruments test), a test to confirm suspected endogeneity of the energy variable (Wu-Hausman test) and a test to check the exogeneity of the instruments (Sargan test). All three are shortly discussed:

Weak Instruments test This test inspects the first stage regression where the subset of regressors X that are considered the endogenous variables X_{en} are regressed on the instruments and all remaining exogenous regressors $X_{\text{en}} \sim [Z_{IV},\, X_{\text{ex}}]$. A Wald test is performed with the restricted model $H_0 :\; X_{\text{en}} \sim X_{\text{ex}}$ under the null hypothesis that the instruments Z_{IV} are weak and do not contribute to the explanation of X_{en} The statistic is $\chi^2(m)$ distributed with m the number of instruments (/restrictions).

Wu-Hausman exogeneity test The Wu-Hausman test compares a restricted model without instruments $H_0 :\; Y \sim X$ with an alternative where the fitted values from the first stage of IV are added to the regressor set (see Equation 5.16) $Y \sim [X,\, \hat{X}_{\text{en}}]$. Under the null of exogenous errors adding the instrument does not benefit estimation. The statistic is $\chi^2(k)$ where k is the number of endogenous variables. As we will be checking for the individual energy mix variables, $k = 1$ for our case.

Sargan overidentification (instrument exogeneity) test The Sargan test is a LM test on the residuals of the IV regression (ε in Equation 5.17). The instruments should be exogenous and thus not related to the error term in the regression. The error term is regressed on the instruments $\varepsilon \sim Z_{IV}$ and its quality of fit R^2 determines the LM statistic by multiplying it with the number of residuals $\text{LM} = n\mathrm{R}^2$ which is asymptotically distributed as $\chi^2(m - k)$ with m the number of instruments and k the number of endogenous variables under the H_0 of exogenous instruments. Hence the Sargan test can only be calculated in the overidentified case where $m > k$.

5.5.3 IV Estimation Results

The Instrumental Variable estimation results are presented in Table 5.3 and Table 5.4. The first table uses T.n, the true temperature range within a 5 or 10 year block, and T.m, the mean annual temperature range over the block, as instruments. This over identification where there are two IVs against one endogenous energy mix variable allows us to test the exogeneity assumption of the instruments with the Sargan test. However the cost of using two highly related instruments is in the thereby incurred efficiency loss. The second table estimates the IV models without over identification. This allows more efficient test results, but executing the Sargan test is not possible.

The results for table Table 5.3 and Table 5.4 both are much stronger for the averaged (top half of table) variables than for the differenced variables. In fact, the results for the averaged variables look promising. First we look at the bottom half of the table, the differenced models.

The Wald test rejects[17] 5/36 differenced models in the two IVs model and 19/36 models in the single IV estimation. Additionally if the weak coefficients test of these differenced energy mix variable models are considered, filtering the weak fit/weak regressors leaves only 12/36 and 5/36 differenced models where IV is perhaps possible.

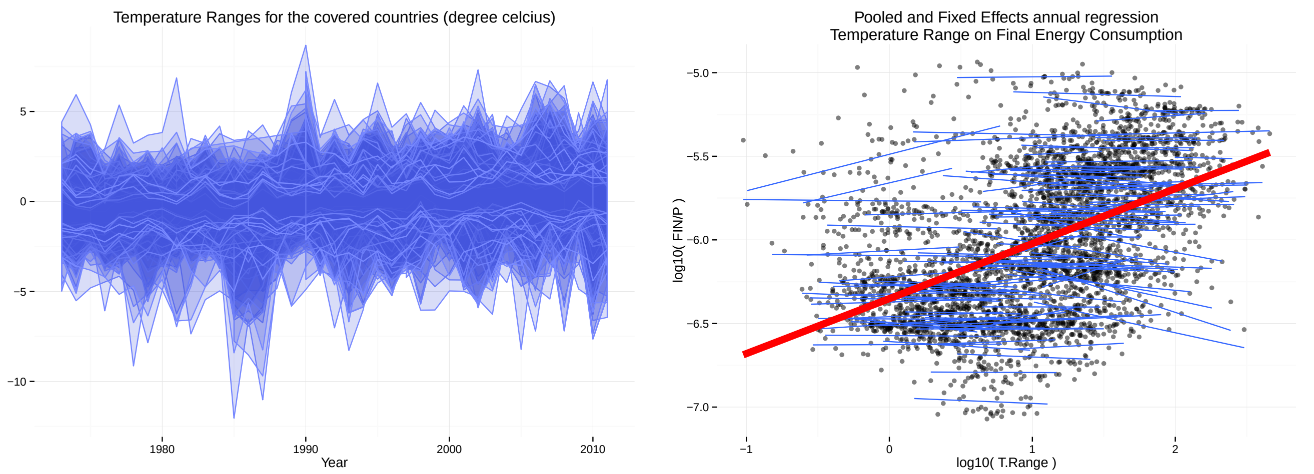

Figure 5.6: The temperature range annual timeseries for the sample. Right: Scatterplot of annual temperature range versus final energy consumption. The pooled regression shows a positive slope, however the country fixed effects estimates are flat. This shows that the temperature sensitivty is in the individual direction and not intra country (time changes) direction. Graph: author.

To examine why the temperature range performs so bad in the differenced context, we plot its timeseries to look if there is enough variation. See Figure 5.6. This does not appear to be the problem. Next the first stage regression of the IV procedure is reviewed. The log final energy consumption FIN (transformed to logs and per capita terms) is plotted against the log temperature range. The shape of the scatter and the red OLS linear model fit suggest a general upward relation, and a significant relation. However if the observations are grouped per country and separately fitted (blue fits) this positive relation disappears. This suggest that the temperature instrument primarily explains individual (country) heterogeneity.

The IV regression does a much better job in the averaged context rejecting only 2 and 6 models respectively for instruments T.n& T.m and just T.n based on the joint significance Wald test. If the overall fit is not insignificant and the strength of the instruments is high enough (weakness is rejected), the Wu-Hausman test can be interpreted to determine weather endogeneity (correlation with the error process) is a problem with the investigated regressor. For the models with Initial Production Wu-Hausman does not reject exogeneity of the energy variables, thus the estimates are consistent. And indeed the estimates β_{IV} of the Initial Production regressions where the weakness is rejected are close to the estimates using OLS.

The strongest results of the IV regressions are in the Fixed Effects models with averaged energy mix variables. Considering the two IVs model, energy is a good instrument for final consumption, primary supply and fossil fuels FIN, TPES and FOSSIL, and also good for the utilisations OTHER, TRANSP and moderate for IND and TRANSP.ALT. Table 5.4 with only T.n confirms this list but questions the quality of TRANSP. Temperature range is not a good instrument for the production, electricity and biofuels (PROD, E and B). The Sargan shows some signs of lack of exogenity of the temperature variable. Primarily when it is used with the 10 year panel. Nevertheless the instrument seems very suitable for the aggregates FIN and TPES and the utilisations. The IV estimate of practically all energy production and consumption levels grows more negative. For the final consumption the elasticity goes from about -0.03 to about -0.10. For the other estimates the ratio β_{IV}/β also evaluates to a factor 3 to 10. Given that the coefficients of the (panel)

[17] Asymptotics instead of F-test due to the two stages used in IV estimation.

OLS and the IV estimates are negative we conclude that the endogenous energy mix variables are positively related to the error process. Consider the process of E on Y with error u:

$$\begin{aligned} Y &= ... + \beta E + u \\ &= ... + \beta\left(f_E(..) + v\right) + u \quad \text{with } \mathrm{cor}(u, v) = \rho \\ &= ... + \beta f_E(..) + \beta v + u \\ &= ... + \tilde{\beta} f_E(..) + w \end{aligned} \tag{5.18}$$

E is generated using some $f_E()$ and an error v. That error is correlated to the error in the process for Y: u which makes E endogenous. If correlation ρ is positive, and if $\beta < 0$ then $w = \beta v + u$ generates a downward bias. Hence the biassed estimate $\tilde{\beta}$ is too high. Thus from Table 5.3 we conclude that the energy usage is endogenous and is positively related to the error process in the GDP regressions. The average causal effect from total energy consumption to GDP is higher in magnitude then OLS estimation suggests. This result shows that the throttling effect of energy supply on growth rates is stronger then suggested from the OLS analysis.

IV Regression Conclusion The temperature IV estimation separates the energy path, Energy→GDP from the wealth path GDP→Energy. It does so by using the temperature driven energy usage Temperature→Energy which is not reversible. By assumption the temperature influenced (manual agriculture) wealth is small compared to the energy driven (industry) wealth. The instrument works for a select number of cases where the energy mix variable driven by temperature is a logical assumption, such as the levels of the energy aggregates. It shows us that for these cases the wealth related energy usage is a positive function of wealth. This increases the energy usage compared to the case where all energy usage would stem from industry and would be productive for wealth. This upward bias in energy usage when this endogeneity is not handled, results in a underestimation of the energy effect on GDP.

Table 5.3: IV regression results using two temperature range metrics. Instruments are block temperature range and average annual temperature range T.n and T.m. Regression estimates with fixed effects β_{FE} and without β (repeated from Table 5.2). Inference with Arellano [1] standard errors. Significance $^+$, *, **, *** indicate significance on the 10, 5, 1, and 0.1% level. The performed tests are a joint significance Wald test, a Weak instruments test, a Wu-Hausman test against an exogehous energy regressor and a Sargan test against exogeneous instruments.

