A STOCHASTIC FRONTIER ANALYSIS APPROACH FOR ESTIMATING ENERGY DEMAND AND EFFICIENCY IN THE TRANSPORT SECTOR OF LATIN AMERICA AND THE CARIBBEAN

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Abstract

In this paper, a stochastic frontier analysis approach is applied to estimate energy demand functions in the transport sector. This approach allows us to obtain energy efficiency measures at country level that are a robust alternative to the energy intensity indicators commonly used for international comparisons. A transitive multilateral price index is constructed for aggregating the diverse energy components employed in the sector. Due to the likely unobserved heterogeneity among countries, the use of a random parameters model is proposed to accommodate these differences and to obtain different income and price elasticities per country. The estimated model is compared with alternative approaches of addressing this issue such as latent class, true fixed effects or true random effects models. This study is the first to use a random parameters stochastic frontier approach in the estimation of energy demand functions. The proposed procedure is applied to Latin America and the Caribbean, where the transport sector represents a large share of total energy consumption.

Keywords: energy demand in transport; energy efficiency; random parameters stochastic frontier model; transitive multilateral price index; Latin America and the Caribbean.

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1. Introduction

Since the 1970s oil crisis, monitoring energy efficiency has become an essential goal of economic and energy policies in many countries around the world. This concern grew in the late 1980s as a result of the increasing awareness of global warming. A key issue in the strategy of the countries that aim to reduce their energy consumption and mitigate their greenhouse gas emissions is the adoption of measures that improve the efficiency of energy use in all economic sectors and especially in those that are energy intensive, as in the case of transport.

As shown in Figure 1, from data of the Latin American Energy Organization (OLADE in Spanish), the transport sector represents the highest energy consumption in Latin America and the Caribbean. The share of this sector within the overall energy consumption has remained high and steady during recent decades. However, according to the Economic Commission for Latin America and the Caribbean (ECLAC, 2010) it is expected that the transport of passengers and goods increases in the near future. Moreover, combined with the separated way in which public policies on infrastructure and transport have traditionally been conducted, this will result in an augmentation in the use of energy and particularly of oil derivatives consumption. It is thus necessary to conduct studies focused on the energy consumption of this sector that can help to identify and mitigate the environmental sustainability issues that are mentioned in the "Millennium Development Goals" proposed by ECLAC (2005).

[Insert Figure 1 here]

Per capita energy consumption in Latin America and the Caribbean is currently low in comparison with other parts of the world. However, since the 1990s, it has experienced significant growth, as shown in Figure 2. This growth has been common within the different areas of the region, but in particular it can be observed that the largest increment has taken place in the countries of Central America and the Caribbean which are those that show lower volumes of transport energy use as a share of total energy use.[1] However the low per capita consumption of Latin America and the Caribbean does not necessarily imply high efficiency in the use of energy, as a significant part of the population of these countries lack the funds to have access to private cars. In this context, the rapid development of the region in the medium term might lead to unsustainable increases in the energy consumption of the transport sector and to the associated emissions of greenhouse gases. For example, between 1990 and 2007, the vehicle fleet that was used in Brazil, Mexico, Chile and Colombia increased by 53 million vehicles, with 40% of this increase concentrated between 2003 and 2007. Therefore it is crucial to elaborate orderly development strategies that favour public transport and promote energy efficiency.

[Insert Figure 2 here]

Figure 3 shows the change in energy price in the transport sector between 1990 and 2010 in the areas of the region.[2] The scenario of low energy prices in the 1990s contrasts with the inflationary process that was experienced in the first decade of the 21st century. This phenomenon was especially pronounced in South American countries and led many countries within the whole region, especially those that were net

[1] We have not included Mexico within Central America in the figures since the weight of this country distorted the average values for the region.

[2] The information about the construction of this energy price can be found in the Appendix. These prices are the final prices at which the consumer is faced after taxes and subsidies.

importers of energy, to adopt programs to improve energy efficiency. These measures aim, on the one hand, to modernise public transport to incentivise its use, renovate the vehicle fleets, introduce biofuels as alternatives to oil, promote the use of hybrid and electric vehicles, and promote the use of trains and subways in certain activities. On the other hand, the infrastructure network should be improved in tandem with logistical solutions to the provision of services, such as the adoption of intelligent measures that optimise transport routes and favour intermodality (ECLAC, 2010).

[Insert Figure 3 here]

One important issue that should be highlighted is that in many of those countries strong subsidies have been applied on fuel prices and this has been more conspicuous when oil prices have remained high. Fuel pricing policies in Latin America have not been traditionally based on marginal or opportunity costs and as a consequence, fuel prices have been far below world market prices (Rogat, 2007). Although the situation started to change at the end of the 1980s within some countries that applied energy reforms, in several countries of the region strong energy subsidies currently persist (e.g., Ecuador, Mexico and Venezuela). Di Bella *et al.* (2015) estimate that the weight of fuel subsidies have represented on average about 1% of GDP for the period 2011-2013 and about 3.8% when energy subsidies (including electricity) and negative externalities are accounted for in the analysis. These authors remark that oil-rich countries and those with poorer institutions tend to subsidise fuel more. In general, subsidies generate price distortions that may lead to an inefficient use of energy, which in the end can have negative effects on the environment and the economic growth of the countries.

Due to the reasons previously mentioned, reducing energy consumption in the transport sector has become a fundamental concern within Latin American and Caribbean countries. To help achieve the goal of identifying those countries that are references (benchmarks) in efficient use of energy, various quantitative indicators related to the energy efficiency of the countries have been developed for international comparisons. There is no single definition totally accepted for the concept of energy efficiency, both in terms of the economy as a whole or specifically for the transport sector. Ang (2006) and Stead (2001) indicate that the most commonly used indicator is the ratio of energy consumed to GDP. This measure of energy intensity has the advantage of simplicity in its calculation and easy interpretation, thus leading to its continued use in international statistics. Since energy intensity is simply the inverse of the energy productivity indicator, decreasing levels of the indicator represent a reduction in the energy that is required to generate a unit of national production.

The U.S. Energy Information Administration (EIA, 1995) has frequently highlighted the need to adequately define an alternative measure of energy efficiency. However, energy intensity is still used as a synonym or "substitute" of energy efficiency even though variations of this type of indicators can reflect the influence of other factors different from changes in energy efficiency such as modifications in the structure of GDP or the effect of environmental factors.[3] Moreover, the values that can take these indicators are not within a specific range and therefore it makes difficult the calculation of potential energy savings. In particular, as stated by the EIA, the transportation sector

[3] The International Energy Agency (IEA, 2014) also recognises that the use of energy intensity as a proxy for energy efficiency can generate untrustworthy results. Despite significant interest in the measurement of energy efficiency, its calculation for the transport sector is a difficult task. This organization proposes indices of energy intensity for the sector that are calculated using various disaggregated indicators obtained from large quantities of information. Due to this requirement, it is impossible to calculate this measure for all Latin American and Caribbean countries.

is one of the most complex sectors to determine whether efficiency gains have really occurred, so proposing new approaches to measure actual energy efficiency levels is undoubtedly an appealing challenge.

