# VARIABLE SELECTION IN THE ANALYSIS OF ENERGY CONSUMPTION-GROWTH NEXUS

CAMARERO MARIAM[a], FORTE ANABEL[b], GARCIA-DONATO GONZALO[c], MENDOZA YURENA*[d], ORDOÑEZ JAVIER[a, e]

[a]*Departamento de Economía. Universidad Jaume I. Grupo de Investigación en Integración Económica (INTECO)*

[c]*Departamento de Economía y Finanzas. Universidad de Castilla y la Mancha.*

[b]*Departamento de Estadística e Investigación Operativa. Universidad de Valencia.*

[d]*Departamento de Economía Aplicada II. Universidad de Valencia.*

[e]*Instituto de Economía Internacional (IEI) and Universidad Popular Autónoma del Estado de Puebla (UPAEP)*

**Corresponding author. Tel.: +34 963 825 427; fax: +34 963 828 354. E-mail address: Yurena.me.le@gmail.com (Y.Mendoza)*

## Abstract

There is abundant empirical literature that focuses on whether energy consumption is a critical driver of economic growth. The evolution of this literature has largely consisted of attempts to solve the problems and answer the criticisms arising from earlier studies. One of the most common criticisms is that previous work concentrates on the bivariate relationship, energy consumption-economic growth. Many authors try to overcome this critique using control variables. However, the choice of these variables has been ad hoc, made according to the subjective economic rationale of the authors. Our contribution to this literature is to apply a robust probabilistic model to select the explanatory variables from a large set of potential candidates in the case of the US from 1949 to 2010, not only for an aggregate analysis but also for a sector analysis. The results highlight the critical role of public spending and energy intensity in the explanation of growth. Furthermore, since the study reveals different explanatory variables for each sector, it indicates the importance of policy decisions specifically aimed at different sectors.

*Keywords:* Energy Consumption, Economic Growth, Control Variables, Causality, Probabilistic Model, Variable Selection

## 1. Introduction and Motivation

There are several economic theories that have traditionally been applied to the relationship between energy consumption and growth. One particular debate centres on two competing economic theories: ecological economic theory and neoclassical growth theory. Ecological economic theory considers the scarcity of energy resources as a limitation to growth. In contrast, neoclassical growth theory (such as Solow's 1956 model) states that energy resources are not essential inputs for growth, arguing that technological progress and substitution possibilities may serve to circumvent scarcity problems.

The evidence in favour of one of these hypotheses has direct policy implications. If energy is a neutral input for growth, policymakers could design compatible environmental conservation policies and economic growth strategies. Conversely, ecological economists argue that a sustainable growth path would be hard to achieve if energy sources are a critical input.

A further distinction in the literature is concerned with the causal link between energy consumption and growth. Based on the results obtained, four hypotheses are established: i) The "growth hypothesis" states that energy consumption is crucial for economic growth and consequently there is a unidirectional causal relationship from energy consumption to growth. Countries or economic sectors for which this hypothesis is verified are energy dependent as policies that restrain energy use lead to a decrease in the growth rate; ii) If there is a unidirectional causality from economic growth to energy consumption, the "conservation hypothesis" would be validated. In this case, environmental conservation measures that reduce energy consumption will not have negative effects on economic growth; iii) A bidirectional relationship between energy consumption and growth is known as the "feedback hypothesis". In this scenario, conservation policies aimed at reducing energy consumption could decrease economic growth performance, and changes in growth will in turn be reflected in energy consumption; iv) The last hypothesis - the "neutrality hypothesis" - states that there is no correlation between energy consumption and economic growth and thus the implementation of measures that will reduce energy consumption does not affect the path of economic growth.

An abundance of empirical literature has attempted to address this issue over the last 30 years, beginning with the seminal paper by Kraft and Kraft (1978). To classify the evidence produced since that paper, four generations of studies are mentioned in the literature.[1]

The first generation of studies applies the VAR methods developed by Sims (1972) to analyse causality between energy consumption (EC) and GDP where GDP is used as a proxy for economic growth. However, these studies do not account for the time series properties of the variables, i.e., their order of integration. The second generation of studies attempts to overcome this limitation by using the Engel and Granger cointegration approach that allows for non-stationary variables.

The main drawback of that technique is the limited analysis of a bivariate setting and, therefore, a third generation of studies extends the framework to a multivariate perspective, as in Johansen (1991). A fourth, more recent generation of studies has attempted to avoid the problems of a short data span that, for many countries, makes it difficult to apply multivariate methods. Panel es-

[1] See for example Belke et al. (2011)

timation techniques provide consistent estimates of the long-term relationships and, at the same time, account for cross-sectional information and compensate for the scarcity of time series data for some variables. However, as shown by the surveys of Ozturk (2010), Payne (2010) and Coers and Sanders (2013) the evidence for the EC-growth nexus is mixed. The main reasons given in the literature for these discrepancies are the application of a variety of econometric approaches, the heterogeneity of the countries analysed and the differences in the time span of the samples. Additionally, certain authors argue that the main factors that explain the mixed evidence are the limitations of the bivariate approach and the associated problem of omitted variables. There are multiple potential channels that can influence such a complex relationship, the majority of which may be concealed by the bivariate. Several control variables have been introduced to address this omitted variable bias, and Table 1 presents some of those most widely-used in the literature, which we added to our study database[2].