Averaged			Fixed Effects							Initial Production					
		/cap	β_{IV}	β	Wald	Weak	WH	Sargan		β_{IV}	β	Wald	Weak	WH	Sargan
FIN	5	×	−0.1035***	−0.0312**	555.5***	8.6***	3.9*	1.6	FIN	−0.0006	−0.0039	264.0***	50.8***	0.2	0.2
	10	×	−0.1070***	−0.0261*	380.0***	16.1***	11.0***	0.9		−0.0019	−0.0070	190.1***	31.6***	0.1	7.5**
TPES	5	×	−0.1151***	−0.0314**	532.7***	7.9***	4.3*	1.2	TPES	−0.0009	−0.0021	264.0***	33.3***	0.0	0.2
	10	×	−0.1102***	−0.0261*	378.2***	16.1***	11.1***	1.2		−0.0019	−0.0056	190.0***	20.3***	0.0	7.5**
PROD	5	×	0.0254**	−0.0032	549.5***	0.6	0.1	9.4**	PROD	0.0007	−0.0012	255.7***	5.7**	0.1	0.1
	10	×	−0.0205***	−0.0064	430.5***	0.2	0.0	26.6***		−0.0084***	−0.0018	168.9***	5.3**	1.2	5.1*
E	5	×	−0.2037***	−0.0085	164.4**	1.2	7.2**	0.4	E	−0.0009	−0.0009	263.9***	29.7***	0.0	0.2
	10	×	−0.1682***	−0.0068	129.3	1.6	8.4**	4.2*		0.0040	−0.0030	187.4***	17.8***	0.5	7.2**
B	5	×	−0.0725***	0.0011	312.1***	4.1*	10.0**	0.0	B	0.0066***	0.0003	247.6***	2.5$^+$	0.4	1.6
	10	×	−0.1368***	−0.0011	69.2	1.1	13.4***	0.0		−0.0147***	0.0008	117.1***	1.6	2.2	0.4
FOSSIL	5	×	−0.0982***	−0.0247**	499.9***	5.3**	3.8$^+$	2.4	FOSSIL	−0.0002	0.0002	263.8***	25.5***	0.0	0.2
	10	×	−0.1073***	−0.0210*	311.9***	10.0***	12.8***	0.8		−0.0027	−0.0028	189.9***	16.4***	0.0	7.4**
IND	5	×	−0.0555***	−0.0123*	534.2***	3.2*	1.3	7.3**	IND	0.0002	−0.0011	260.2***	30.9***	0.1	0.1
	10	×	−0.1219***	−0.0091	165.1**	4.4*	17.6***	0.4		−0.0045$^+$	−0.0032	187.1***	20.6***	0.1	7.2**
OTHER	5	×	−0.0981***	−0.0313**	554.4***	8.8***	4.2*	0.5	OTHER	−0.0007	−0.0085*	264.4***	84.5***	2.0	0.2
	10	×	−0.0960***	−0.0289**	394.9***	13.4***	8.2**	4.2*		0.0025	−0.0103*	187.2***	44.0***	2.7	7.3**
TRANSP	5	×	−0.0761***	−0.0118	513.5***	9.9***	5.5*	1.5	TRANSP	0.0025	0.0055*	265.1***	2.5$^+$	0.0	0.2
	10	×	−0.0916***	−0.0064	295.4***	10.1***	12.9***	4.4*		−0.0312***	0.0039	141.6***	3.6*	2.6	4.1*
TRANSP.ALT	5	×	0.3006**	0.0156	399.6***	5.7**	7.3**	0.8	TRANSP.ALT	0.0005	−0.0187*	263.7***	47.0***	0.6	0.2
	10		0.4451**	0.0344	192.8***	5.4**	17.2***	0.2		−0.0173	−0.0244*	191.4***	28.0***	0.0	7.2**
Differenced															
FIN	5	×	0.8705***	0.4305***	644.0***	3.3*	3.1$^+$	1.0	FIN	0.0652	0.4387***	289.0***	4.2*	2.7$^+$	0.1
	10	×	1.709***	0.3895***	145.7*	2.2	15.3***	0.4		0.3361**	0.4211***	249.8***	2.7$^+$	0.1	8.7**
TPES	5	×	1.008***	0.4779***	604.5***	2.6$^+$	3.2$^+$	1.6	TPES	0.0938	0.4895***	299.8***	3.2*	2.2	0.1
	10	×	2.497***	0.4295***	77.7	1.2	18.8***	0.0		0.5738***	0.4725***	256.3***	1.9	0.1	8.0**
PROD	5	×	0.6720$^+$	0.0858	184.9***	1.2	6.3*	0.5	PROD	0.3035$^+$	0.0955$^+$	207.6***	0.1	0.0	0.0
	10	×	0.7024**	0.0801	162.3**	2.7$^+$	10.6**	3.4$^+$		0.4059***	0.1124*	143.4***	4.8**	4.0*	0.3
E	5	×	−3.539**	0.2144**	19.9	0.1	9.1**	0.1	E	0.0427	0.2348**	275.9***	1.7	0.3	0.2
	10	×	−1.268$^+$	0.1081	67.9	0.4	4.6*	3.3$^+$		1.051$^+$	0.1395	56.4***	0.5	2.4	1.3
B	5	×	0.4560***	0.0260	336.7***	3.7*	9.3**	0.1	B	0.3358***	0.0416*	177.4***	1.4	1.7	0.6
	10	×	0.0139	0.0590	470.2***	2.3	0.0	20.5***		0.1800*	0.0555	195.8***	0.5	0.1	2.9$^+$
FOSSIL	5	×	0.7311***	0.3198***	554.4***	2.6$^+$	3.1$^+$	1.9	FOSSIL	0.0660	0.3383***	293.0***	3.2*	1.6	0.1
	10	×	1.415***	0.2316**	104.8	1.7	15.6***	0.5		0.3661***	0.2802**	228.1***	1.7	0.1	7.6**
IND	5	×	−0.7554***	0.1969***	135.0	0.2	1.8	2.1	IND	0.0143	0.1965***	264.3***	5.9**	1.8	0.1
	10	×	0.2517***	0.1474**	459.2***	0.3	0.0	29.4***		0.1901***	0.1522**	199.1***	5.9**	0.1	6.7**
OTHER	5	×	0.5772***	0.3363***	728.9***	7.3***	2.0	0.4	OTHER	0.1666$^+$	0.3356***	313.6***	1.5	0.2	0.0
	10	×	0.7941***	0.3486***	438.9***	7.8***	6.4*	4.8*		0.4304***	0.3620**	242.5***	0.1	0.0	9.5**
TRANSP	5	×	0.7781***	0.1825***	258.4***	1.6	6.3*	0.1	TRANSP	0.2511***	0.1942***	307.7***	0.1	0.0	0.2
	10	×	0.5971**	0.0867$^+$	202.3***	1.2	3.3$^+$	9.3**		0.6057*	0.1046$^+$	96.8***	1.9	4.3*	0.7
TRANSP.ALT	5	×	−0.3425**	−0.3211**	667.1***	3.6*	0.0	10.7**	TRANSP.ALT	−0.1742	−0.3086*	271.9***	7.0***	0.1	0.0
	10		−1.301*	−0.1937	323.7***	1.9	1.6	17.2***		1.932	−0.2532	73.1***	2.5$^+$	8.9**	0.3

Table 5.4: IV regression results using block temperature range. Instrument is block temperature range T.n. Regression estimates with fixed effects β_{FE} and without β (repeated from Table 5.2). Inference with Arellano [1] standard errors. Significance $^+$, *, **, *** indicate significance on the 10, 5, 1, and 0.1% level. The performed tests are a joint significance Wald test, a Weak instruments test and a Wu-Hausman test against an exogehous energy regressor.