The main goal of this paper is to adapt the methodological proposal of Filippini and Hunt (2011, 2012) to the case of the energy consumption in the transport sector of Latin America and the Caribbean. This approach is applied to obtain measures of energy efficiency that are adjusted by specific features of the countries (such as fuel prices, GDP or population density) and can be used to make consistent comparisons of countries' performance over time as these measures are always bounded between zero and one. Furthermore, the current study estimates various frontier demand functions using alternative approaches. We find that a random parameters model is the approach that best takes into account the heterogeneity in our sample and allows us to obtain specific price and income elasticities for each analysed country. To the best of our knowledge, this study is the first to apply this methodology for both the transport sector and the Latin American countries.[4]

This paper is organised as follows. In Section 2, we define the demand for energy in the transport sector by providing a brief review of the existing literature. Additionally, we propose the use of a Stochastic Frontier Analysis (SFA) approach and the application of several models for addressing unobserved heterogeneity when estimating energy demand frontier models. In Section 3 we present the database and the econometric specification of our models. The results of the estimations are presented in Section 4 and finally, Section 5 ends the paper with a summary and the presentation of conclusions.

2. Energy demand of the transport sector

Demand for transport is derivative in nature, as the goal of moving goods and people is not to perform the journey but to reach a certain destination. In other words, demand is derived from the mobility of passengers and goods. This mobility, in turn, leads to energy or fuel demand, which is necessary for transport.

The previous research in the literature on the modelling of energy consumption for transport can be clustered into works that apply econometric techniques, artificial intelligence approximations, multi-criteria analysis and simulation methods (for a review see Limanond *et al.*, 2011; or Suganthi and Samuel, 2012). The first group includes multiple linear regression models (Limanond *et al.*, 2011), partial least square regressions (Zhang *et al.*, 2009) and the analysis of time series and cointegration (Samimi, 2003; Galindo, 2005; Sa'ad, 2010; and Hao *et al.*, 2011). The second group includes studies of artificial neural networks (Dreher *et al.*, 1999; Murat and Ceylan, 2006; and Limanond *et al.*, 2011) and harmony search algorithms (Haldenbilen and Ceylan, 2005; and Ceylan *et al.*, 2008). Some studies have combined the analysis of time series and fuzzy logic (Al-Ghandoor *et al.*, 2012). In the prediction of energy consumption for vehicles, the use of multi-criteria analysis should be noted, such as in the works of Lu *et al.* (2008, 2009). Lastly, the most prominently used simulation model has been the Long-range Energy Alternatives Planning System (LEAP), which allows

[4] The scarcity of empirical analyses in this context has been conditioned by the availability of statistics. In fact, in many Latin American countries, there is no formal link between institutions that are in charge of providing information on energy and transport. Consequently, in this paper, all variables that are relative to energy consumption are based on the authors' own work on the data provided by OLADE.

planning alternative scenarios for energy demand in the transport sector. The works that use this method include Bauer *et al.* (2003), Manzini (2006), Pradhan *et al.* (2006) and Islas *et al.* (2007).

Therefore, there is an extensive body of literature on the economics of transport that estimates various energy consumption functions or the respective functions of fuel use for different types of vehicles. The current study belongs to the line of econometric approximations of energy demand from the transport sector that estimates price and income elasticities that are related to energy consumption (see, for example, Dahl, 1995). In their literature review, Graham and Glaister (2002) observe that, as a general rule, price elasticities that are obtained in the short term are commonly between -0.2 and -0.3 and those obtained in the long term are between -0.6 and -0.8. For the case of income elasticities, they find that these are often greater than one (between 1.1 and 1.3) in the long term and between 0.35 and 0.55 in the short term. The papers that are included in their review generally analyse countries of the Organization for Economic Cooperation and Development (OECD).

In contrast to the previous work, Wohlgemuth (1997) presents also elasticities for several countries that are not OECD members. In terms of Latin America and the Caribbean, the elasticities for Brazil and Mexico[5] are presented. In the long term, the income elasticities for Brazil take values between 0.88 and 1.10 and the price elasticities go from -0.10 to -0.26. For the case of Mexico the income elasticities vary between 0.99 and 1.72 and the price elasticities are between -0.04 and -0.21. Also for the case of Mexico and using a data sample for the period 1965-2001, Galindo (2005) finds in the long-run a smaller income elasticity (0.541) than in the abovementioned paper and a price elasticity non-statistically different from zero. In the short-run this author obtains a large income elasticity (0.836) jointly with a small price elasticity (-0.089).

On the other hand, Rogat and Sterner (1998) provide a unique analysis of the gasoline demand in Latin America. In that paper several econometric models are estimated to obtain price and income elasticities of 13 countries in Latin America for the period 1960-1994. These authors find remarkably different results for their sample of countries. They obtain short-run price elasticities that are between -0.04 (Venezuela) and -0.27 (El Salvador) and short-run income elasticities that are between 0.01 (Honduras) and 0.66 (Paraguay). As it is usual they find larger long-run elasticities, in absolute terms, than in the short-run. The values go from -0.16 (Bolivia) to -1.71 (Mexico) for the price elasticities and from 0.06 (Honduras) to 1.63 (Guatemala) for the income elasticities. The broad variety of results found by these authors evidences the needing of taking into account the heterogeneity between these countries to estimate fuel demand.

2.1. A stochastic frontier approach for energy demand in transport

Based on the efficiency and productivity literature, Filippini and Hunt (2011, 2012) suggest the use of a parametric approach of stochastic frontiers to estimate aggregate energy demand functions. The main goal of those authors is to obtain measures of energy efficiency that can be used as alternatives to the standard indicators of energy intensity mentioned in the previous section. These efficiency measures are based on the comparison of the energy consumption of the countries with respect to the

[5] Although in Wohlgemuth (1997), Mexico is included in the group of countries that are not members of the OECD, this country was already a member since May 18, 1994.

minimum energy consumption predicted by the frontier, which assumes the optimising behaviour of companies and individuals. Therefore, the basic aim of using this approach is obtain an assessment of the energy efficiency of the countries and thus differs from the main objective of the methods presented in the previous section, i.e., modelling and forecasting the energy demand.

The use of energy demand frontier functions to estimate energy efficiency is an approach that is based on the concept of productive efficiency and input specific technical efficiency. The application of this type of models has gained relevance in recent years (see Evans *et al.*, 2013; Filippini and Hunt, 2011, 2012, 2015a, 2015b; Filippini and Zhang, 2016; Filippini *et al.*, 2014; Lundgren *et al.*, 2016; and Orea *et al.*, 2015). A theoretical explanation of this approach was originally introduced by Huntington (1994) and has been recently developed by Filippini and Hunt (2015a). In this latter paper, the use of the following three parametric methodologies for estimating energy efficiency is discussed: input requirement functions, Shephard input distance functions and input demand frontier functions.