[2]See Table 2

Table 1: Control Variables Used in the Growth-EC nexus literature

| VARIABLES | REASONS | AUTHORS |
| --- | --- | --- |
| Employment (EMP) | Economic growth depends on other variables such as technology, energy and employment. | Yu and Hwang (1984); Stern (1993); Cheng (1998); Ghali and El-Sakka (2004); Soytas and Sari (2006); Climent and Pardo (2007); Bowden and Payne (2010); Lee and Chang (2008); Lee et al. (2008); Sari et al. (2008); Bartleet and Gounder (2010); Menyah and Wolde-Rufael (2010); Shahbaz et al. (2011); Eggoh et al. (2011); Menegaki (2011); Yildirim et al. (2012); Soytas and Sari (2007); Payne and Taylor (2010) |
| Energy Prices: Natural Gas Price (NG_P), Coal Price (C_P), Oil Price (O_P), Energy Price Index. | Crucial role of energy costs in the production function. | Glasure and Lee (1995, 1996); Glasure (2002); Lee and Lee (2010); Costantini and Martini (2010); Belke et al. (2011) |
| Government Spending (SPE) | Governments may use active fiscal policies to compensate for the negative effects of energy shocks (i.e., oil shocks). | Glasure and Lee (1996); Glasure (2002); Akinlo (2008) |
| Gross Fixed Capital Formation: Private Investment (PI), Fixed Investment (FI), Non Residential Investment (NR), Structural Investment (SI), Equipment and Software Investment (ESI), Residential (R), Public Investment (IPU). | Employment and capital are arguments in any aggregate production function. Also used in neoclassical literature to capture energy substitution effects. | Stern (1993, 2000); Cheng (1996); Cheng and Lai (1997); Cheng (1998, 1999); Ghali and El-Sakka (2004); Oh and Lee (2004b,a); Lee (2005); Soytas and Sari (2006); Soytas et al. (2007); Bowden and Payne (2010); Lee and Chang (2008); Lee et al. (2008); Payne and Taylor (2010); Yuan et al. (2008); Bartleet and Gounder (2010); Menyah and Wolde-Rufael (2010); Eggoh et al. (2011); Yildirim et al. (2012); Coers and Sanders (2013); Apergis and Payne (2009); Payne (2009) |

| | | |
|---|---|---|
| Money Supply (RMO) | According to Glasure and Lee (1996) “the combined effects of money and government expenditure in the relationships between US energy consumption and employment components account for more than 35% of the variance in energy consumption”. | Glasure and Lee (1996); Glasure (2002) |
| Energy Intensity (EIN) | Employed to represent improvements in efficient energy use, as well as to capture structural changes in the economy. | To the best of our knowledge, this variable has not been explicitly included in studies in this literature. |
| Energy Efficiency (EEF) | Efficiency changes may be a suitable variable to explain the dynamics of the relationship EC-growth. | The same as EIN. |
| Source of energy production: Coal (COAL), Natural Gas (GAS), Crude Oil (OIL), Natural Gas Plant Liquids (NGPL), Nuclear (NUC). | The disaggregation of different energy sources allows a better understanding of the EC-growth ratio | Yu and Choi (1985); Fatai et al. (2004); Wolde-Rufael (2004); Lee and Chang (2005); Zamani (2007); Yuan et al. (2008); Sari et al. (2008); Yang (2000) |
| Consumer Price Index (CPI) | Sometimes used as a proxy for energy prices. | Bartleet and Gounder (2010); Eggoh et al. (2011); Kahsai et al. (2012) |
| Business sector Productivity (B_P), Non-farm business sector Productivity (NF_P), Non-financial corporate sector Productivity (NFI_P) | Labour productivity can be decomposed into: energy productivity (GDP per energy unit) and energy intensity (energy per labour unit). Sustainable growth not only implies an increase in energy efficiency but also in the productivity of other inputs, such as labour and capital. | Taylor (2008) |

| | | |
|---|---|---|
| Exports: Goods Exports (X_G), Services Export (X_S) Imports: Goods Imports (M_G), Services Imports (M_S) | Both exports and imports are major variables to a first approximation to the Pollution Haven Hypothesis[3]. | Narayan and Smyth (2009); Lean and Smyth (2010a,b); Sadorsky (2011, 2012) |

However, to the best of our knowledge, the control-variables have frequently

[3]The Pollution Haven Hypothesis (PHH) states that trade and capital liberalisation may shift pollution-intensive activities from countries with stringent environmental regulation to countries with lax regulations. To test for the PHH it would be necessary to conduct a more detailed disaggregation of the trade data into clean and "dirty" imports and exports as well as the bilateral flows among the classified countries, taking into account their levels of environmental regulation stringency.

been chosen ad hoc, with the result that the studies in most cases lack statistical motivation. The complexity of this relationship, along with multiple causality channels that can affect it, make it a crucial issue that deserves consideration. From an application perspective, the task of selecting the control variables is complicated due to the multiple combinations generated between the main relationship and all of the potential control variables. The main contribution of this study therefore consists of the application of a Bayesian variable selection procedure that, by considering economic growth as exogenous, allows for the evaluation of the posterior probability of including in the model a variable selected from a large group of possible candidates. Additionally, our approach takes into account the dynamic nature of the exogenous variable by considering a lag of the dependent variable as a fixed explanatory covariate. As discussed by Keele and Kelly (2006) the inclusion of such lags in the statistical model prevents serial correlation in the residuals. We apply this methodology to US data for the aggregate variables and for the sector breakdown of growth and the sources of energy consumption. The United States was chosen for two reasons: first, the availability of data for both the longer time span and for a significant set of related variables and sector disaggregation; second, the United States is responsible for one of the largest world shares of pollutants emissions.

In the following section, we present a brief summary of our methodological approach. Section 3 section describes the data and includes a discussion of the results. Finally, Section 4 presents the conclusions of the study.

## 2. Econometric methodology

### *2.1. Bayesian methods for model selection*

We have argued that an important aspect in the analysis of the relation between growth and EC is the incertitude regarding the role of certain variables as control variables. The potential impact of these variables on growth is endorsed by the specialised literature (see Table 1) but their inclusion in the model explaining the response variable is not clear. A central motivation of this this paper is to ensure that this major source of variability is formally considered through the Bayesian paradigm. This type of situation defines a particular model selection problem known as variable selection, formally introduced in the next section.