Averaged			Fixed Effects						Initial Production				
		/cap	β_{IV}	β	Wald	Weak	WH		β_{IV}	β	Wald	Weak	WH
FIN	5	×	−0.0775***	−0.0312**	619.0***	13.2***	1.2	FIN	−0.0020	−0.0039	264.3***	85.2***	0.0
	10	×	−0.1214***	−0.0261*	342.6***	22.2***	10.8**		0.0142**	−0.0070	178.5***	43.3***	3.3$^+$
TPES	5	×	−0.0867***	−0.0314**	602.0***	11.5***	1.3	TPES	−0.0022	−0.0021	264.1***	59.4***	0.0
	10	×	−0.1278***	−0.0261*	334.7***	21.4***	11.1***		0.0162**	−0.0056	175.0***	28.6***	2.8$^+$
PROD	5	×	0.1570***	−0.0032	118.7	0.8	3.5$^+$	PROD	−0.0007	−0.0012	257.5***	8.2**	0.0
	10	×	−1.239**	−0.0064	1.4	0.0	18.2***		0.0159***	−0.0018	104.1***	2.7	2.2
E	5	×	−0.5578***	−0.0085	26.4	0.1	3.2$^+$	E	−0.0018	−0.0009	263.8***	54.2***	0.0
	10	×	−0.6440***	−0.0068	11.3	0.4	17.8***		0.0120**	−0.0030	178.1***	31.8***	2.4
B	5	×	−0.0733***	0.0011	304.4***	0.2	0.2	B	0.0063***	0.0003	249.1***	5.0*	0.4
	10	×	−0.1555***	−0.0011	54.6	1.0	7.8**		−0.0114***	0.0008	137.8***	2.8$^+$	1.2
FOSSIL	5	×	−0.0744***	−0.0247**	580.2***	9.3**	1.5	FOSSIL	−0.0019	0.0002	263.4***	38.8***	0.1
	10	×	−0.1218***	−0.0210*	270.9***	13.9***	12.3***		0.0128***	−0.0028	173.2***	21.6***	2.3
IND	5	×	−0.0726***	−0.0123*	462.0***	6.2*	2.4	IND	−0.0013	−0.0011	260.5***	39.8***	0.0
	10	×	−0.1180***	−0.0091	172.3**	8.6**	15.9***		0.0107***	−0.0032	168.6***	21.5***	2.6
OTHER	5	×	−0.0779***	−0.0313**	611.0***	10.4**	1.2	OTHER	−0.0013	−0.0085*	265.0***	155.0***	1.5
	10	×	−0.1436***	−0.0289**	266.8***	12.3***	11.8***		0.0090*	−0.0103*	179.2***	75.8***	6.4*
TRANSP	5	×	−0.2496***	−0.0118	134.9	0.8	3.0$^+$	TRANSP	−0.0092*	0.0055*	252.8***	2.6	0.1
	10	×	−0.1590***	−0.0064	157.4*	7.6**	16.3***		0.0552***	0.0039	109.9***	1.9	1.4
TRANSP.ALT	5		0.2287**	0.0156	479.0***	7.9**	2.8$^+$	TRANSP.ALT	−0.0068	−0.0187*	264.9***	59.9***	0.1
	10		0.4777**	0.0344	174.1***	8.2**	15.3***		0.0496$^+$	−0.0244*	173.6***	30.7***	3.4$^+$
Differenced													
FIN	5	×	1.717***	0.4305***	186.9***	0.7	2.6	FIN	0.0615	0.4387***	287.5***	8.3**	2.8$^+$
	10	×	1.942***	0.3895***	111.7	3.1$^+$	15.0***		−0.6904*	0.4211***	76.2***	2.4	5.6*
TPES	5	×	2.913***	0.4779***	68.8	0.3	3.4$^+$	TPES	0.0758	0.4895***	292.8***	6.2*	2.3
	10	×	2.572***	0.4295***	72.6	2.0	16.6***		−1.033*	0.4725***	54.6***	1.2	4.7*
PROD	5	×	1.817$^+$	0.0858	28.0	0.1	3.2$^+$	PROD	0.0907$^+$	0.0955$^+$	272.1***	0.1	0.0
	10	×	0.8382**	0.0801	123.7	5.0*	15.0***		0.6920***	0.1124*	75.6***	0.9	1.4
E	5	×	−2.645**	0.2144**	33.4	0.2	4.2*	E	0.0832	0.2348**	285.9***	3.1$^+$	0.2
	10	×	−31.62$^+$	0.1081	0.2	0.0	18.9***		−2.038$^+$	0.1395	12.7$^+$	0.1	2.0
B	5	×	4.753***	0.0260	4.9	0.0	0.3	B	−0.0465*	0.0416*	263.0***	0.7	0.0
	10	×	−0.8556*	0.0590	90.6	2.0	9.0**		1.053*	0.0555	33.1***	0.4	2.4
FOSSIL	5	×	2.972***	0.3198***	34.0	0.1	3.5$^+$	FOSSIL	0.0576	0.3383***	289.3***	6.3*	1.7
	10	×	1.732***	0.2316**	69.8	2.1	15.9***		−0.7047**	0.2802**	61.1***	1.4	3.9*
IND	5	×	−1.486***	0.1969***	49.5	0.4	5.2*	IND	0.0289	0.1965***	270.0***	10.9**	1.4
	10	×	6.441***	0.1474**	3.4	0.1	19.5***		−0.3396**	0.1522**	109.9***	4.3*	3.6$^+$
OTHER	5	×	0.7800***	0.3363***	561.0***	2.9$^+$	1.3	OTHER	0.1206	0.3356***	301.6***	1.9	0.2
	10	×	1.200***	0.3486***	244.1***	7.2**	11.3***		−2.440*	0.3620**	13.2$^+$	0.2	2.8$^+$
TRANSP	5	×	1.019***	0.1825***	155.5*	0.7	2.6	TRANSP	0.2987***	0.1942***	296.7***	0.1	0.0
	10	×	1.555**	0.0867$^+$	39.1	1.4	16.8***		8.259*	0.1046$^+$	0.7	0.0	1.7
TRANSP.ALT	5		1.619*	−0.3211**	271.2***	3.3$^+$	4.8*	TRANSP.ALT	−0.4474***	−0.3086*	271.7***	0.7	0.0
	10		153.5*	−0.1937	0.1	0.0	18.4***		6.090	−0.2532	12.4$^+$	0.1	1.8

Chapter 6

Summary and Discussion

Summary In this thesis the relations between *Energy Mix and Gross Domestic Product (*GDP*)* are explored by means of a panel model with energy mix summaries. These variables proxy for the total per capita consumption, the technological development level, the international position and the utilization of energy. To our knowledge this was the first investigation of this kind. The analysis resulted in a group of *energy mix variables* that explain a significant portion of GDP growth in a classic production function model with capital and labor factors. To counter suspected endogeneity in some of energy mix variables a temperature range instrumental variable is constructed and used. The strongest effects are the *energy aggregates* such as final energy consumption and the *international trade proxies* such as the nett trade position or the trade dependence.

Discussion and outlook The main shortcoming of this research is the relative short timeseries. While among the longest in its class, the timeseries is too short to perform dynamic modeling as the processes are very slow. Dynamic modeling is a strategy that could certainly benefit GDP modeling as the series are highly persistent. Also modeling in wealth levels remains of interest as this more directly shows the different levels of conditional equilibria.

Second there is some weakness in, and there are some arguments opposing exogeneity, using temperature as an instrument for energy mix variables. Finding good instruments is always a difficult task as it relies on normative qualities and underlying economic ideas. An improvement in the temperature instrument would be to include weighting the local temperature by population in the construction and to correct for latitude dependent climate. And an improvement in application of the instrumental variable approach would be to construct the exogenous projection in the instruments on a lower timescale as the blocks tend to filter out some variation in the instrument.

For several energy mix variables the temperature instrument is not a good instrument as the economic argument that temperature drives energy usage does not hold for them. For these variables other instruments can be conceived and constructed if they are suspected of endogeneity in a model with wealth. For example for the trade related energy mix variables trade quota on energy or bans can be used.

Off course there also is selection bias in the data: rich and developed countries have more effective statistical institutions and provide better and more detailed data. Institutions such as the World Bank (WB) and the United Nations (UN) are continuously striving to help these countries improve in collecting and sharing.

Interesting future directions would be to investigate causality relations of energy mix variables with GDP. For example with dynamic models and tests, such as co-integration analysis and Granger causality. Causality between energy and GDP is a topic that has drawn a lot of attention and has not yet yielded a unified vision. Both the instrumental variable approach and the energy mix variables could be of added value in this field. These techniques could be employed to individual country analyses where a longer history is obtainable. This makes estimating dynamical models more feasible.

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Abbreviations

AIC	Akaike Information Criterion	35
BP	Breusch-Pagan	39
DW	Durbin-Watson	39
GCF	Gross Captial Formation	18, 35, 55
GDI	Gross Domestic Investment	18
GDP	Gross Domestic Product	3–5, 7–18, 22, 31, 32, 36–38, 41, 43, 44, 47, 48, 50, 60
GHCN	Global Historical Climatology Network	27
GHCN-M	Global Historical Climatology Network-Monthly	27
HAC	Heteroscedasticity and Autocorrelation-Consistent	14, 31, 38–41, 65
HC	Heteroscedasticity-Consistent	38, 65
IEA	International Energy Agency	4, 15, 29
IID	Independent and Identically Distributed	38, 39, 65
ISO2	ISO 3166-1 alpha-2	61
ISO3	ISO 3166-1 alpha-3	38, 57, 61, 64
IV	Instrumental Variable	44–47
KGOE	kilogrammes of oil equivalent	20
LM	Lagrange Multiplier	39, 46
MTOE	mega tonnes of oil equivalent	34, 43, 45
OLS	Ordinary Least Squares	31, 38, 39, 41, 46, 47, 65
PPP	Purchasing Power Parity	17
PWT	Penn World Table Version 8.0	15–18
SIC	Schwarz Information Criterion	35
TPS	Thin Plate Spline	27–29
UN	United Nations	15, 16, 50
UNSD	United Nations Statistics Division	15
VAR	Vector Auto-Regressive	4
WB	World Bank	15–18, 50

List of Variables

P.r	Growth rate of the population	35
PROD	Production capacity	24
PSEFF	Power station efficiency	24
RENEW.F	Renewables primary fraction	24
T	Temperature instrumental variable	30
T.n	Block temperature range	35
TPES	Total Primary Energy Supply	24
TRADE.DEP	Dependence on foreign trade, trade position	24
TRADE.DEP.FOSSIL	Dependence on foreign trade for fossil fuels	24
TRADE.POS	Net trade position	24
TRADE.POS.FOSSIL	Net trade position for fossil fuels	24
TRADE.VOL	Trade volume	24
TRANSP	Transportation	24
TRANSP.ALT	Electricity (alt. Fuel) in Transportation	24
TRANSP.F	Transportation consumption fraction	24
Y	GDP in constant 2005 US Dollar	16
Y_P.dl	Dependent variable, annualized difference of log production	34
YP0	Initial Production	14, 35

Appendix A

1. Figure A.1: ISO 3166-1 alpha-3 (ISO3) reference map.
2. Table A.2: ISO 3166-1 alpha-3 (ISO3) country names.
3. Figure A.3: country-year coverage of data.
4. Section A.4: Polygon gridding for Temperature IV.
5. Section A.5: Robust Standard Errors for panel models.
6. Figures A.6.1-A.6.6: Sankey plots of energy mix.