At this point, it should be mentioned that, as it is frequently highlighted in the efficiency and productivity analysis literature, there are different type of approaches that can be used (namely, parametric, nonparametric and semiparametric) to estimate production/cost frontiers. Moreover, each one of the approaches has their own advantages and disadvantages. Therefore, the selection of an appropriate estimation method is debatable and may influence the obtained results and the subsequent regulatory policy suggestions. The best that a researcher can do is to explore alternative model specifications and carry out suitable model selection tests to choose the most appropriate model for a given approach. In that sense, Coelli *et al*. (2005) suggest exploring alternative models to assess the adequacy and robustness of the results obtained when a parametric approach is applied. In this paper, we estimate different energy demands using alternative specifications and we carry out several model selection tests to be confident about the consistency of our preferred model, given the parametric approach that has been used.

The basic model that is estimated by Filippini and Hunt (2011) is an input demand frontier function that takes advantage of the traditional specification of the SFA models that was initially proposed by Aigner *et al.* (1977) (hereinafter ALS). They also estimate other models developed in the efficiency and productivity literature, such as the True Random Effects (TRE) model presented by Greene (2004, 2005a, 2005b) or the formulation of Mundlak (1978) that was proposed for an estimator of random effects by Farsi *et al.* (2005). The standard ALS model can be presented for the case of energy demand in the logarithmic form as follows:

$$\ln Q = \ln f(P, Y, X, \beta) + v + u \tag{1}$$

where Q represents the quantity of the demanded energy, P is the price of energy, Y represents income, X refers to other control variables and β are the parameters that are associated with the variables that are included in the model and can be directly interpreted as elasticities. The random term in this model is compound and is formed by v, which follows a normal distribution with zero mean and constant variance, σ_v^2, and u, which is an asymmetric error that follows a half-normal positive distribution to capture the inefficiency of energy demand in the same way that it is defined in cost functions of many empirical applications in the SFA literature. This model reflects the minimum amount of energy necessary to produce any given level of energy services. Therefore the positive deviations from the estimated frontier demand are captured by the asymmetric error term that can be interpreted as inefficiency in the use of input energy (Filippini and Orea, 2014). Based on the conditional mean of the inefficiency term proposed by Jondrow *et al.* (1982), the efficiency level for each observation can be easily obtained from the estimates of u. The efficiency obtained with this model is a measure bounded between zero and one (or 100%). The difference between 1 and this measure of efficiency shows the amount of energy consumption that could be reduced in this country while maintaining the same level of transport services.

It should be emphasised again that the goal of using this approach in the paper is to obtain appropriate and comparable measures of energy efficiency at country level. Apart from the standard distributional assumptions about the random error, in this and next models (presented below) no particular parametric functional forms are imposed for the inefficiency term. Therefore, if we were interested in forecasting energy efficiency trends, we should make certain *ad hoc* and additional assumptions such as, for instance, to expect that energy efficiency improvements of recent years are going to be similar in next years. Alternatively, the model could be estimated including the expected values of the introduced variables to obtain *ex ante* estimates of future energy efficiency. However, the use of both approaches heavily relies on specific assumptions about future features of the economy that make this type of projections very risky and unreliable.

2.2. Treating unobserved heterogeneity with a random parameters model

Based on the influential work of ALS, a broad body of literature has been developed to attempt to precisely measure the efficiency of the studied individuals (firms, countries, etc.) with various methodological proposals that allow for solving specific problems that affect the obtained results. One of the main weaknesses of the basic model that is proposed in Equation (1) is that despite the fact that its specification allows to control for random noise, the presence of unobserved heterogeneity between the studied individuals can bias the efficiency measures (see Greene, 2005a, 2005b).

This heterogeneity is typically considered an unobserved determining factor of the estimated production or cost frontier, and inefficiency is interpreted as the distance to the frontier once heterogeneity has been taken into account. Multiple empirical strategies, each one with specific advantages and drawbacks, have been developed to solve this problem. A first approach that can be applied, is the use of a specification that accounts for unobserved heterogeneity through the intercept, as is the case of the True Fixed Effects (TFE) and TRE models proposed by Greene (2004, 2005a, 2005b). The TFE model includes a series of country-specific intercepts that are simultaneously estimated with the remaining parameters of the model and allow the distinction between unobserved heterogeneity (which does not change over time) and inefficiency. In this approach, unobserved heterogeneity is modelled as an individual-specific intercept and, therefore, is a neutral or parallel movement of the function that maintains the remaining common parameters for all individuals. On the other hand, in the TRE model the intercept is modelled as a random variable that, as in the case of the TFE model, also permits disentangling time-invariant unobserved heterogeneity from time-varying inefficiency. After the estimation of this model it is possible to obtain *ex post* values of the intercept that can vary from country to country. The estimation of both models (TFE and TRE) implies that specific characteristics of the energy demand are the same for all the countries analysed. This assumption is difficult to justify for such a heterogeneous region as Latin America and the Caribbean. If the countries in the sample have different demand characteristics such as price or income elasticities, we should estimate a model that allows us to take these features into account.

An alternative approach to control for unobserved heterogeneity that seems to be more adequate for the current context is the Latent Class Stochastic Frontier Model (LCSFM), such as the model proposed by Orea and Kumbhakar (2004) and Greene (2004, 2005b). This model allows for estimation of different parameters for countries that belong to distinct groups and share similar characteristics. The characteristics of the countries in each group differ and thus, given that the countries that belong to the same class share the same set of parameters, this approach controls for the heterogeneity "between groups". In other words, the latent class procedure allows us to control for heterogeneity in the slopes (the estimated coefficients of the variables introduced in the model), which is unobserved and associated with country groups. The estimation of a model of this type implies the existence of *J* groups of countries, which show differences among themselves in terms of their behaviour function. Additional variables can be included in the probabilities of class membership. If such variables are not included, the model uses the goodness of fit of each class to identify the distinct groups.

However, the abovementioned latent class model can be viewed as an approximation to a Random Parameters Stochastic Frontier Model (RPSFM) where heterogeneity between countries is modelled through a discrete distribution, instead of through a continuous parameter variation (Greene, 2005b).[6] In our context, this model can be presented as follows:

$$\ln Q_{it} = \ln f(P_{it}, Y_{it}, X_{it}, \beta_i) + v_{it} + u_{it} \tag{2}$$

where *i* represents the country, *t* stands for the period, β_i is the vector for the parameters (which are randomly distributed) estimated for each country *i*, and the random term, as in the previous model, is composed of $v_{it} \sim N(0,\sigma_v^2)$ and $u_{it} \sim N^+(0,\sigma_u^2)$.[7] It is important to note that in this type of approach, some parameters are allowed to be "fixed" across countries while others are random by researcher's decision. In that sense, it should also be noted that the TRE model can be viewed as a special case of a fully specified random parameters model in which the only random parameter (β_i) in the model is the intercept (Greene, 2004, 2005b).

Because of the variety of approaches to control for unobserved heterogeneity that can be applied, it is needed to apply statistical tests to choose the most appropriate model in each application. In the literature, the most commonly used tests are the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and some of their variants. Apart from incorporating the value of the likelihood function, these criteria penalise (with different weights) the increase in the number of parameters that are estimated in each model. As shown by Fonseca and Cardoso (2007), the general form for most of the statistical information criteria is:

$$-2 \ln LF + C \tag{3}$$

where the first term is twice the negative logarithm of the maximum likelihood which decreases when the complexity of the model increases. The second term, *C*, penalises too complex models, and increases with the number of parameters of the model. In these information criteria, the preferred model is that one that shows the lowest value

[6] We thank one of the referees for pointing out this issue.