In model selection problems, the true statistical model is unknown and this uncertainty is explicitly considered (as opposed to estimation problems where the true model is given). The Bayesian approach to model selection has a number of appealing theoretical properties nicely described in Berger and Pericchi (2001). However, our paper takes advantage of a lesser-known and barely-used characteristic of this methodology: the richness and interpretability of results. The end product of the Bayesian approach is the posterior distribution over the model space; a probability mass function that assigns to each entertained model its probability conditional on the data observed. What makes this function so rich and useful is that it permits the evaluation of any question relevant to the analyst in probabilistic terms, which is, it may be argued, the natural way to report evidence. For instance, the probability that EC influences growth once all control variables are considered can be assessed in the light of the data observed. These types of summaries, which we introduce in 2.2, are called inclusion probabilities.

Despite its appeal, the Bayesian implementation is not without significant difficulties that are likely to preclude its broad use in economic studies. These difficulties are associated with the assignment of the prior distribution and the necessity of approximating the posterior distribution due to of the intractable size of the set of entertained models (which grows with the number of potential explanatory variables). These difficulties are addressed by using the `R` package `BayesVarSel` Garcia-Donato and Forte (2015), which is a user-friendly interface for the methodology proposed in the papers Zellner and Siow (1984); Zellner (1986); Zellner and Siow (1980); Liang et al. (2008); Scott and Berger (2010, 2006); Bayarri et al. (2012); García-Donato and Martínez-Beneito (2013).

### 2.2. The Variable Selection problem

With respect to variable selection, each entertained model corresponds to a specific subset of a group of (e.g., $p$) initially considered potential explanatory covariates. Therefore, the model space has $2^p$ models and each competing model $M_i$ for $i = 0, \ldots, 2^p - 1$ relates the response variable to a subset of $k_i$ covariates, such as:

$$\boldsymbol{y} = \alpha_0 \mathbf{1}_n + \alpha_1 \boldsymbol{y}_{-1} + \boldsymbol{X}_i \boldsymbol{\beta}_i + \boldsymbol{\varepsilon}, \qquad \boldsymbol{\varepsilon} \sim \mathcal{N}_n(\mathbf{0}, \sigma^2 \boldsymbol{I}) \tag{1}$$

where $\boldsymbol{y}$ is the $n$ dimensional vector of observations for the response variable; $\boldsymbol{X}_i$ is the $n \times k_i$ design matrix; $\boldsymbol{\beta}_i$ is the $k_i$ vector of linear regressors and finally, $\boldsymbol{y}_{-1}$ represents the $n$ dimensional vector with the lagged dependent variable. Notice that the intercept and $\boldsymbol{y}_{-1}$ are considered as fixed covariates (but with an unknown effect $\alpha_0$ and $\alpha_1$ within each model) contained in all entertained models. Slightly abusing notation, we denote by $M_0$ the simplest model containing only the fixed part. Finally, $\boldsymbol{\varepsilon}$ is a white noise error. As a referee pointed out, departures from the assumptions that underlie the models considered (Gaussian linear models) could be an issue in our approach. In our data we did not observe severe violations of such assumptions. More generally, and when normality is the main concern, the recent study by Maruyama and Strawderman (2012) is quite revealing since it is theoretically demonstrates that in a framework similar to ours, the Bayes factors are independent of the assumed distribution of $\boldsymbol{\varepsilon}$, as long as it is spherically symmetric (a large family of distributions). This intuitively points to the conclusion that the results here presented are quite robust to the Gaussian hypothesis. We denote by $M_i(\boldsymbol{y} \mid \boldsymbol{\beta}_i, \boldsymbol{\beta}_0, \sigma)$ the corresponding joint density of the random vector $\boldsymbol{y}$ under $M_i$. The posterior distribution assigns its conditional posterior probability to each model given the data and is formally defined by the Bayes theorem:

$$P(M_i \mid \text{data}) = m_i(\boldsymbol{y})\, P(M_i)/C.$$

Above, $P(M_i)$ is the prior probability, $C$ is the normalising constant and $m_i(\boldsymbol{y})$ is the marginal density for $\boldsymbol{y}$ under model $M_i$:

$$m_i(\boldsymbol{y}) = \int M_i(\boldsymbol{y} \mid \boldsymbol{\beta}_i, \boldsymbol{\beta}_0, \sigma)\, \pi_i(\beta_0, \boldsymbol{\beta}_i, \sigma)\, d\beta_0\, d\boldsymbol{\beta}_i\, d\sigma, \tag{2}$$

where $\pi_i$ is the prior distribution for the model-specific parameters of $M_i$ and the most problematic element in the whole setting. There are a number of technicalities behind the choice of prior, which are described in the following section to improve the readability of the study. An important practical aspect of the Bayesian approach to model selection is the summarisation of the information contained in the posterior distribution. With respect to estimation problems, this method routinely uses posterior summaries (e.g., the posterior mean or median) plus a measure of uncertainty (e.g., credible intervals). Regards to model selection, where the space mapped probabilistically is discrete without any possible ordering, these summaries are neither appropriate nor well defined. One possibility is to report the posterior mode (in this context normally called the highest posterior probability model) and its posterior probability. However, in large model spaces such as this, posterior probabilities are small and many models share the same probability which would render this study of little use. An interesting summary includes the probabilities for each potential covariate which are defined as

$$p(x_i \mid \boldsymbol{y}) = \sum_{\{M_l\colon\, x_i \in M_l\}} P(M_l \mid \boldsymbol{y}), \quad i = 1, 2, \ldots p$$

and should be interpreted as evidence (on a probabilistic scale) that $x_i$ explains the response variable. Apart from their appeal as summaries, the inclusion probabilities have a number of theoretical properties recently studied in Barbieri and Berger (2004). We will make intensive use of these inclusion probabilities to summarise the results in our analyses.