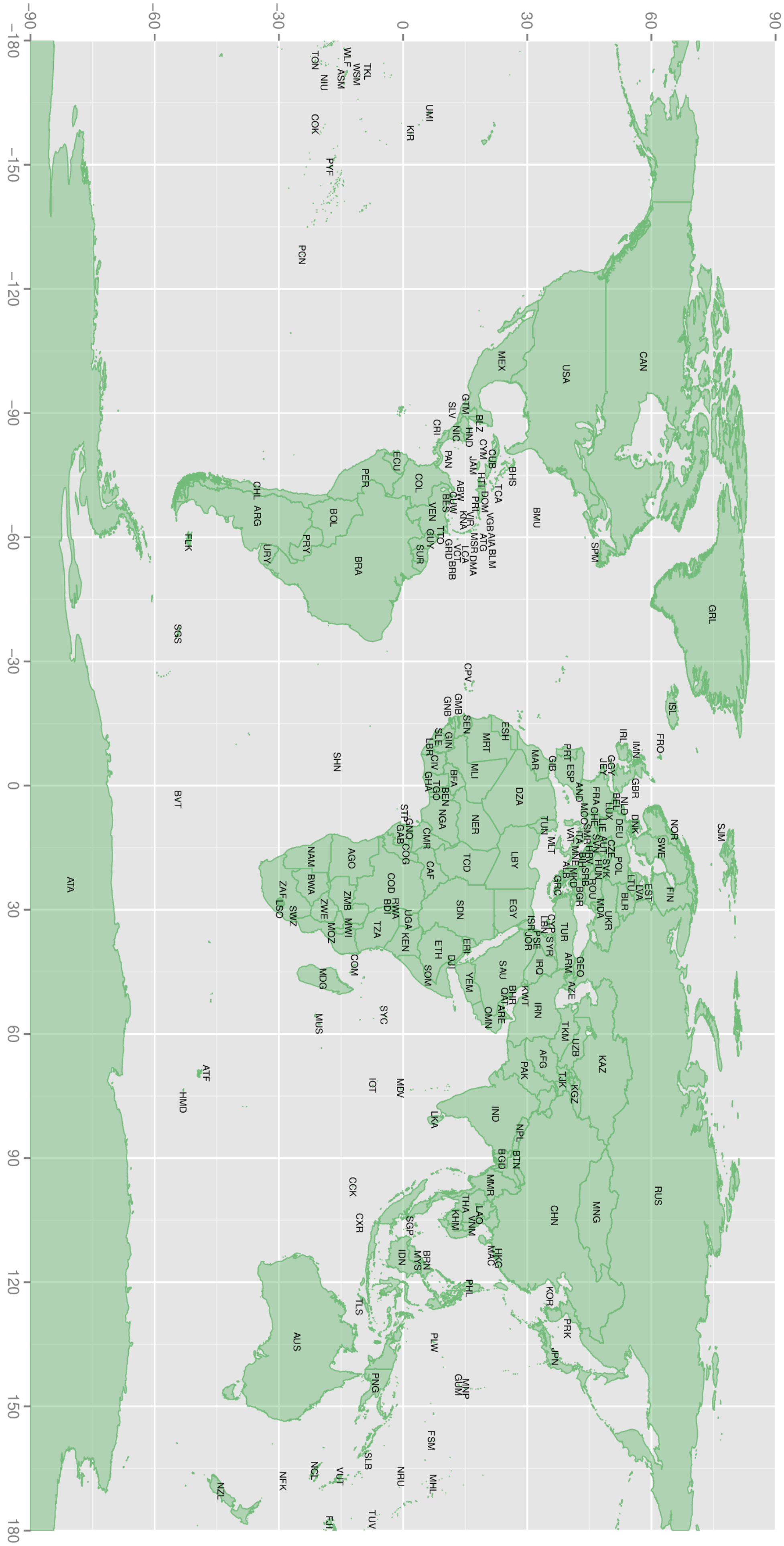

Figure A.1: Worldmap with ISO3 country codes for reference. Graphic: author

Table A.2: ISO3 Country codes. Countries/regions with polygon data Figure A.1. Underlined: also in energy mix dataset. Italic: only in energy data.

ISO3	Country
AFG	Afghanistan
ALB	Albania
DZA	Algeria
ASM	American Samoa
AND	Andorra
AGO	Angola
AIA	Anguilla
ATA	Antarctica
ATG	Antigua & Barbuda
ARG	Argentina
ARM	Armenia
ABW	Aruba
AUS	Australia
AUT	Austria
AZE	Azerbaijan
BHS	Bahamas
BHR	Bahrain
BGD	Bangladesh
BRB	Barbados
BLR	Belarus
BEL	Belgium
BLZ	Belize
BEN	Benin
BMU	Bermuda
BTN	Bhutan
BOL	Bolivia
BES	Bonaire, St.Eustatius & Saba
BIH	Bosnia & Herzegovina
BWA	Botswana
BVT	Bouvet Island
BRA	Brazil
IOT	British Indian Ocean Terr.
BRN	Brunei Darussalam
BGR	Bulgaria
BFA	Burkina Faso
BDI	Burundi
KHM	Cambodia
CMR	Cameroon
CAN	Canada
CPV	Cape Verde
CYM	Cayman Isl.
CAF	Central African Rep.
TCD	Chad
CHL	Chile
CHN	China
CXR	Christmas Island
CCK	Cocos Isl.
COL	Colombia
COM	Comoros
COG	Congo
COD	Congo, Dem. Rep. of the
COK	Cook Isl.
CRI	Costa Rica
CIV	Côte d'Ivoire
HRV	Croatia
CUB	Cuba
CUW	Curaçao
CYP	Cyprus
CZE	Czech Republic
DNK	Denmark
DJI	Djibouti
DMA	Dominica
DOM	Dominican Republic
ECU	Ecuador
EGY	Egypt
SLV	El Salvador
GNQ	Equatorial Guinea
ERI	Eritrea
EST	Estonia
ETH	Ethiopia
FLK	Falkland Isl.
FRO	Faroe Isl.
FJI	Fiji
FIN	Finland
FRA	France
PYF	French Polynesia
ATF	French Southern Terr.
GAB	Gabon
GMB	Gambia
GEO	Georgia
DEU	Germany
GHA	Ghana
GIB	Gibraltar
GRC	Greece
GRL	Greenland
GRD	Grenada
GUM	Guam
GTM	Guatemala
GGY	Guernsey
GIN	Guinea
GNB	Guinea-Bissau
GUY	Guyana
HTI	Haiti
HMD	Heard&McDonald Isl.
VAT	Vatican City
HND	Honduras
HKG	Hong Kong
HUN	Hungary
ISL	Iceland
IND	India
IDN	Indonesia
IRN	Iran, Islamic Rep. of
IRQ	Iraq
IRL	Ireland
IMN	Isle of Man
ISR	Israel
ITA	Italy
JAM	Jamaica
JPN	Japan
JEY	Jersey
JOR	Jordan
KAZ	Kazakhstan
KEN	Kenya
KIR	Kiribati
PRK	Korea, Dem. People's Rep.
KOR	Korea, Rep.
KSV	Kosovo
KWT	Kuwait
KGZ	Kyrgyzstan
LAO	Lao People's Dem. Rep.
LVA	Latvia
LBN	Lebanon
LSO	Lesotho
LBR	Liberia
LBY	Libya
LIE	Liechtenstein
LTU	Lithuania
LUX	Luxembourg
MAC	Macao
MKD	Macedonia
MDG	Madagascar
MWI	Malawi
MYS	Malaysia
MDV	Maldives
MLI	Mali
MLT	Malta
MHL	Marshall Isl.
MRT	Mauritania
MUS	Mauritius
MEX	Mexico
FSM	Micronesia
MDA	Moldova
MCO	Monaco
MNG	Mongolia
MNE	Montenegro
MSR	Montserrat
MAR	Morocco
MOZ	Mozambique
MMR	Myanmar
NAM	Namibia
NRU	Nauru
NPL	Nepal
NLD	Netherlands
NCL	New Caledonia
NZL	New Zealand
NIC	Nicaragua
NER	Niger
NGA	Nigeria
NIU	Niue
NFK	Norfolk Island
MNP	Northern Mariana Isl.
NOR	Norway
OMN	Oman
PAK	Pakistan
PLW	Palau
PSE	Palestine, State of
PAN	Panama
PNG	Papua New Guinea
PRY	Paraguay
PER	Peru
PHL	Philippines
PCN	Pitcairn
POL	Poland
PRT	Portugal
PRI	Puerto Rico
QAT	Qatar
ROU	Romania
RUS	Russian Fed.
RWA	Rwanda
BLM	St. Barthélemy
SHN	St. Helena
KNA	Saint Kitts & Nevis
LCA	St. Lucia
SPM	St. Pierre & Miquelon
VCT	St. Vincent & Grenadines
WSM	Samoa
SMR	San Marino
STP	Sao Tome & Principe
SAU	Saudi Arabia
SEN	Senegal
SRB	Serbia
SYC	Seychelles
SLE	Sierra Leone
SGP	Singapore
SVK	Slovakia
SVN	Slovenia
SLB	Solomon Isl.
SOM	Somalia
ZAF	South Africa
SGS	S-Georgia & S-Sandwich Isl.
ESP	Spain
LKA	Sri Lanka
SDN	Sudan
SUR	Suriname
SJM	Svalbard & Jan Mayen
SWZ	Swaziland
SWE	Sweden
CHE	Switzerland
SYR	Syrian Arab Republic
TWN	Taiwan
TJK	Tajikistan
TZA	Tanzania
THA	Thailand
TLS	Timor-Leste
TGO	Togo
TKL	Tokelau
TON	Tonga
TTO	Trinidad & Tobago
TUN	Tunisia
TUR	Turkey
TKM	Turkmenistan
TCA	Turks & Caicos Isl.
TUV	Tuvalu
UGA	Uganda
UKR	Ukraine
ARE	United Arab Emirates
GBR	United Kingdom
USA	United States
UMI	U.S. Min. Outl. Isl.
URY	Uruguay
UZB	Uzbekistan
VUT	Vanuatu
VEN	Venezuela
VNM	Vietnam
VGB	Virgin Isl., British
VIR	Virgin Isl., U.S.
WLF	Wallis & Futuna
ESH	Western Sahara
YEM	Yemen
ZMB	Zambia
ZWE	Zimbabwe