[7] The estimation procedure of this type of model can be found in detail for instance in Greene (2002, 2004, 2005b).

according to (3). In this paper, we use several criteria to select the preferred model (see later on in Section 4).

3. Econometric specification and data

This section presents the data and the econometric specification of the models to be estimated that were presented above. Incomplete panel data are used, for the 1990-2010 period, from the following 24 countries in Latin America and the Caribbean: Argentina, Barbados, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, Uruguay and Venezuela.[8] The econometric specification of our basic ALS model with a translog specification is the following:

$$\ln Q_{it} = \alpha + \sum_{p=1}^{5} \beta_p \ln Z_{pit} + \frac{1}{2}\sum_{p=1}^{5}\sum_{q=1}^{5} \beta_{pq} \ln Z_{pit} \ln Z_{qit} + \beta_{ST} ST_{it} + v_{it} + u_{it} \quad (4)$$

where for notational ease, the vector Z stands for Y, P, POP, DEN and t. It should be pointed out that Q, Y, P, v, u and β are defined as in prior equations. Analogously to Filippini and Hunt (2011, 2012), we include other explanatory control variables[9] such as *POP*, which represents the population; *ST*, which is the share of the transport sector in the economy; *DEN*, population density; and *t*, the time trend.

Table 1 shows the descriptive statistics of these variables. It should be mentioned that the dependent variable, *Q*, represents the final energy consumption of the transport sector, expressed in thousands of toe. It is obtained by adding the total of the energy consumption in internal transport[10] for each country for both passengers and goods. The types of energy that are included in this aggregate are natural gas, Liquefied Petroleum Gas (LPG), electricity, gasoline (which includes biofuel), kerosene (jet fuel), diesel oil and fuel oil. *Y*, is the GDP of each country and is measured in millions of 2005 US dollars at Purchasing Power Parity (PPP). *POP* is the mean population for each country, as measured in thousands of inhabitants.

P is an energy price index calculated as the weighted sum of mean prices (in real terms) of the types of energy used in the transport sector. It should be mentioned that these are final prices after taxes and subsidies, so it is expected that our estimates are not going to be altered by the level of subsidisation of the countries and hence only consumers' behaviour is captured. Because OLADE and other energy international agencies do not provide any price index for the total of the countries of Latin America and the Caribbean, we have calculated a transitive multilateral price index that allows

[8] The sample is composed of a total of 503 observations. The observation for Barbados in 2010 is not included because it is unavailable. Of the 27 country members of OLADE, Belize and Haiti are not included due to the lack of data. Furthermore, Cuba is not included in the sample, as the inclusion of this country in the analysis does not allow for the convergence of estimates in some models because the estimated function does not fulfil the convexity property and, in other models, the obtained values for efficiency are virtually zero. Due to these results, the observations for this country are considered to be outliers and, thus, we exclude them from the sample.

[9] However, in our model, we do not include meteorological variables because we analyse energy demand in the transport sector and such variables do not play a relevant role as in the modelling of total energy demand or the residential sector of a country. However, possible persistent meteorological differences would be controlled for in our preferred model, which precisely allows the treatment of unobserved heterogeneity.

[10] Internal transport includes domestic aviation, domestic shipping, roads and railways and excludes international maritime and air transport.

for consistent comparisons between countries throughout the sample period (see Appendix). We have chosen the use of this type of index instead of standard ones such as Paasche, Laspeyres, Fisher or Törnqvist, because all of them present the same problem. They allow for comparisons of each country with itself over time and between countries in terms of price changes, but they do not allow for comparisons of price levels between countries throughout time. In practice, the use of these simpler indices implies the assumption that each country has a specific time-invariant effect due to the absence of differences in price levels, which artificially introduces heterogeneity into the model. Studies that use international data should employ transitive multilateral indices to overcome this difficulty.

ST is the ratio of Gross Value Added (GVA) in transport and the total GVA for each economy, and it is expressed in percentages. Lastly, *DEN* reflects the ratio between the population in thousands of inhabitants and the area of each country in km^2.[11] Concerning the data sources, the variables *Q*, *P* and *POP* are derived from the Energy-Economic Information System of the OLADE. The variables *ST* and *DEN* are obtained from ECLAC. The variable *Y* is obtained from the data in the Penn World Table (PWT 7.1) presented by Heston *et al.* (2012).

[Insert Table 1 here]

Among the explanatory variables that we have included in our specification, those more correlated with the dependent variable are *Y* and *POP* (>90%). The correlation with the remaining variables introduced is low, being *DEN* the one that have the largest negative correlation (-22%) with energy consumption. Urban population was alternatively considered for the calculation of DEN since it may be seen by some people as a more appropriate measure to estimate energy efficiency. However, the results that are obtained are virtually identical to those obtained when the previous variable is used so we have finally used total population for the calculation of population density.

4. Estimates and results

Table 2 shows the results of the ALS model estimation with the standard Cobb-Douglas and translog specifications. If we focus first on the Cobb-Douglas specification, we can observe that all the variables that are included in the models are statistically significant at 99% (except the time trend squared) and show the expected signs. The values of the income and price elasticities are 0.81 and -0.23, respectively. These elasticities are found within the range of values that are obtained in the demand for energy in transport papers, as discussed in Section 2. It should be noted that as we are not considering the panel structure of the data in this model, the coefficients can be interpreted as long-run elasticities. The coefficient of the population variable has a positive sign, which indicates that population increases lead to, *ceteris paribus*, increases in the energy demand. A similar interpretation can be made for the share of the transport sector in the economy, which can be understood as a proxy for the degree of transport development. It can be expected that a more developed sector results in greater welfare for society, which is achieved through greater energy consumption. However, density presents a negative sign, indicating that the countries that are more densely populated have, *ceteris paribus*, lower transport energy demand due to the

[11] The lack of homogenous information or a sufficient timeframe on the transport infrastructure, stock of vehicles, distances travelled or goods and passenger traffic indicators, impedes the inclusion of these types of variables in the estimated demands.

smaller average distances that companies and individuals travel. After controlling for the remaining variables in the estimation, the positive sign of the time trend shows that energy consumption increased throughout the sample period (as shown in Figure 2), which may indicate technical regress in the sector. The mean value of efficiency is 87.4%. Nevertheless, great variability is found among the observations, with minimum and maximum values of 66.2% and 94.7% respectively.[12]

[Insert Table 2 here]

An issue that recurrently arises in applied research is the choosing of the model specification. More flexible functions (e.g., translog) are generally preferred to those more straightforward (e.g., Cobb-Douglas). However, the estimation of more flexible functions can involve the non-fulfilment of some properties required by the models to be estimated and the arising of multicollinearity problems (see, e.g., Coelli *et al.*, 2005; or Filippini and Hunt, 2015a). Therefore the election of which model should be used in each context is ultimately an empirical question. In this paper we have also estimated a model in which all the variables except one, the share of the transport sector in the economy, are included and interact with each other in a translog specification. The share of the transport sector has been introduced in that model, but its interactions with the remaining variables are not included due to the small variance of this variable (see Table 1) that mainly reflects between-countries variation and hence it can be considered that acts, in a way, as some sort of "country-specific individual effect".[13] The estimation of this model allows us to analyse the possible nonlinearity of some variables and the evolution of the estimated elasticities over time.