*2.3. The robust prior*

The assignment of the prior distribution in model selection is a complex issue and many papers have been written on this topic (see Liang et al., 2008; Zellner and Siow, 1980, 1984; Zellner, 1986). More recently, Bayarri et al. (2012) adopt a new perspective to assign the prior density whereby they propose a list of criteria that should be fulfilled to drive a variable selection problem. The authors then use these criteria to propose a specific prior distribution over the parametric space, which has been proven to provide a reliable theoretical result at relatively small computational cost. This prior, known as the Robust prior, is:

$$\pi_i^R(\boldsymbol{\beta}_0, \boldsymbol{\beta}_i, \sigma) = \pi(\boldsymbol{\beta}_0, \sigma) \times \pi_i^R(\boldsymbol{\beta}_i \mid \boldsymbol{\beta}_0, \sigma) = \sigma^{-1} \times \int_0^\infty \mathcal{N}_{k_i}(\boldsymbol{\beta}_i \mid \mathbf{0}, g\, \boldsymbol{\Sigma}_i)\, p_i^R(g)\, dg, \tag{3}$$

where $\boldsymbol{\Sigma}_i = Cov(\hat{\boldsymbol{\beta}}_i) = \sigma^2\, (\boldsymbol{V}_i^t \boldsymbol{V}_i)^{-1}$ is the covariance of the maximum likelihood estimator of $\boldsymbol{\beta}_i$ with

$$\boldsymbol{V}_i = (\boldsymbol{I}_n - \boldsymbol{X}_0(\boldsymbol{X}_0^t \boldsymbol{X}_0)^{-1} \boldsymbol{X}_0^t) \boldsymbol{X}_i \tag{4}$$

and

$$p_i^R(g) = \frac{1}{2}\sqrt{\frac{1+n}{k_i+k_0}}\,(g+1)^{-3/2}1_{g\in(\frac{1+n}{k_i+k_0}-1,\infty)}\,, \tag{5}$$

and zero otherwise. Above, $k_0$ denotes the number of fixed covariates which in our case is $k_0 = 2$. Despite its complex appearance, the main advantage of this prior, apart from its reliable theoretical properties, is that it provides marginal densities in an analytic way (i.e., integral in 2 can be solved algebraically), which is an important computational advantage. We adopt this prior in our analyses of the GDP. Finally, regarding the prior distribution $Pr(M_i)$ for the model space we assume that all the models are equally probable a priori ($P(M_i) = 1/2^p$). An interesting alternative includes the proposal in Scott and Berger (2006, 2010) of using $P(M_i) \propto \binom{p}{k_i}^{-1}$), which is designed to control for multiplicity. To implement the described variable selection approach, we use the `R` package `BayesVarSel`. In particular, we use the function `GibbsBvs` to obtain approximations to the posterior inclusion probability of covariates based on the methodology in García-Donato and Martínez-Beneito (2013). Note that the very large number of entertained models ($> 2^{32}$) makes it very difficult to exactly compute posterior probabilities since the constant C involves a summation with that very large number of terms.

## 3. Data and Results

### *3.1. Data description*

In the analysis of the critical variables that should be taken into account to explain both aggregate and sectoral US growth in Industry, Commerce and Transport, this paper uses annual data for the period 1949 to 2010. We have considered the variables previously used in the literature and that are available in the case of the US, as well as additional variables that we consider suitable for capturing the above-mentioned multiple transmission channels. The data and their sources are described in Table 2.

Table 2: Data Source

| VARIABLES | MEASURE | DATA SOURCE |
|---|---|---|
| Growth | Real = VA/VAPI millions dollars. | US Bureau of Economic Analysis (http://www.bea.gov/) |
| Employment (EMP) | Full time and part time employees in millions. | US Bureau of Economic Analysis (http://www.bea.gov/) |
| Energy Consumption (EC) | Billion BTU | US Energy Information Administration (http://www.eia.gov/) |
| Consumption of: Total Energy Non-Renewable (TNR), of Total Energy Renewable (TR), Coal (C), Natural Gal (NG), Petroleum (P), Hydroelectric Power (HP), Biomass (BIO) | Billion BTU | US Energy Information Administration (http://www.eia.gov/) |
| Energy Prices: Natural Gas Price (NG_P), Coal Price (C_P) | NG_P: Natural Gas Wellhead Price.C_P: Dollars per Short Ton.All the prices are in chained (2005) dollars, calculated by using GDP implicit price deflators. | US Energy Information Administration (http://www.eia.gov/) |

| | | |
|---|---|---|
| Oil Price (O_P) | Real Oil Price (in $/bbl.). Prices are based on historical free market (stripper) prices of Illinois Crude as presented by IOGA. Prices are adjusted for inflation to December 2012 prices using the Consumer Price Index (CPI-U) as presented by the Bureau of Labor Statistics | http://inflationdata.com/Inflation/Inflation_Rate/Historical_Oil_Prices_Table.asp |
| Government Spending (SPE) | Government Spending (Real). Total Spending -total ($/bbl.) 2005. | http://www.usgovernmentspending.com/spending_chart_1940_2017USk_13s1li011mcn_F0t |
| Gross Fixed Capital Formation: Private Investment, Fixed Investment (FI), No Residential Investment (NR), Structure Investment, Equipment & Software Investment (ESI), Residential Investment (R), Public Investment (IPU), Private Investment (PI), Structure Investment (SI), Total Investment (IT). | Investment in Fixed Assets and Consumer Durable Goods ($/bbl.). | US Bureau of Economic Analysis (http://www.bea.gov/) |
| Money Supply (RMO) | Real money. Reserve Assets, SDR millions. | OCDE |

| | | |
|---|---|---|
| Energy Intensity (EIN) | Primary Energy (billion BTU) / GDP in billions of chained 2005 dollars | Primary Energy Consumption: EIA US Energy Information Administration (http://www.eia.gov/).GDP: US Bureau of Economic Analysis (http://www.bea.gov/) |
| Energy Efficiency (EEF) | GDP in billions of chained 2005 dollars / Primary Energy Consumption (billion BTU) | Primary Energy Consumption: EIA US Energy Information Administration (http://www.eia.gov/).GDP: US Bureau of Economic Analysis (http://www.bea.gov/) |
| Source of energy production: (COAL), Natural Gas (GAS), Crude Oil (OIL), Natural Gas Plant Liquids (NGPL), Nuclear (NUC) | Total energy Production. Billion BTU. | http://www.eia.gov/ |
| Consumer Price Index (CPI) | All Urban Consumers - (CPI-U) US city average 1982-84=100 | US Department Of Labor Bureau of Labor Statistics |
| Business sector Productivity (B_P), Non-farm business sector Productivity (NF_P), Non-financial corporate sector Productivity (NFI_P) | Output per hour. Type of Measure: Index, base year 2005=100 | http://www.bls.gov/data/ |

| | | |
|---|---|---|
| Exports: Goods Exports (X_G), Services Export (X_S) Imports: Goods Imports (M_G), Services Imports (M_S) | Output per hour. Type of Measure: Index, base year2005=100. Millions of dollars, seasonally adjusted | US Bureau of Economic Analysis (http://www.bea.gov/) |