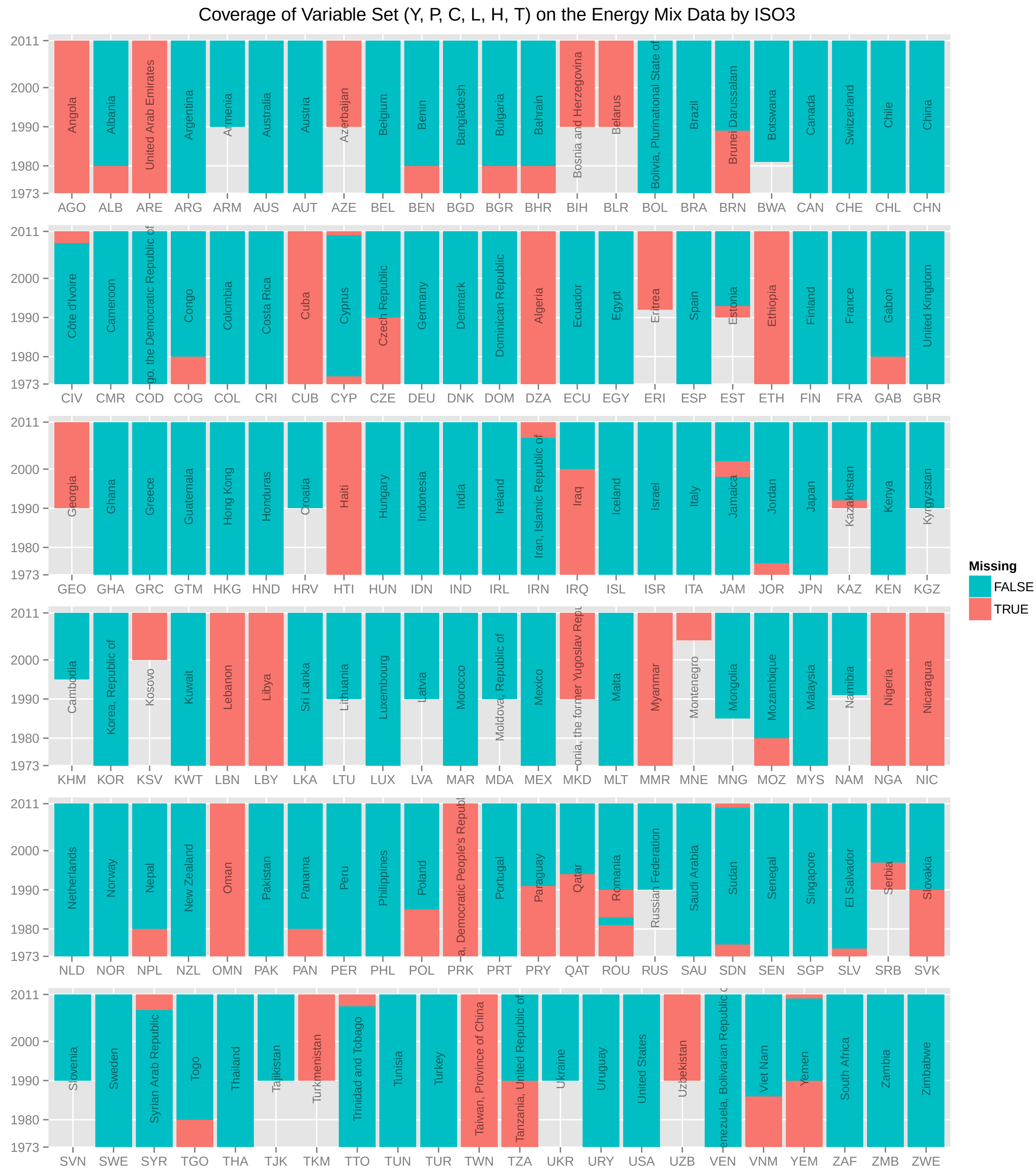

Figure A.3: Coverage of the collected variables relative to the energy mix dataset. The graph shows all country-years for which energy data is available. The coloring shows how many energy observations are left out due to missing values in the set of variables. Included in the set of variables are: GDP and population series (Y, P), the collected proxies for capital (C) and labor (L, H) and the temperature variable series (T). Graph: author.

A.4 Country polygon data

To link the gridded temperature data to countries, the location of the landmass of these countries is used. The information regarding these locations is derived from country boundary polygons. These polygons are transformed (clipped) into a grid that matches the temperature data. Of these parts the area is used to merge the temperature and country information.

Origin & description The dataset with the boundary/coastline polygons is collected from Eurostat, the statistical office of the European Union situated in Luxembourg.[1] The selected dataset is a scale 1:3 million closed polygon set of wWorld countries in 2010.[2] The country polygons are plotted in Figure 4.3. The raw shape dataset consists 254 polygons coded by two character identifiers. Not all of these polygons are part of countries. Most identifiers are coded according to ISO 3166-1 alpha-2 (ISO2), and are easily transformed to the 3 character ISO3 format used trough out this thesis. (See Figure A.1 and Table A.2 for the ISO3 codes). Several non ISO2 code conflicts in the dataset are are solved manually:

- Drop 8 uninhabited atols. IDs: `CP, XA, XB, XJ, XL, XM, XN, XO`
- Rename non ISO2 ID for Greece: `EL`, to ISO2:`GR` $\mapsto$ ISO3:`GRC`
- Rename non ISO2 ID for United Kingdom: UK, to ISO2:`GB` $\mapsto$ ISO3:`GBR`
- Add 8 (conflict) regions to mother: `XC-XE`$\cup$`CHN` `XD-XH`$\cup$`IND` `XF`$\cup$`EGY` `XG`$\cup$`KEN` `XI`$\cup$`JPN` `XK`$\cup$`SDN`
- Split ID `AN` in Curacao ISO3:`CUW` and Bonaire, St. Eustatius and Saba ISO3:`BES`

This leaves 239 countries in polygon set. The set of countries considered is presented in Panel 2:

ISO3 codes of countries in polygon and energy dataset. **Panel 2**

ABW AFG <u>AGO</u> AIA <u>ALB</u> AND <u>ARE</u> <u>ARG</u> <u>ARM</u> ASM ATA ATF ATG <u>AUS</u> <u>AUT</u> <u>AZE</u> BDI <u>BEL</u> <u>BEN</u> BES BFA <u>BGD</u> <u>BGR</u> <u>BHR</u> BHS <u>BIH</u> BLM <u>BLR</u>
BLZ BMU <u>BOL</u> <u>BRA</u> BRB <u>BRN</u> BTN BVT <u>BWA</u> CAF <u>CAN</u> CCK <u>CHE</u> <u>CHL</u> <u>CHN</u> <u>CIV</u> <u>CMR</u> <u>COD</u> <u>COG</u> COK <u>COL</u> COM CPV <u>CRI</u> <u>CUB</u> CUW CXR CYM
<u>CYP</u> <u>CZE</u> <u>DEU</u> DJI DMA <u>DNK</u> <u>DOM</u> <u>DZA</u> <u>ECU</u> <u>EGY</u> <u>ERI</u> ESH <u>ESP</u> <u>EST</u> <u>ETH</u> <u>FIN</u> FJI FLK <u>FRA</u> FRO FSM <u>GAB</u> <u>GBR</u> <u>GEO</u> GGY <u>GHA</u> GIB GIN
GMB GNB GNQ <u>GRC</u> GRD GRL <u>GTM</u> GUM GUY <u>HKG</u> HMD <u>HND</u> <u>HRV</u> <u>HTI</u> <u>HUN</u> <u>IDN</u> IMN <u>IND</u> IOT <u>IRL</u> <u>IRN</u> <u>IRQ</u> <u>ISL</u> <u>ISR</u> <u>ITA</u> <u>JAM</u> JEY <u>JOR</u>
<u>JPN</u> <u>KAZ</u> <u>KEN</u> <u>KGZ</u> <u>KHM</u> KIR KNA <u>KOR</u> <u>*KSV*</u> <u>KWT</u> LAO <u>LBN</u> LBR <u>LBY</u> LCA LIE <u>LKA</u> LSO <u>LTU</u> <u>LUX</u> <u>LVA</u> MAC <u>MAR</u> MCO <u>MDA</u> MDG MDV <u>MEX</u>
MHL <u>MKD</u> MLI <u>MLT</u> <u>MMR</u> <u>MNE</u> <u>MNG</u> MNP <u>MOZ</u> MRT MSR MUS MWI <u>MYS</u> <u>NAM</u> NCL NER NFK <u>NGA</u> <u>NIC</u> NIU <u>NLD</u> <u>NOR</u> <u>NPL</u> NRU <u>NZL</u> <u>OMN</u> <u>PAK</u>
<u>PAN</u> PCN <u>PER</u> <u>PHL</u> PLW PNG <u>POL</u> PRI <u>PRK</u> <u>PRT</u> <u>PRY</u> PSE PYF <u>QAT</u> <u>ROU</u> <u>RUS</u> RWA <u>SAU</u> <u>SDN</u> <u>SEN</u> <u>SGP</u> SGS SHN SJM SLB SLE <u>SLV</u> SMR
SOM SPM <u>SRB</u> STP SUR <u>SVK</u> <u>SVN</u> <u>SWE</u> SWZ SYC <u>SYR</u> TCA TCD <u>TGO</u> <u>THA</u> <u>TJK</u> TKL <u>TKM</u> TLS TON <u>TTO</u> <u>TUN</u> <u>TUR</u> TUV <u>*TWN*</u> <u>TZA</u> UGA <u>UKR</u>
UMI <u>URY</u> <u>USA</u> <u>UZB</u> VAT VCT <u>VEN</u> VGB VIR <u>VNM</u> VUT WLF WSM <u>YEM</u> <u>ZAF</u> <u>ZMB</u> <u>ZWE</u>

`AAA` = polygon data, <u>`AAA`</u> = polygon and energy data, <u>*AAA*</u> = only energy data

Two countries that were not yet independent in 2010, so without separate polygon data, are added manually to the area calculation results: Kosovo (`KSV`) and Taiwan (`TWN`). Adding `KSV` and `TWN` gives 241 countries.

Flat cell area assumption If it is assumed that the grid cells are flat, the $5° \times 5°$ grid cells have the same area expressed in squared (longitude/latitude) degrees: $25°^2$. However the area in square kilometres varies with latitude. This effect is visualised in the left two plots in Figure A.4, where a three dimensional flat gridded globe is plotted with cells coloured according to their area in square kilometres. The right plot in Figure A.4 shows the variation in area for the 36 latitude rings. The area for the grid cells is calculated algebraically. The steps followed in the derivation are:

1. The area of a ring is the difference between the area of two spherical caps.
2. The area of a cell is a (longitudinal) fraction of a ring around a sphere.