In this translog specification we can also observe that most of the first-order coefficients show the expected sign and have similar magnitude to those obtained in the Cobb-Douglas.[14] This outcome gives us confidence about the robustness of our results and the elasticities estimated. Surprisingly, except for population, none of the coefficients of the squared terms are statistically significant. This should not be taken as an evidence of the lack of a nonlinear effect of these variables, as this circumstance may be captured by the interactions between variables that result significant in every case. In particular, the positive coefficient for the interaction between price and time trend and the negative coefficient for the interaction between income and time trend, show that both elasticities decrease over time in absolute terms. This declining trend in price and

[12] A reviewer's suggestion that the inefficiency in our model might include a behaviour that would be the consequence of low energy prices in certain countries led us to estimate a heteroscedastic model of the type proposed by Reifschneider and Stevenson (1991), Caudill and Ford (1993) and Caudill *et al.* (1995). The estimation of this model allows us to test whether there is a correlation between energy prices and energy efficiency that may bias our results. The coefficients that are estimated with such a model for the variables in the frontier are practically identical to those obtained in the ALS model, and the price is not statistically significant in the inefficiency term. The values of the efficiencies that are obtained in this heteroscedastic model are similar to those obtained in the ALS model, with a 96% correlation between the two measures. Thus, we can assume that this issue is not biasing the results in our application.

[13] We have not included all the interactions among variables in the translog specification as this generates a problem of wrong skewness of the residuals. This problem seems to be caused by the wrong functional form of the mentioned translog and the multicollinearity issue that is generated. However, when estimating energy demand frontier functions, the wrong skewness problem can also arise from the presence of both allocative and technical efficiency within the estimated energy efficiency. For a discussion on this topic see Filippini and Hunt (2015a).

[14] All the variables introduced in the model are expressed in logarithms and in deviations with respect to the arithmetic mean (which is equivalent to normalising the original variables using the geometric mean). This allows us to interpret the first-order coefficients of the translog function as elasticities evaluated at the sample mean and thus they can be directly compared to those estimated in the Cobb-Douglas.

income elasticities can also be observed in other energy demand papers (see for instance, Fouquet, 2012). Moreover, it should be mentioned that the Cobb-Douglas is clearly rejected in favour of the translog specification according to the values of the log-likelihood functions and the number of parameters in each model. Therefore, the translog specification will be the one preferred and henceforth will be used to estimate and choose among the alternative models that control for unobserved heterogeneity.

Our data sample covers a period of 21 years and hence another issue that should be analysed is the probability of existence of some kind of structural break due to, for instance, financial crises or other macroeconomic events. The test suggested by Chow (1960) has been used as a simple way to check if we should estimate separated models for dissimilar subsamples within our overall sample. Table 3 shows the values of the Chow test statistic when three different years (1999, 2000 and 2001) are considered as points of structural break. We have performed this test for those years in view of the great increase of fuel prices observed since the end of the 1990's (see Figure 3). Taking into account that the null hypothesis of this test is that the coefficients of the two regressions for the different subsamples are equal, a rejection of this hypothesis would indicate that we should estimate separated demand functions. We can observe that the hypothesis cannot be rejected at a confidence level of 95% for all the years. Therefore we do not believe that a structural break can imply an issue in our analysis.

[Insert Table 3 here]

Figure 4 shows the different information criteria that are used as selection tests to choose the preferred model: the traditional AIC and BIC and some of their variants, the modified AIC criterion (AIC3), the corrected AIC (AICc), the AICu and the consistent AIC (CAIC), which can be considered a variation of the AIC and the BIC.[15] Although our paper is focused on the application of a random parameters procedure to estimate an energy demand frontier model, for robustness grounds we have compared the performance of that approach with other methods commonly used in SFA literature (mentioned in Section 2.2) to control for unobserved heterogeneity. The ALS (which does not control for unobserved heterogeneity), the TFE, the TRE and the latent class models are presented along with the estimated RPSFM model. It seems clear that there is a significant improvement in the performance of all the models when compared with the standard ALS model. We can observe that the TFE and specially the TRE and LCSFM[16] models monitor fairly well the unobserved heterogeneity that exists in our sample. However it seems that the use of a random parameters specification is the model that fits best to the characteristics of our data and, thus, we consider it to be the preferred choice.

[Insert Figure 4 here]

Table 4 shows the parameters estimates of the RPSFM model in which the intercept and all the first-order coefficients are allowed to be randomly distributed. The means for random parameters in this model are significant, show the expected signs and are of a reasonable order of magnitude as in the ALS model presented before.

[15] Additional details on these criteria can be found in Fonseca and Cardoso (2007).

[16] The LCSFM presented in the figure is a latent class model with three classes with a Cobb-Douglas specification which includes per capita income and density as separating variables in the probabilities of class membership. This model can be considered as our preferred model within the latent class approach. It must be said that this model cannot be estimated with more than three classes or alternatively with three classes and a translog specification due to problems of lack of convergence. More information about this type of procedure can be found in Orea and Kumbhakar (2004) or Greene (2005b).

Moreover, the scale parameters for the distributions of these random parameters are also significant which means that there are relevant differences across countries, not only in the intercept but also in the slopes of the variables introduced in the analysis. As in the ALS model, again almost all the coefficients of the squared terms are not statistically significant while on the contrary many of the interaction terms are statistically significant. As previously mentioned, the main advantage of using this approach is that it allows us to obtain individual elasticities for each country in our sample.

[Insert Table 4 here]

The most relevant variables included in demand analysis are generally income and price. In Table 5 we provide the income and price elasticities of the demand computed at country level for our sample when the RPSFM model is applied. The country with the most inelastic demand for income is Peru (0.649), while the most elastic one is Dominican Republic (0.942). There are some similarities between our results and the findings of Rogat and Sterner (1998). In the short-run, they find that Chile, El Salvador and Guatemala are among those countries that show larger income elasticities and that is something that we also find in our analysis. The same happens to Honduras and Mexico that are among those countries with lower income elasticities. In the case of price elasticities, El Salvador and Uruguay are in both studies among the countries with more elastic demands, while Argentina, Bolivia and Venezuela show low price elasticities. Probably the most dissimilar result is the price elasticity for Mexico that in our case it shows one of the most elastic demands while Rogat and Sterner (1998) find this country among those with more inelastic demand. However, it should be mentioned that they find that this country is the one with the most elastic demand in the long-run. If we compare our results with those obtained by Wohlgemuth (1997) for the case of Brazil and Mexico, and Galindo (2005) for Mexico, we observe that we obtain lower income elasticities but larger price elasticities.