Since not all the variables listed in Table 2 are available at the sectoral level, Table 3 clarifies whether variables are aggregate or sectoral. Only the variables with the extension _C, _I or _T are sectoral; for example, in the commercial sector, variables for Growth, Energy consumption (EC), Total energy non-renewable (TNR), Total energy renewable (TR) and Employment (EMP) correspond to sectoral data whereas all other variables included in the analysis for this sector are aggregates. The gross value added used in each sector (commercial, industrial and transport) therefore relates to that of the corresponding sector.

Table 3: Covariates for each sector

| Covariate | Sector | | | |
|---|---|---|---|---|
| | Aggregated | Commercial | Industrial | Transport |
| ln(Growth) | ✓ | ✓(_C) | ✓(_I) | ✓(_T) |
| ln(EC) | ✓ | ✓(_C) | ✓(_I) | ✓(_T) |
| ln(TNR) | ✓ | ✓(_C) | ✓(_I) | ✓(_T) |
| ln(TR) | ✓ | ✓(_C) | ✓(_I) | – (NA's) |
| ln(EMP) | ✓(EMPT_TO) | ✓(EMP_T) | ✓(EMP_I) | ✓(EMP_T) |
| ln(C) | – | – | ✓(_I) | – (NA's) |
| ln(N) | – | – | ✓(_I) | ✓(_T) |
| ln(P) | – | – | ✓(_I) | ✓(_T) |
| ln(HP) | – | – | ✓(_I) | – |
| ln(BIO) | – | – | ✓(_I) | – |
| NG_P | ✓ | ✓ | ✓ | ✓ |
| C_P | ✓ | ✓ | ✓ | ✓ |
| O_P | ✓ | ✓ | ✓ | ✓ |
| ln(SPE) | ✓ | ✓ | ✓ | ✓ |
| PI | ✓ | ✓ | ✓ | ✓ |
| FI | ✓ | ✓ | ✓ | ✓ |
| NR | ✓ | ✓ | ✓ | ✓ |
| SI | ✓ | ✓ | ✓ | ✓ |
| ESI | ✓ | ✓ | ✓ | ✓ |
| R | ✓ | ✓ | ✓ | ✓ |
| IPU | ✓ | ✓ | ✓ | ✓ |
| IT | ✓ | ✓ | ✓ | ✓ |
| ln(EIN) | ✓ | ✓ | ✓ | ✓ |
| EEF | ✓ | ✓ | ✓ | ✓ |
| ln(COAL) | ✓ | ✓ | ✓ | ✓ |
| ln(GAS) | ✓ | ✓ | ✓ | ✓ |
| ln(OIL) | ✓ | ✓ | ✓ | ✓ |
| ln(NGPL) | ✓ | ✓ | ✓ | ✓ |
| ln(NUC) | ✓ | ✓ | ✓ | ✓ |
| CPI | ✓ | ✓ | ✓ | ✓ |
| RMO | ✓ | ✓ | ✓ | ✓ |
| B_P | ✓ | ✓ | ✓ | ✓ |
| NF_P | ✓ | ✓ | ✓ | ✓ |
| NFI_P | ✓ | ✓ | ✓ | ✓ |
| ln(X_G ) | ✓ | ✓ | ✓ | ✓ |
| ln(X_S ) | ✓ | ✓ | ✓ | ✓ |
| ln(M_G) | ✓ | ✓ | ✓ | ✓ |
| ln(M_S ) | ✓ | ✓ | ✓ | ✓ |

### *3.2. Results*

To present the results, we mainly summarise the posterior distribution with the posterior inclusion probabilities of EC and each of the potential control variables. These probabilities should be interpreted as the evidence shown by the data that a potential variable explains growth once the potential control variables have been taken into account. The inclusion probabilities of each sector considered in this paper are presented in figures 1, 2, 3 and 4 in the following section.

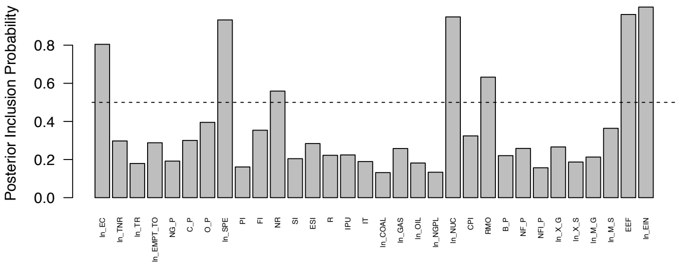
In the context of the literature on the growth-energy consumption nexus, the authors attempt to determine whether growth is energy-dependent and if there is a link showing direction of causality. However, this bivariate relation could be affected by many other variables. Therefore, the main focus of this paper is to assess not only if EC drives growth but also if other potential control variables from a fairly large database could also explain growth. Our methodology sorts the potential explanatory variables by their probability with respect to explaining growth.

Although we believe (based on the paper of Barbieri and Berger (2004)) that researchers who want to model growth should take into account all the variables with an associated probability greater than 0.5, in order to improve the readability of the paper we only offer an interpretation of those with an inclusion probability greater than 0.7. This does not mean, however, that variables with probabilities between 0.7 and 0.5 are not relevant, and, accordingly they are reported in the corresponding tables. We should note that the main objective of this paper is not to interpret all the critical variables, as that would require further, more in-depth study, but rather to help researchers evaluate which variables are key in explaining growth, and provide a guide to selecting the most relevant variables.