[1] `http://epp.eurostat.ec.europa.eu`, visited Jan-2014

[2] Data url, visited Jan-2014, © EuroGeographics for the administrative boundaries, code: `CNTR_2010_03M_SH`
`http://epp.eurostat.ec.europa.eu/portal/page/portal/gisco_Geographical_information_maps/popups/references/administrative_units_statistical_units_1`

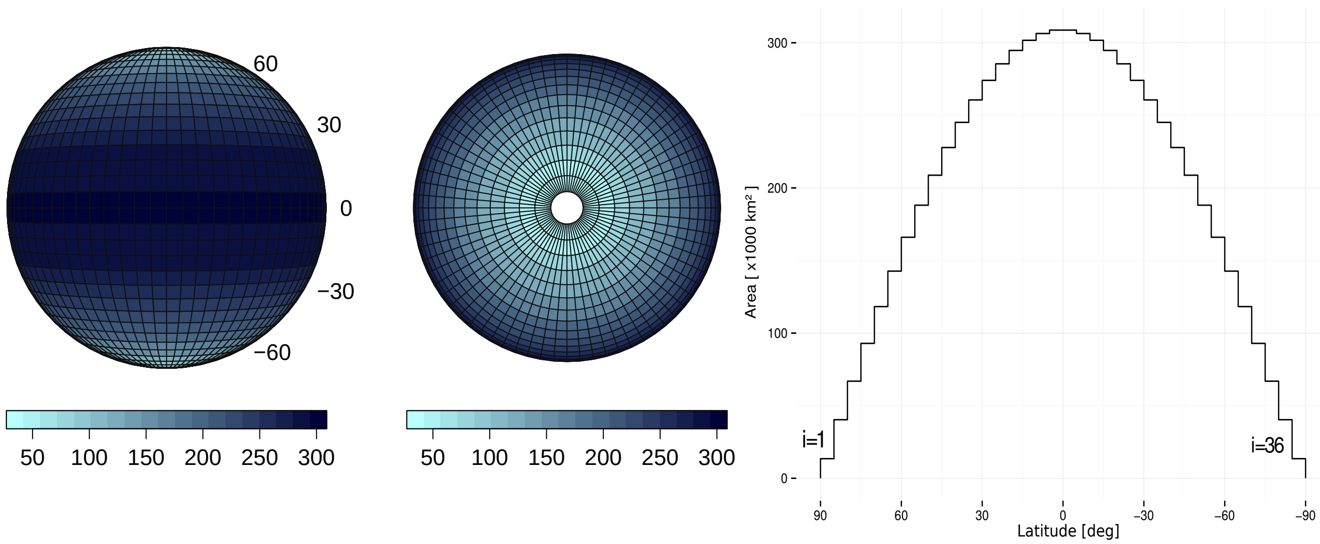

Figure A.4: 3D plot and line plot of the flat cell area approximation for the 5x5 degree grid. The cells are 5 by 5 degree squares on a Mercator plot, but their areas differ depending on latitude. The 3D plots are colored by cell area, and the areas are in 1000's of km^2. Graph: author

For the first step, we calculate the area of a ring around a sphere by the difference between two spherical caps. The area of a spherical cap is found by Equation A.1:

$$\begin{aligned} A_{cap}\left(\text{lat}\right) &= 2\pi R h \\ &= 2\pi R \cdot (1 - \sin \text{lat}) R \\ &= 2\pi R^2 \cdot (1 - \sin \text{lat}) \\ &= 2\pi R^2 - 2\pi R^2 \sin \text{lat} \end{aligned} \tag{A.1}$$

Where h is the height of the cap, R is the radius of the earth[3] and lat is the latitude of the cap's baseline. For the sine function the latitude has to be converted to radians. The area of a ring, defined by two latitudes, is now found by the difference between the two caps. See Equation A.2.

$$\begin{aligned} A_{ring}\left(\text{lat}_1,\, \text{lat}_2\right) &= \left|A_{cap}\left(\text{lat}_1\right) - A_{cap}\left(\text{lat}_2\right)\right| \\ &= \left|(2\pi R^2 - 2\pi R^2 \sin \text{lat}_1) - (2\pi R^2 - 2\pi R^2 \sin \text{lat}_2)\right| \\ &= 2\pi R^2 \left|\sin \text{lat}_2 - \sin \text{lat}_1\right| \end{aligned} \tag{A.2}$$

The absolute value is allowed since the area is positive. This saves us from sorting the latitudes. Now to find the area of a cell with these latitudes and the longitudes lon_1 and lon_2 the longitudinal fraction the ring can be used as the area density does not depend on longitude. Again this fraction is positive. The cell area becomes Equation A.3:

$$\begin{aligned} A_{cell}\left(\text{lat}_1,\, \text{lat}_2,\, \text{lon}_1,\, \text{lon}_2\right) &= \frac{|\text{lon}_1 - \text{lon}_2|}{360} A_{ring}\left(\text{lat}_1,\, \text{lat}_2\right) \\ &= 2\pi R^2 \frac{|\text{lon}_1 - \text{lon}_2|}{360} \left|\sin \text{lat}_2 - \sin \text{lat}_1\right| \\ &= 2\pi R^2 \frac{|\Delta \text{lon}|}{360} \left|\Delta \sin \text{lat}\right| \end{aligned} \tag{A.3}$$

Where shorthand Δ is used for differencing.

[3] Mean earth radius $R \triangleq 6\,371$ km, so $R^2 = 40\,589\,641$ km^2

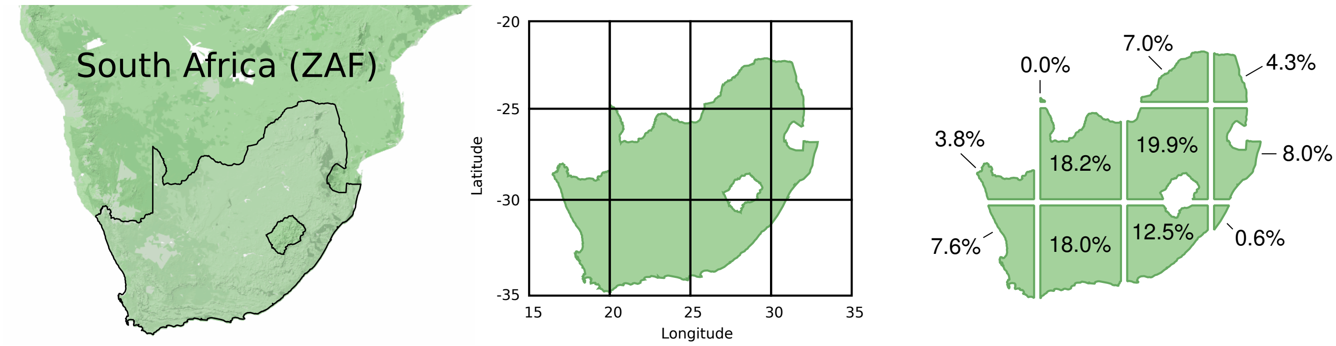

Figure A.5: Calculation process of area fractions. The country polygons are plotted in a Mercator projection and clipped according to the 5x5 degree cells. For each piece the area is calculated in squared degrees $[\,\circ 2\,]$ and from that, using the flat cell approximation, in squared kilometres $[\,\mathrm{km}^2\,]$. Than the relative contribution to the total area of the country is determined. Graph: author.

Clipping The `C++` library `Clipper`[22] is used to calculate the intersections of the $5° \times 5°$ grid cells and the country polygons, and the area in degree squared $[\circ 2]$. The clipping process is visualised schematically in Figure A.5 for South Africa. For each grid cell in the lattice that is touched by the bounding box of the country polygon, the intersection between the country and this cell is calculated. The country is sliced into grid sized pieces. For each piece the area is calculated in squared degrees $[\,\circ 2\,]$ as the polygon coordinates are latitude and longitude degrees. From this area in $[\,\circ 2\,]$, knowing that all $5° \times 5°$ cells have area $25^{\circ 2}$, the fraction of this cell occupied by this country can be calculated as:

$$\mathrm{frac}_{deg} = \frac{A_{piece}\,[\,\circ 2\,]}{A_{cell}\ \ [\,\circ 2\,]} \quad = \frac{A_{piece}\,[\,\circ 2\,]}{25^{\circ 2}}$$

Now the area in $[\,\mathrm{km}^2\,]$ for this piece can be approximated by multiplying the degree squared area fraction $\mathrm{frac}_{\mathrm{deg}}$ by the area of the cell in $A_{cell}\,[\,\mathrm{km}^2\,]$ using (A.3):

$$A_{piece}\,[\,\mathrm{km}^2\,] = \mathrm{frac}_{deg} \cdot A_{cell}\,[\,\mathrm{km}^2\,]$$

Note that this approximation is exact if the piece is 100% or 0% land covered and if the density is constant in the lateral direction within the cell. The error is maximal if only the lower or upper half of the cell is covered in land. In the upper hemisphere the area in $[\,\mathrm{km}^2\,]$ is overestimated if the only upper half of the cell is covered, in the lower hemisphere this is reversed. The magnitude of the area error can be found by[4]:

$$\begin{aligned}
\varepsilon &= 0.5A_{cell}(\mathrm{lat}, \mathrm{lat}+\delta) - A_{cell}(\mathrm{lat}, \mathrm{lat}+0.5\delta) \\
&= 2\pi R^2 \frac{\Delta\mathrm{lon}}{360}\Big(0.5\big|\sin\mathrm{lat} - \sin(\mathrm{lat}+\delta)\big| - \big|\sin\mathrm{lat} - \sin(\mathrm{lat}+0.5\delta)\big|\Big) \\
|\varepsilon| &= 2\pi R^2 \frac{\Delta\mathrm{lon}}{360}\Big|0.5\big|\sin\mathrm{lat} - \sin(\mathrm{lat}+\delta)\big| - \big|\sin\mathrm{lat} - \sin(\mathrm{lat}+0.5\delta)\big|\Big| \\
&\leq 2\pi R^2 \frac{\Delta\mathrm{lon}}{360}\Big|0.5\sin\mathrm{lat} - 0.5\sin(\mathrm{lat}+\delta) - \sin\mathrm{lat} + \sin(\mathrm{lat}+0.5\delta)\Big| \\
&\leq 2\pi R^2 \frac{\Delta\mathrm{lon}}{360}\Big|\sin(\mathrm{lat}+0.5\delta) - 0.5\big(\sin(\mathrm{lat}) + \sin(\mathrm{lat}+\delta)\big)\Big|
\end{aligned} \tag{A.4}$$

Where δ is the latitude step, or grid size, which is $5°$.