[Insert Table 5 here]

Table 5 also provides information about the energy efficiency of the countries in our sample computed using our preferred model. The mean energy efficiency that is obtained is 93.2%, ranging this value between 91.3% (Trinidad and Tobago) and 94.2% (Guatemala). These results indicate that there are not large differences in the energy efficiency among countries. They also reflect that all of them can reduce their energy consumption at least 6%, while the less efficient countries have a margin of up to 9%. Although this could be seen as a small number, it should be taken into account that these savings are non-negligible given the size of the transport sector in these countries. Moreover, these potential savings are however obtained without explicitly considering possible "rebound effects". This phenomenon captures the idea that part of the savings from increases in the efficiency level in the use of energy can be offset by increases in the demand for energy services derived from the marginal cost reduction of those energy services. Orea *et al.* (2015) have recently proposed a model that allows to model and measure energy efficiency and rebound effect when an energy demand function is estimated through an SFA approach. However, this approach has not been generalised to a random parameters framework yet.

If we focus on the individual efficiency scores in our sample, we observe that the three countries with the greatest energy efficiency are Guatemala, Brazil and Ecuador.[17]

[17] In some sense, the most efficient countries in our sample seem to correspond to countries that, according to ECLAC (2010), have adopted distinctive measures for the improvement of public transport in their cities. In this report, it is highlighted the Bus Rapid Transit (BRT) system implementation in

The remaining countries should attempt to follow the energy policies of those countries most efficient that can be considered their "benchmarks". As part of the political measures to improve energy efficiency, governments should pay special attention to the increase of actual fuel consumption in road transport which involves the largest share of energy consumption in transport. Leaving aside the quality of road infrastructures, the main reason in worsening on-road fuel economy is the driving of vehicles at non-optimum speed (Bonilla and Foxon, 2009). This issue together with the age and maintenance of the vehicle fleet should be properly addressed within the political agendas as a priority objective in the near future.

Finally, as mentioned before, energy indicators have traditionally been used to measure energy efficiency in countries. The most commonly used indicator of energy intensity is the ratio of energy consumption to GDP in a country. Table 5 also shows the value of this indicator for the transport sector of each country and presents a ranking of "energy intensity". The table also shows the mean efficiencies that are obtained for each country with the RPSFM model. The correlation coefficients of both measures for each country are in some cases, such as Bolivia (-0.951), Paraguay (-0.848) and Venezuela (-0.827), quite high and negative. This result indicates, as expected, that energy efficiency improvements are associated with decreases in the energy intensity indicators. However there is a low correlation between these measures for some countries (such as Barbados, Nicaragua and Argentina) and it is even positive in one country (Ecuador), indicating that the evolution of energy intensity indicators is associated with circumstances other than energy efficiency improvements. Moreover, using the Spearman's rank correlation coefficient, we observe that the mentioned differences generate quite dissimilar rankings of countries according to their energy efficiency (22% of correlation). This result is of the same order of magnitude as those previously obtained by Filippini and Hunt (2012) for the case of US residential energy demand. This outcome can be taken as evidence that the efficiency measures that are derived from the estimation of energy demand frontier models are more appropriate than those provided by energy intensity indicators.

5. Conclusions

In this paper, we estimate stochastic frontier demand functions to measure the level of energy efficiency of the transport sector in Latin America and the Caribbean by using panel data from 24 countries for the 1990-2010 period. Due to the different types of energy that are used in the transport sector, it is necessary to employ an index that aggregates the set of energy prices for the estimation of these demands. International energy and statistical agencies do not provide energy price indicators for all of the countries in the sample and thus, we construct a transitive multilateral index, which allows for consistent comparisons of energy price among countries throughout time.

The estimated models are a basic stochastic frontier and diverse models that allow us to control for unobserved heterogeneity in our sample. The results indicate that

Curitiba (Brazil). This system was started in 1972 as part of a general policy of urban planning. Other noted examples are the BRT TransMilenio, which has been developed since 2000 in Bogotá (Colombia). The innovations of this system have made it the most solid BRT of the world and have led it to develop an extension plan of this system to seven additional cities. In Mexico City (Mexico), a BRT system has been implemented, named Metrobús, as a complement to the extensive subway system of the city. In Guatemala City (Guatemala), a trans-urban system was developed in 2009 with the aim of improving efficiency and reducing contamination indices of the transport sector in the city.

the specification that best fits an energy demand in this context is a random parameters model. In this model, significant differences in income and price elasticities are observed within the sample. The estimation of our model allows us to identify the most efficient countries in energy consumption (Guatemala, Brazil and Ecuador) that are indeed some of those that have successfully implemented programs of improved public transport in some of their cities. As a policy recommendation, it should be suggested that the remaining countries should follow the example of these countries identified as benchmarks. The adaptation of the national transport sector policies implemented in the most efficient areas of the region might help those countries lagging behind to improve their energy efficiency and reduce their levels of urban contamination.

In addition, this paper shows that the commonly used indicators of energy intensity cannot consistently be used as a reasonable reference for energy efficiency in the transport sector. Using efficiencies that are obtained through a frontier approach, we find that although the mean efficiency is relatively high, there is room for energy savings and, thus, for a reduction of greenhouse gas emissions. However, according to the likely existence of rebound effects, it is possible that increases in energy efficiency do not involve the expected reduction in energy consumption. This concept should be considered in future research for measuring energy efficiency in the transport sector of Latin America and the Caribbean.

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Table 1. Descriptive statistics

Variable	*Units*	*Mean*	*Std. Dev.*	*Max.*	*Min.*
Q	Thousands of toe	6,141	12,434	69,384	18
Y	Millions of US dollars (2005)	164,968	339,168	1,800,000	713
POP	Thousands of inhabitants	20,517	38,114	195,498	91
P	Energy price index (See Appendix)	174.56	108.64	850.66	3.76
ST	%	4.02	1.59	12.74	1.07
DEN	Thousands of inhabitants / km^2	0.10	0.14	0.63	0.00

Table 2. Parameter estimates of the ALS frontier demand models

	ALS (Cobb-Douglas)			**ALS (translog)**		
Variable	*Est.*		*t-ratio*	*Est.*		*t-ratio*
Frontier param.						
Intercept	7.098	***	405.450	7.033	***	358.523
$\ln Y_{it}$	0.810	***	39.720	0.851	***	37.450
$\ln POP_{it}$	0.182	***	8.834	0.099	***	3.763
$\ln P_{it}$	-0.229	***	-15.138	-0.354	***	-13.104
ST_{it}	0.047	***	7.103	0.001		0.159
$\ln DEN_{it}$	-0.096	***	-12.031	-0.075	***	-7.683
t	0.013	***	6.960	0.022	***	9.505
$\frac{1}{2} (\ln Y_{it})^2$				0.044		1.601
$\frac{1}{2} (\ln POP_{it})^2$				-0.335	***	-5.330
$\frac{1}{2} (\ln P_{it})^2$				0.006		0.247
$\frac{1}{2} (\ln DEN_{it})^2$				0.020		1.299
$\frac{1}{2} t^2$	-0.001		-1.537	0.001		1.009
$\ln Y_{it} \cdot \ln POP_{it}$				0.122	**	2.176
$\ln Y_{it} \cdot \ln P_{it}$				0.302	***	6.320
$\ln Y_{it} \cdot \ln DEN_{it}$				0.053	***	3.082
$\ln Y_{it} \cdot t$				-0.028	***	-8.187
$\ln POP_{it} \cdot \ln P_{it}$				-0.318	***	-6.723
$\ln POP_{it} \cdot \ln DEN_{it}$				-0.096	***	-5.995
$\ln POP_{it} \cdot t$				0.025	***	7.613
$\ln P_{it} \cdot \ln DEN_{it}$				-0.151	***	-8.118
$\ln P_{it} \cdot t$				0.004	*	1.852
$\ln DEN_{it} \cdot t$				0.007	***	5.642
Compound error						
$\sigma = (\sigma_v^2+\sigma_u^2)^{(1/2)}$	0.257	***	590.578	0.229	***	618.651
$\lambda = \sigma_u/\sigma_v$	0.886	***	7.411	1.464	***	8.992
Log-likelihood	52.689			173.477		