*3.2.1. Aggregate growth results*

Concerning the aggregate growth, our results confirm the importance of

Figure 1: Inclusion probabilities for each of the potential covariates considered in the aggregate study. The dashed line indicates a probability of 0.5




**energy consumption** (**EC**) in explaining US aggregate growth given that it has a posterior inclusion probability of 0.80. Therefore, the application of our probabilistic model shows EC and growth to be highly correlated, highlighting energy-dependence which is the main issue raised in the literature. The fact that EC is a significant explanatory variable of growth can be interpreted in favour of the growth hypothesis. However, energy consumption is not included as an endogenous variable in our model and thus it is not possible to test or to reject the feedback hypothesis.

Concerning the role of the *potential control variables*, our study demonstrates that only certain candidate variables explain aggregate growth. We found strong evidence for the inclusion of energy intensity (probability 1), energy efficiency (0.96), nuclear power (probability 0.95) and public spending (0.93). A lower probability inclusion is found for *RMO* and *NR*.

According to our probabilistic model, the variable with the highest probability of explaining growth is *energy intensity* (*EIN*). Historically, total US primary energy consumption has been growing at a similar rate as economic activity. Present day energy consumption continues to increase (with this trend

| | Incl.prob. |
|---|---|
| $\ln(EC)$ | 0.8046 |
| $\ln(EIN)$ | 1.0000 |
| $EEF$ | 0.9612 |
| $\ln(NUC)$ | 0.9485 |
| $\ln(SPE)$ | 0.9326 |
| $RMO$ | 0.6323 |
| $NR$ | 0.5591 |

Table 4: Aggregate analysis: posterior inclusion probabilities larger than 0.5

set to continue according to AEO, 2010) but at a slower rate than economic activity. This implies that there has been a progressive improvement in the US energy intensity ratio. Two factors may be responsible: first, the larger share of services in growth and, second, the increase in efficiency in other more energy intense sectors. Our methodology has been able to capture the direct link that exists between energy intensity and growth. An alternative interpretation of energy intensity is the rate of output return achived by energy consumption, i.e. energy efficiency (*EEF*). As economies develop they tend to improve the energy efficiency of their industrial sectors; however higher living standards imply more energy-consuming human activities, as shown in the study by Corless (2005) that analyses the top 40 largest national economies (GDP) by plotting GDP per capita against energy efficiency.

In descending order, we found that *nuclear power* ($NUC$) has the highest probability of inclusion. This is not surprising considering that the US is the country with the largest installed nuclear power capacity: approximately 20% of the total amount of electricity generated comes from nuclear reactors. Since 1951, when the first reactors were installed, nuclear power has had a predominant role in the US energy mix[4]. The uncertainty with respect to oil and gas

[4]Nuclear power plays an important role in US electricity, with 101 gigawatts (GW) of capacity accounting for 19% of electricity generation in 2012 (AEO, 2013).

reserves, together with the scarcity of renewable energy has increased the relative importance of nuclear power. According to the IEA, a nuclear energy contribution of approximately 3.8 trillion kilowatt hours is expected in 2030, in contrast to a contribution of 2.7 trillion kilowatt hours in 2006. Apergis and Payne (2009) have argued that nuclear energy plays a crucial role in the design of environmental strategies. This energy source can address the needs of countries with a is rapidly growing energy demand.

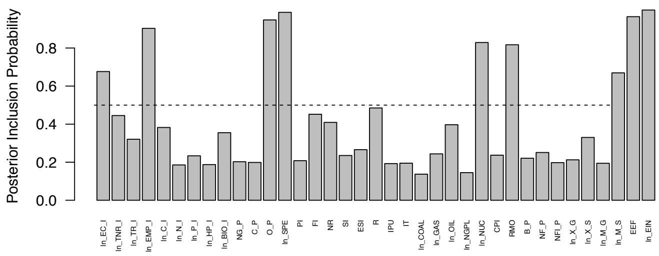
The next explanatory variable with a high probability, as shown in Table 2, is *public spending* (or *SPE*). There is no discussion in the literature regarding the crucial role that fiscal policies play in a country's output growth. The debate only concerns the cyclical or counter-cyclical nature of public spending. We find that this is one of the variables with a higher probability (0.8862) of explaining aggregate growth.

*3.2.2. Industrial sector results*

Our study reveals that **energy consumption in the industrial sector (EC_I)** is a significant sectoral explanatory variable of growth as its inclusion probability is higher than 0.5. Although we have decided not to discuss those variables with a probability lower than 0.7 we comment on this case for two reason: first, it is very close (0.68) to the threshold we have established in this paper; second, this variable is critical in order to answer the main hypothesis of this paper (Is energy the only determinant variable to explain growth?). From an economic point of view, this result is logical considering that the industrial sector is the largest energy consumer accounting for one-third of total US energy consumption.

Among the *potential control variables* for the Industrial sector, our study finds seven of them to be relevant (*EIN, SPE, EEF, O_P, EMP_I, NUC,*

Figure 2: Inclusion probabilities for each of the potential covariates considered in the industrial sector. The dashed line indicates a probability of 0.5




*RMO*), with the remainder having an inclusion probability that is below 0.7. In what follows we present an outline of certain economic arguments for the relevance of these variables.

*Energy intensity* (*EIN*) is relevant according to our statistical methodology (inclusion probability of 1.0). The industrial sector currently represents approximately 14% of US growth but consumes more than one third of total available US energy resources. Therefore, improving energy intensity in this sector would contribute to the reduction of greenhouse gases and enhance economic efficiency. Even if it is difficult to increase energy efficiency in the industrial sector, this sector provides significant returns on programme investments that will directly affect energy intensity. Our methodology demonstrates the significance of energy inputs in relation to industrial output.