[4]Subadditivity property of absolute value: $|a+b| \leq |a| + |b|$ results in $||a| - |b|| \leq |a-b|$

The error $|\varepsilon|$ in Equation A.4 is maximal for the poles. For latitudes 90°, 85°, 80°, 60° and 30° the error is maximally 3 368, 3 342, 3 291, 2 843 and 1 557 km^2 respectively. On the equator, the error is maximally 147 km^2. If the errors are calculated relative to the area of the cell, that is $|\varepsilon|/A_{cell}$, than for the selected 6 latitudes, 90°, 85°, 80°, 60°, 30° and 0°, the error is maximally 25%, 8.3%, 4.9%, 1.7%, 0.6% and 0.05% respectively. As can be seen on Figure 4.3 most countries lay between latitudes 60° and −60° for which the maximal flat cell error is reasonably bounded.

The result of the polygon clipping is a database with columns for the country (ISO3), the cell indices i and j (see Equation 4.1), and the area in [∘2] and approximated in [km^2]. To construct the weight each cell should have for a particular country, the relative contribution to the total area for that country is calculated. The cell areas are divided by the total area of the country. The result is a vector of fractions for each country that sum to 1 and have a value > 0 for all cells that have landmass. This is schematized in the right image in Figure A.5.

Two missing countries are added to this database of area weights: Kosovo and Taiwan. Kosovo was included in Serbia `SRB` in 2010 and Taiwan was included in China `CHN`. Both are added as a single cell with weight 1.0. The bounding box of Kosovo `KSV` is approximately (43.3°.. 41.8°N, 20.0°.. 21.8°E) and the capital Pristina has coordinates (42.7°N, 21.2°E). So for `KSV` cell $\{10, 41\} \mapsto$ (45°.. 40°N, 20°.. 25°E) is selected. Taiwan `TWN` has an approximate bounding box of (25.3°.. 21.9°N, 120.0°.. 122°E) and the capital Taipei City has coordinates (25.0°N, 121.5°E). Therefore Taiwan is assumed to have 100% of land in cell $\{14, 61\} \mapsto$ (25°.. 20°N, 120°.. 125°E).

In Panel 3 the head and tail of the Country-Area Grid database are presented. In total 2 142 country-cells have a nonzero area of which 1 429 cells are unique (not shared between countries). Most of the grid cells are occupied by only one or two countries (1 035 and 213 respectively). However for example cell $\{15, 24\}$ in the Caribbean is shared by 10 country codes as almost all the Lesser Antiles are in this cell.

Sample of the calculated Country-Area-Grid table **Panel 3**

```
        ISO3  i  j     areadeg        areakm      perckm
     1:  ABW 16 22  0.00504732      60.90802 0.334957912
     2:  ABW 16 23  0.01002120     120.92981 0.665042088
     3:  AFG 11 49  3.08408000   30242.96872 0.047231680
     4:  AFG 11 50 11.45530000  112332.45557 0.175434184
     5:  AFG 11 51  5.84321000   57299.42714 0.089486856
   ---
  2138:  ZMB 22 43  0.20493900    2415.88493 0.003207224
  2139:  ZWE 22 42 12.54570000  147892.62944 0.377559743
  2140:  ZWE 22 43 11.21500000  132205.92228 0.337512655
  2141:  ZWE 23 42  4.38787000   50107.32620 0.127920568
  2142:  ZWE 23 43  5.38558000   61500.68572 0.157007034
```

A.5 Robust Standard Errors

Consider a general OLS model $y_i = x_i^\top \beta + \varepsilon_i$ with $i \in 1..n$ or stacking all individuals matrix form $y = \beta X + u$. If the error terms in the model are exogenous to the regressors, expressed mathematically by $\mathbb{E}\left[\varepsilon_i | x_i\right] = 0$, and the error variance is homoskedastic and independent, $\mathrm{Var}(\varepsilon_i|x_i) = \Omega = \sigma^2 I$. That is ε is IID. Then β is estimated by $\hat{\beta} = \left(X^\top X\right)^{-1} X^\top y$ and the variance of the estimate is found by:

$$\begin{aligned} \widehat{\mathrm{Var}}(\hat{\beta}) &= (X^\top X)^{-1} X^\top \Omega X (X^\top X)^{-1} \\ &= \hat{\sigma}(X^\top X)^{-1} \end{aligned} \tag{A.5}$$

However if the assumption on the homoskedasticity of ε_i not holds the second step in the variance equation for $\hat{\beta}$ is not possible and an estimate for $\hat{\Omega}$ has to be found. This is usually done by using the estimated residuals from $\hat{u} = \left(I - X(X^\top X)^{-1} X^\top\right) y = (I - H)y$ in a constrained form for the covariance matrix for the error term (see implementations of Zeileis (2004) [41] and Croissant and Millo (2008) [11])[5]. For example $\Omega = \mathrm{diag}(\omega_1..\omega_n)$ with $\omega_i = \hat{u}_i^2$ (White standard errors) or with a down weighting of influential observations by scaling with the hat matrix diagonals $\omega_i = \frac{\hat{u}_i^2}{(1-h_i)^2}$ gives HC standard errors.

Now we focus on finding an equivalent HC estimator for data with time t and individuals i. For our the panel models with fixed effects the regressors are the set $x_{it} \subset (\mathbf{S}_{it},\ \mathrm{E.}{*}_{it})$ collected in the $T \cdot N \times K$ matrix[6] denoted by X. Baltagi (2008) [2] (p.14) and Arellano (2003) [1] (pp.18–20) describe methods to calculate HC standard errors for fixed effect models. They use the 'within' transformation to demean the regressor set $X \to X^*$ and the response variable $y \to y^*$ to obtain the fixed effects estimate $\hat{\beta}_{FE} = \left(X^{*\top} X^*\right)^{-1} X^{*\top} y^*$. Which allows for the variance of the fixed effects estimator to be estimated by the HAC formula (Equation A.6):

$$\widehat{\mathrm{Var}}(\hat{\beta}_{FE}) = (X^{*\top} X^*)^{-1} \left(\sum_{i=1}^{N} X_i^{*\top} \hat{u}_i^* \hat{u}_i^{*\top} X_i^* \right) (X^{*\top} X^*)^{-1} \quad \text{(Arellano)} \tag{A.6}$$

Where the residual estimates are from the fixed effects estimation by $\hat{u}_i^* = y_i^* - X_i^* \hat{\beta}_{FE}$ where the $\hat{u}_i^*$ is a vector of length T and X_i^* is $T \times K$.[7] If serial correlation is absent, that is if $\mathbb{E}\left[\varepsilon_{it}\varepsilon_{js}\right] = 0 \; \forall \; t \neq s$, White's HC estimation can be used with a common variance in each group (individual). This gives an expression similar to the first equation of Equation A.5 with $\sigma_i^2 = \sum_{t=1}^{T} \hat{u}_{it}^2 / T$ converted to a diagonal matrix for all observations of individual i by $\Omega_i = I_T \otimes \sigma_i^2$ and than to $\Omega_{FE} = \mathrm{diag}(\Omega_1..\Omega_N)$ with diagonal length $N \cdot T$:

$$\widehat{\mathrm{Var}}(\hat{\beta}_{FE}) = (X^{*\top} X^*)^{-1} X^{*\top} \Omega_{FE} X^* (X^{*\top} X^*)^{-1} \quad \text{(White)} \tag{A.7}$$

Not accounting for hetroscedasticity and autocorrelation when it is present results in consistent but inefficient estimations [2], and in biassed standard errors. We should use prefer constant-σ over HC over HAC standard errors where allowed as this results in higher efficiency.

[5] Projection matrix H is called the hat matrix

[6] Dimensions $T \cdot N \times K$: Time $\cdot$ Individuals $\times$ Regressors

[7] Note that for hypothesis testing the degrees of freedom must be compensated for the implicit estimation of the individual means if the model is estimated with the 'within' transformation on the regressors and response variables.