Significance code: * p<0.1, ** p<0.05, *** p<0.01

Table 3. Chow breakpoint test

Year of breakpoint	***Chow test statistic***
1999	1.502
2000	1.393
2001	1.372

Note: F-distribution (22, 459) = 1.565 (95%)

Table 4. Parameter estimates of the frontier demand with a random parameters model specification

RPSFM (translog)						
Variable	***Est.***		***t-ratio***	***Est.***		***t-ratio***
Frontier (means for random param.)				*Scale param. for dist. of random param.*		
Intercept	7.057	***	278.901	0.102	***	8.632
$\ln Y_{it}$	0.802	***	21.337	0.077	***	6.752
$\ln POP_{it}$	0.169	***	4.246	0.058	***	5.565
$\ln P_{it}$	-0.287	***	-9.901	0.108	***	4.600
ST_{it}	0.021	**	2.408	0.098	***	11.245
$\ln DEN_{it}$	-0.071	***	-3.719	0.033	***	3.995
t	0.020	***	8.810	0.008	***	5.126
Nonrandom param.						
$½ (\ln Y_{it})^2$	0.082	*	1.664			
$½ (\ln POP_{it})^2$	-0.250		-1.463			
$½ (\ln P_{it})^2$	-0.013		-0.387			
$½ (\ln DEN_{it})^2$	0.004		0.208			
$½ t^2$	0.000		1.093			
$\ln Y_{it} \cdot \ln POP_{it}$	0.041		0.319			
$\ln Y_{it} \cdot \ln P_{it}$	0.204	***	5.719			
$\ln Y_{it} \cdot \ln DEN_{it}$	0.049		1.043			
$\ln Y_{it} \cdot t$	-0.024	***	-7.872			
$\ln POP_{it} \cdot \ln P_{it}$	-0.226	***	-6.047			
$\ln POP_{it} \cdot \ln DEN_{it}$	-0.119	**	-2.183			
$\ln POP_{it} \cdot t$	0.020	***	5.881			
$\ln P_{it} \cdot \ln DEN_{it}$	-0.055	*	-1.960			
$\ln P_{it} \cdot t$	0.007	***	2.753			
$\ln DEN_{it} \cdot t$	0.002		1.062			
Compound error						
$\sigma = (\sigma_v^2+\sigma_u^2)^{(1/2)}$	0.110	***	11.818			
$\lambda = \sigma_u/\sigma_v$	1.401	***	3.262			
Log-likelihood			449.146			

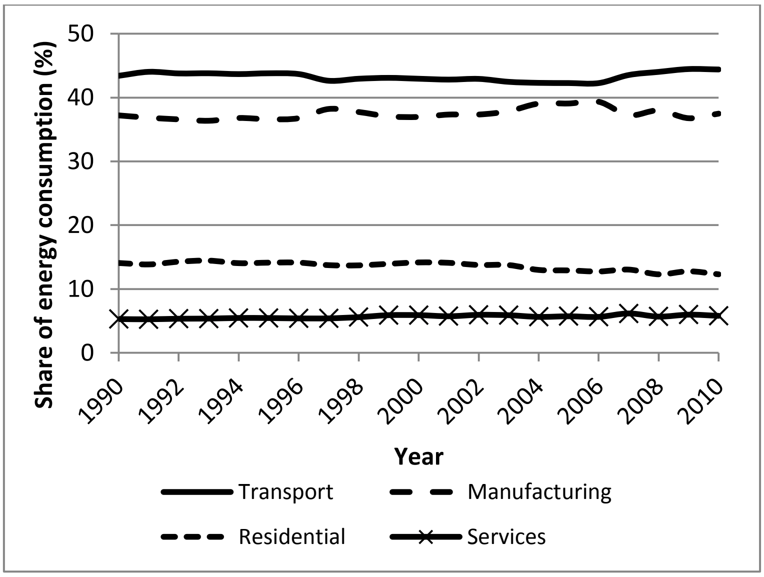
Significance code: * p<0.1, ** p<0.05, *** p<0.01

Table 5. Country-specific elasticities and rankings using energy intensity and energy efficiency scores

Country	Country-specific elasticities		Indicator (Energy/GDP)		Frontier demand (RPSFM)		Correlation (*EI Vs Eff.*)
	β_Y	β_P	*EI*	*Ranking*	*Eff.*	*Ranking*	
Argentina	0.774	-0.170	0.037	14	0.937	7	-0.314
Barbados	0.751	-0.098	0.019	1	0.937	8	-0.286
Bolivia	0.791	-0.180	0.042	19	0.922	21	-0.951
Brazil	0.765	-0.203	0.034	12	0.941	2	-0.512
Chile	0.827	-0.210	0.044	20	0.934	14	-0.627
Colombia	0.895	-0.206	0.032	8	0.935	11	-0.683
Costa Rica	0.794	-0.332	0.032	9	0.937	6	-0.572
Dominican Rep.	0.942	-0.264	0.026	4	0.921	23	-0.693
Ecuador	0.852	-0.273	0.055	22	0.941	3	0.015
El Salvador	0.809	-0.362	0.026	5	0.940	4	-0.626
Grenada	0.847	-0.234	0.029	7	0.935	12	-0.558
Guatemala	0.805	-0.303	0.024	2	0.942	1	-0.633
Guyana	0.828	-0.378	0.066	24	0.926	18	-0.773
Honduras	0.765	-0.233	0.033	10	0.923	20	-0.454
Jamaica	0.760	-0.042	0.038	16	0.926	19	-0.473
Mexico	0.775	-0.371	0.040	18	0.934	15	-0.737
Nicaragua	0.897	-0.323	0.040	17	0.936	10	-0.291
Panama	0.780	-0.186	0.037	15	0.938	5	-0.449
Paraguay	0.801	-0.365	0.054	21	0.922	22	-0.848
Peru	0.649	-0.282	0.025	3	0.929	17	-0.394
Suriname	0.742	-0.108	0.035	13	0.931	16	-0.777
Trinidad and Tobago	0.762	-0.270	0.033	11	0.913	24	-0.462
Uruguay	0.786	-0.446	0.028	6	0.936	9	-0.553
Venezuela	0.887	-0.194	0.062	23	0.935	13	-0.827
Spearman's rank correlation coefficient between both rankings							0.221