*Public spending* (*SPE*) is also relevant. According to the Center on Budget and Policy Priorities, 20% of the US budget is assigned to national defence and security (20%), another 20% to social security, Medicare, Medicaid and the Children's Health Insurance Program (CHIP), 14% goes to safety net programs and, finally, 6% is dedicated to national debt interest payments. Many of these

| | Incl.prob |
|---|---|
| $\ln(EC\_I)$ | 0.6764 |
| $\ln(EIN)$ | 0.9996 |
| $\ln(SPE)$ | 0.9876 |
| $EEF$ | 0.9648 |
| $O\_P$ | 0.9477 |
| $\ln(EMP\_I)$ | 0.9035 |
| $\ln(NUC)$ | 0.8289 |
| $RMO$ | 0.8173 |
| $\ln(M\_S)$ | 0.6694 |

Table 5: Industrial sector analysis: posterior inclusion probabilities larger than 0.5

program areas are crucial for industrial output, such as supplies for the defence department and social and medical spending that generates direct or indirect demand for industrial products. Thus, our results confirm previous findings concerning the nexus between government spending and industrial economic activity (e.g., Nekarda and Ramey (2011)).

The relevance of *Energy efficiency (EEF)* is also logical from an economic point of view, given that the industrial sector is the largest energy consumer. Furthermore, 75% of the total energy of this sector is used by only a small group of industries, comprising chemicals, forest products, and petroleum refining industries, as well as aluminum, glass, metal casting, mining, and steel. Thus, energy efficiency policies focus on industry and manufacturing because there are still enormous opportunities for energy saving in this sector[5].

Another important variable in the explanation of industrial growth is *industrial employment* $(EMP\_I)$. The fact that the results highlight that EC_I is not, unlike EMP_I, a significant variable implies both inputs are substitutes and thus confirms the substitutability hypothesis as stated in the literature.

*Oil price* $(O\_P)$ also has a high probability of explaining the industrial

[5]One of the prime targets is the chemical industry, which uses 29% of all fuel consumed in the US industrial sector.

growth path. Even though there is abundant literature describing the effects of oil prices on the main macro magnitudes, only a few authors have studied oil price sector effects (with respect to industry, Bohi (1989), Lee and Ni (2002), Kilian and Park (2009), Herrera and Pesavento (2009) and Jiménez-Rodríguez (2008)). Despite the different results found concerning the sign and magnitude of the effect of oil on growth, oil price has an unquestionable effect on the industrial sector since fossil fuels are the main energy source for the industry. Our methodology captures this role and assigns oil price a high probability (0.9911) of inclusion in the industrial growth model.

*Nuclear power* $(NUC)$ is another critical control variable to take into account in the modelling of US industrial output. The relevance of nuclear power in the US energy mix is especially important in the industrial sector. The Energy Policy Act of 2005 brought about the development of the Next Generation Nuclear Plant (NGNP) project and has, as a primary aim, the cogeneration of heat and electricity to provide to large industrial energy end-users. Nuclear techniques, many involving radioisotopes, are increasingly used in industry and environmental management. The continuous analysis and rapid response of these nuclear techniques, produces constantly available, reliable flow and analytic data, resulting in reduced costs from increased product quality. Although the private capital share is larger in nuclear power production, the government has actively supported an increase in capacity since the late 1990s and has worked diligently to expedite approval on construction and new plant designs.

*Real Money Supply (RMO)*. The actions of the Federal Reserve designed to increase or decrease the money supply are used by analysts and economists to help predict economic recessions and recoveries. It is therefore logical that the industrial sector, the second most important in the US, is affected by monetary policy decisions.

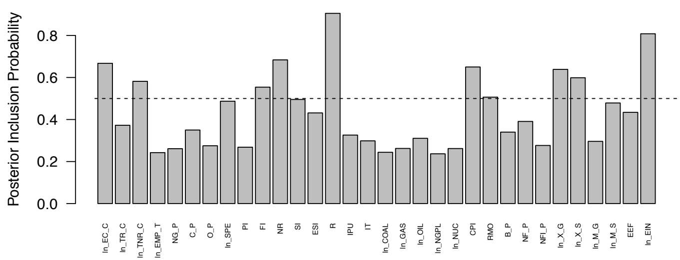
*3.2.3. Transport sector results*

The variables with a posterior inclusion probability above 0.5 for the transport sector are presented in Table 6.

| | Incl.prob |
|---|---|
| $\ln(EC\_T)$ | 0.8426 |
| $NF\_P$ | 0.9095 |
| $B\_P$ | 0.7913 |
| $RMO$ | 0.7822 |
| $\ln(TNR\_T)$ | 0.7399 |
| $\ln(X\_S)$ | 0.6712 |
| $C\_P$ | 0.5715 |
| $IT$ | 0.5679 |
| $PI$ | 0.5060 |

Table 6: Transport sector analysis: posterior inclusion probabilities larger than 0.5

Figure 3: Inclusion probabilities for each of the potential covariates considered in the commercial sector. The dashed line indicates a probability of 0.5




***EC_ T*** (***total transport energy consumption***, the sum of both renewable and non-renewable sources) and *TNR_ T* (*total non-renewable energy consumption in the transport sector*) are variables with a high associated probability of explaining growth in the transport sector. The main determinants of transport demand are economic activity and population growth. According to the 2011 IEO, the US is the world's largest consumer of transportation energy. Moreover, the US energy mix for transport is unbalanced; approximately 93% of energy consumption comes from oil, with the remaining 7% corresponding to natural gas and renewable sources. Despite oil consumption having reached a maximum in 2007, following the IEA there has been a move towards renewable energies. This pattern of energy consumption has been captured by our methodology: although renewable energy consumption data are only available from 1981 onwards, the presence of this information in EC_T is crucial. Otherwise, only total non-renewable energy consumption in transport would have been relevant.

From the remainder of the control variables, the most relevant variables are *RMO*, *NF_P* and B_P, all with an inclusion probability above 0.7.