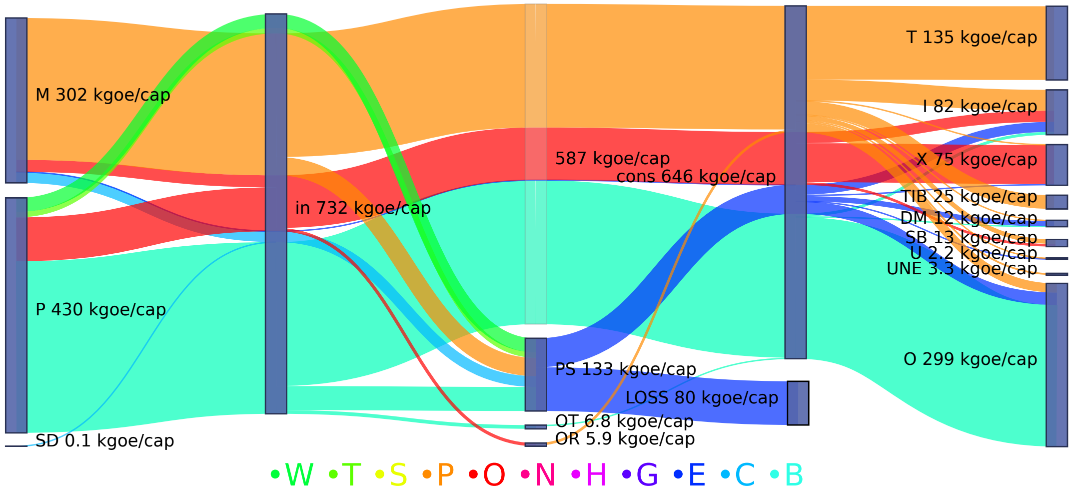

Figure A.6.1: Sankey Plot of Guatamala's (GTM) energy mix in 2005

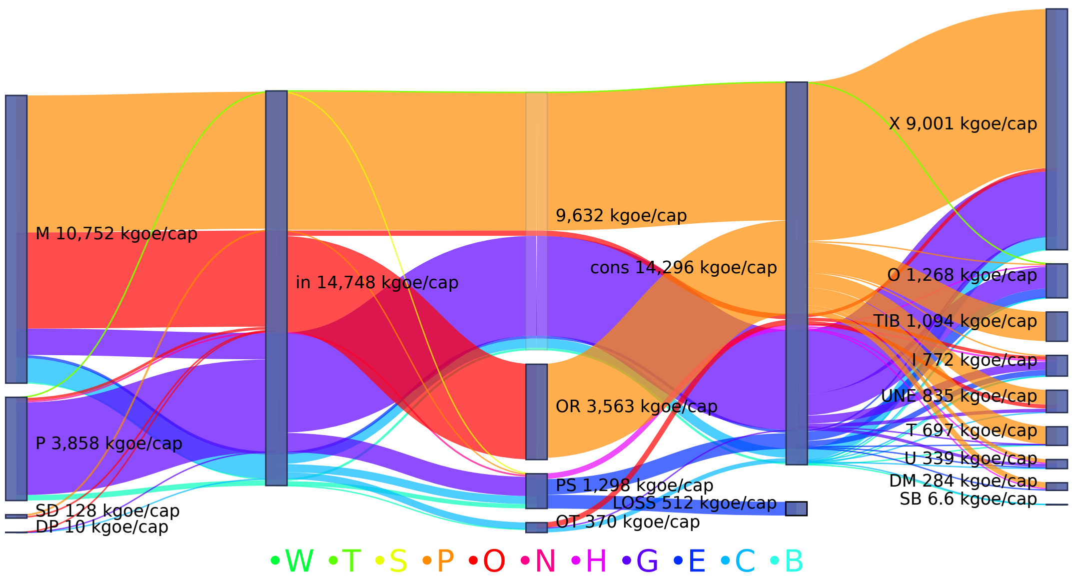

Figure A.6.2: Sankey Plot of Netherland's (NLD) energy mix in 2011

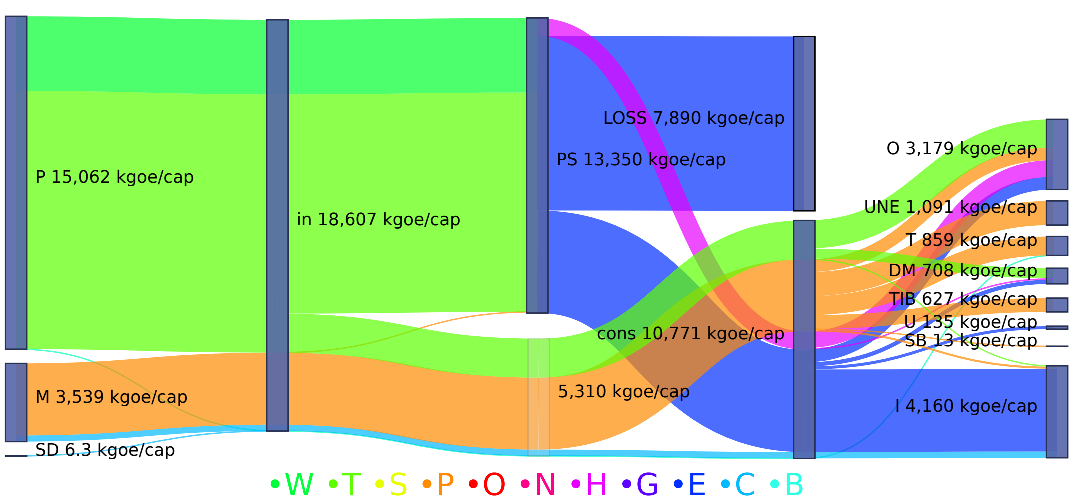

Figure A.6.3: Sankey Plot of Iceland's (ISL) energy mix in 2011

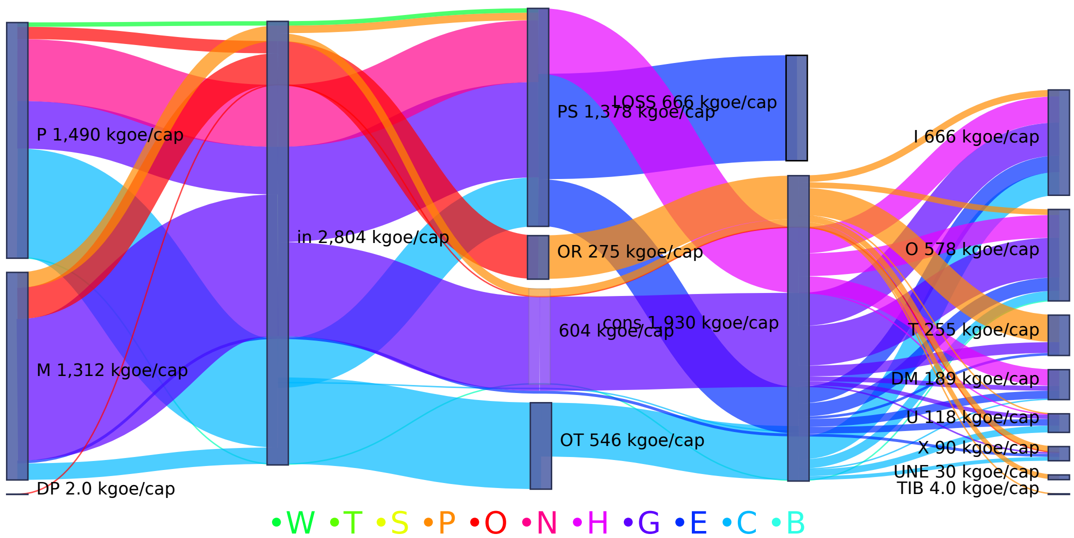

Figure A.6.4: Sankey Plot of Ukraine's (UKR) energy mix in 1998

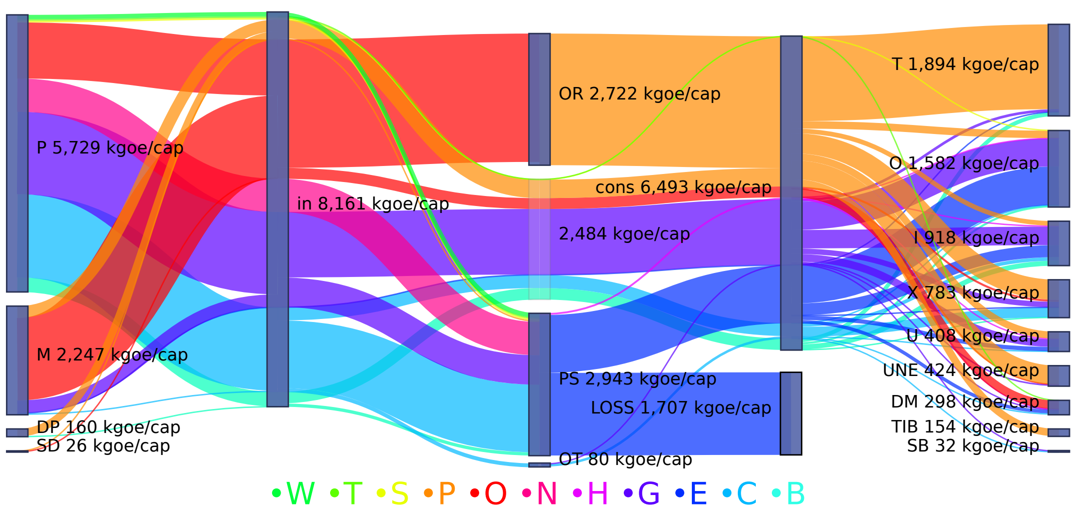

Figure A.6.5: Sankey Plot of America's (USA) energy mix in 2011

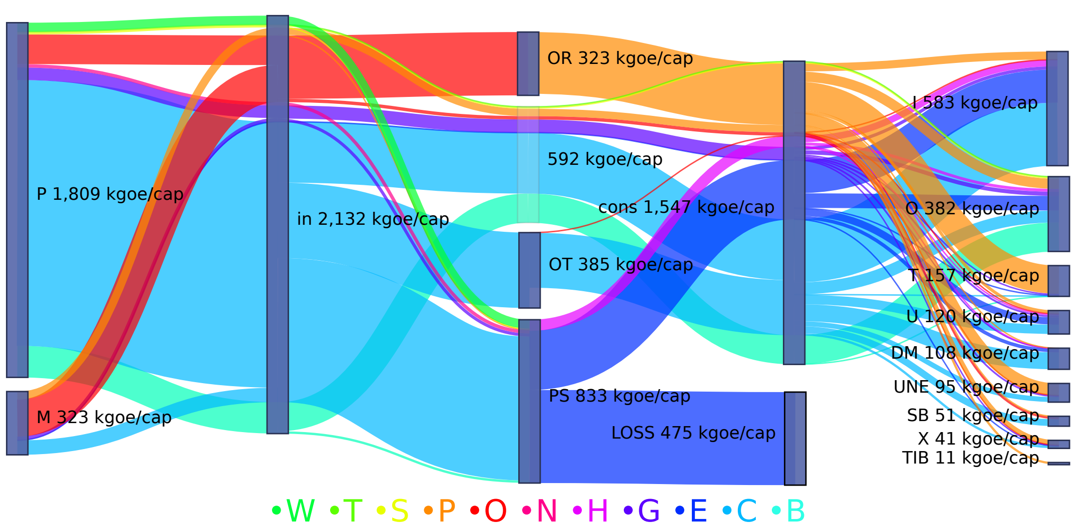

Figure A.6.6: Sankey Plot of China's (CHN) energy mix in 2011

Master of Science Thesis

ERASMUS UNIVERSITEIT ROTTERDAM