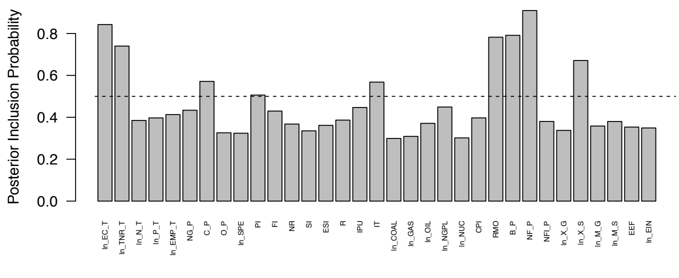
A relevant variable to take into account with respect to the transport sector is *real money supply* (*RMO*). The fact that there is strong correlation between money supply, public expenditure and interest rates is especially relevant in a sector where both public investment and credit availability are crucial for the financing of large transport projects.

The control variable with the highest probability of inclusion is *NF_P*, i.e., non-farm business sector productivity which contains the majority of industrial activities. This sector represents up to 77% of total US GPD. Productivity improvement is a fundamental component in business growth and internalisation and, therefore, it boosts the demand for transport sector services, an effect captured by our probabilistic model. Similar effect is found in the relevance (*B_P*), i.e., *business sector productivity* (Non-farm business, Non-financial corporations, Manufacturing, Durable, Nondurable).

### 3.2.4. Commercial sector results

Table 7 summarises the results for all the variables considered in the commercial sector[6], i.e., services. As we did for the industrial sector, we discuss the energy consumption variable due to its relevance to the main objective of this paper and because it has a probability inclusion close to 0.7. The results show that **energy consumption (EC_C)** is a relevant variable for the commercial sector. According EIA, in 2013, 40% of total US energy consumption was attributed to residential and commercial buildings. Energy consumption by commercial sectors is mostly "building-related" and the main consumption activities therein are: heating, ventilation, cooling, and lighting in manufacturing facilities.

Figure 4: Inclusion probabilities for each of the potential covariates considered in the transport sector. The dashed line indicates a probability of 0.5




Concerning *potential control variables*, our study finds 11 covariates that have a posterior inclusion probability above 0.7 for *R* and *EIN*. We outline below certain economic insights into covariates with the highest probability of

[6]The commercial sector includes the following activities: wholesale trade, retail trade, information, finance, insurance, real estate, rental and leasing, professional and business services, educational services, health care and social assistance, arts, entertainment, recreation, accommodation and food services, and government.

inclusion.

| | Incl.prob. |
|---|---|
| $\ln(EC\_C)$ | 0.6676 |
| $R$ | 0.9054 |
| $\ln(EIN)$ | 0.8082 |
| $NR$ | 0.6839 |
| $CPI$ | 0.6501 |
| $\ln(X\_G)$ | 0.6387 |
| $\ln(X\_S)$ | 0.5989 |
| $\ln(TNR\_C)$ | 0.5818 |
| $FI$ | 0.5541 |
| $RMO$ | 0.5065 |

Table 7: Commercial sector analysis: posterior inclusion probabilities larger than 0.5

The variable with the highest probability of explaining commercial output is residential investment ($R$). An increase in residential investment drives up the demand for non-manufacturing business establishments, such as wholesale businesses, retail stores, warehouses, storage facilities, and health, social and educational institutions, all of which are commercial activities.

Finally, according to our methodology, *energy intensity* (*EIN*) has a significant associated probability. A priori, we may expect the service sector to require lower energy input than other sectors for the production of a single unit of output in comparison to the other sectors. Our approach is able to capture the fact that the commercial sector is less energy-dependent than the other productive sectors.

## 4. Conclusions

There is abundant empirical literature focusing on whether energy consumption is a critical variable in the explanation of economic growth. Even with researchers establishing a positive nexus, no conclusive results have been obtained. The evolution of this literature has mainly consisted of attempts to solve the problems and answer criticisms found in earlier studies. In this context, we classify these problems into two areas: first, those that analyse the bivariate relationship EC-growth while neglecting many potential channels affecting this relationship; second, those that introduce other control variables considered determinants in the EC-growth nexus. This second area of the literature, which is broader in scope, has limitations deriving from the a selection process of the control variables, which are frequently chosen according to the subjective economic rationale of the authors.

Our main contribution is the attempt to overcome the variable limitations by implementing a robust statistical approach to select the covariate variables that explain growth. The outcome of our methodology is the inclusion of the probability for each variable from a large group of potential explanatory variables. Although covariate selection must be completed prior to cointegration or causality testing, this has been neglected in the empirical literature. A limitation in the methodology used here, and as with any model selection technique, is that no model-specific parameters are estimated. Hence, we can say for instance that residential investment influences growth but we cannot specify the magnitude of that effect. To the best of our knowledge, this is still an open question in the field of model selection with only partial answers (an interesting exception being the study in Scott and Berger (2006) within a context much simpler than ours). Nevertheless, this limitation is not a drawback in this study since our main motivation is the identification of variables that affect growth. It could, however, prove problematic for other researchers intending to apply this methodology.

Our results are twofold. First, the empirical evidence confirms the prior expectation that energy consumption is a critical variable to understanding the path of growth because energy consumption has a posterior inclusion probability higher than 0.5 for all sectors. Although in this paper we have established a strict threshold to determine which variables to include, and we only comment on those with a posterior inclusion probability greater than 0.7, we cannot ignore the fact that the results show that there are variables with an inclusion probability of being included in a model higher than 0.5. Moreover, the results highlight the importance of energy intensity in modelling the relationship between growth and energy consumption because of its high probability of inclusion in three of the four models we study. It is equally important to note that our probabilistic model captures the relevance of total energy consumption, i.e., the joint role of renewable and non-renewable energy sources. This study recognises the substantial share that renewable energy has in US output growth. Otherwise, only total non-renewable energy consumption would have a high inclusion probability.

Second, the results highlight the importance of a disaggregate analysis of economic activity because the relevant explanatory variables are not the same for the different sectors under study, namely, the commercial sector, and transport and industry. In fact, nuclear energy production and employment are fairly relevant for only two sector outputs but for these sector are quite critical variables.

Finally, the results reveal the complexity of policy-makers decision-making: the interaction found among the group of variables considered in this paper indicates that policy-makers not only have to design policies that focus on reducing energy consumption, but must also take into account other important macro variables. This complexity is further compounded by the sector differences that prevent the design of an overall policy.

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