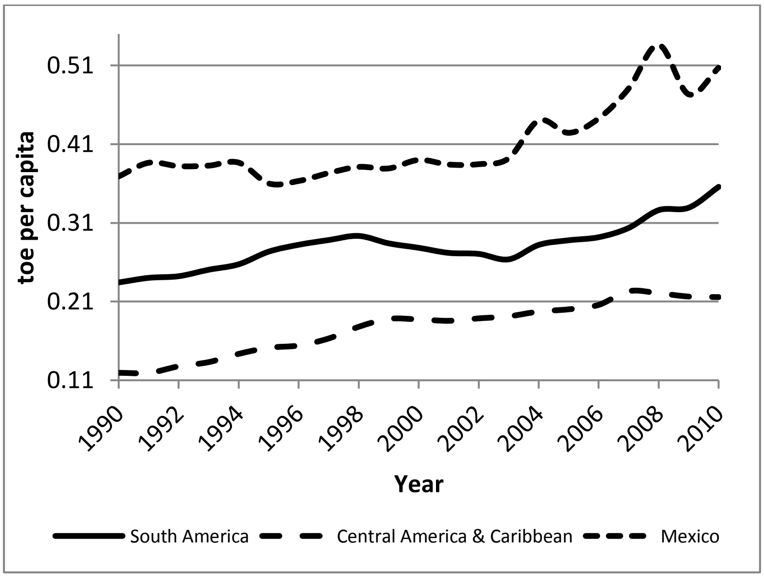
Note: *EI* stands for *Energy Intensity* and *Eff.* is the abbreviation of *Efficiency*

Figure 1. Final energy consumption by activity sector



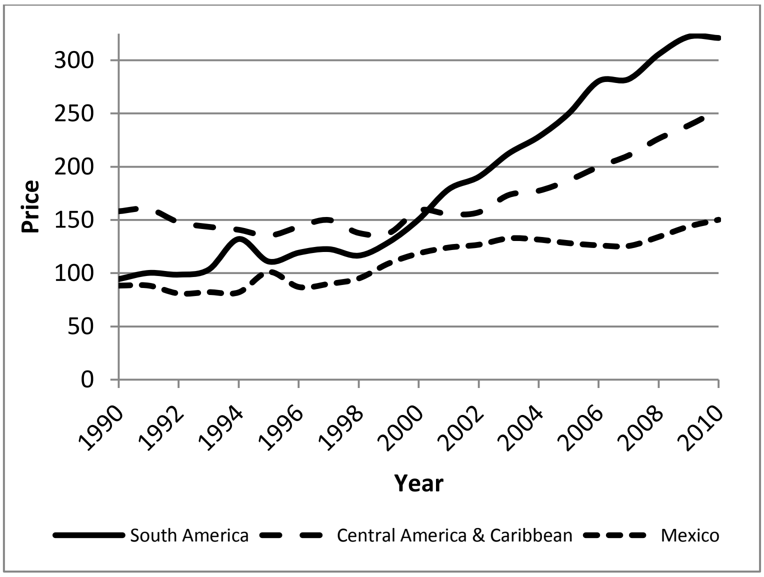
Source: OLADE

Figure 2. Energy consumption in tons of oil equivalent (toe) per capita in transport



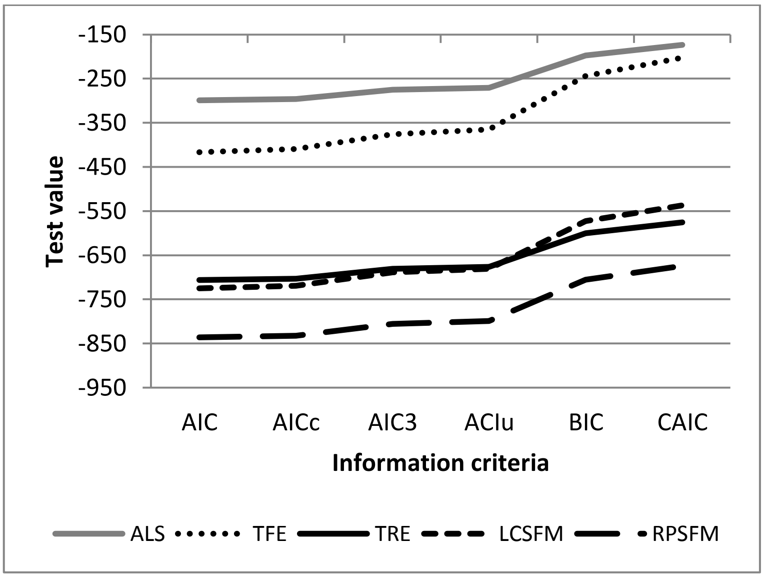
Source: OLADE

Figure 3. Energy price indices in the transport sector



Source: Own elaboration based on data from OLADE

Figure 4. Model selection tests



APPENDIX

Construction of the price index

OLADE provides information on the final prices and quantities consumed of the different types of energy that are used in the general transport sector of Latin America and the Caribbean. However, this agency does not provide a unique price of energy for these countries. To estimate aggregate energy demand in transport, it is necessary to obtain an indicator or index that accounts for the distinct components in the energy consumption of the sector. In general, a compound price index can be defined as follows:

$$PI_{0t} = \frac{\sum_{m=1}^{M} p_{mt}q_{mt}}{\sum_{m=1}^{M} p_{m0}q_{m0}} \tag{A1}$$

where PI_{0t} measures the change in value of the total of the M energy components between the base period 0 and final period t. In this type of index, it is difficult to distinguish between changes in prices and changes in consumed quantities. The two indices that are most commonly used in practice are Laspeyres and Paasche. In the former, the quantities that are consumed in the base year (q_{m0}) are used as weights both in the numerator and denominator. Thus, this index isolates the change in prices without accounting for changes in consumption patterns. The second type of index uses energy quantities from the current period (q_{mt}) as weights, thus simultaneously including variations in prices and quantities. These two indices, therefore, represent two extreme cases and only coincide when relative prices do not experience any variation (i.e., p_{mt}/p_{m0} is constant).

As mentioned in the paper, a price index that allows transitive multilateral comparisons between countries should be ideally used for international comparisons. Here we will use the method proposed by Elteto and Koves (1964) and Szulc (1964). This method, known as EKS, was used by Caves *et al.* (1982) to obtain transitive Törnqvist indices. The formula, in line with Coelli *et al.* (2005), is as follows:

$$\ln PI_{ij}^{CCD} = \frac{1}{2}\sum_{m=1}^{M}\left(\omega_{mj} + \bar{\omega}_m\right)\left(\ln p_{mj} - \overline{\ln p_m}\right) - \frac{1}{2}\sum_{m=1}^{M}\left(\omega_{mi} + \bar{\omega}_m\right)\left(\ln p_{mi} - \overline{\ln p_m}\right) \tag{A2}$$

where ω_{mi} represents the importance held by component m in the energy expenditure of the transport sector within a certain country and year, i, while j represents the country and year of reference, and $\bar{\omega}_m$ is the arithmetic mean of these expenditure amounts for the whole sample. Furthermore, $\overline{\ln p_m}$ represents the average of the logarithm of prices of energy component m for the set of countries.

The intuitive interpretation of Equation (A2) is that to compare the price indices of two countries, each of them is compared to the average country and then the differences from this mean are calculated. Logically, as opposed to other indices, when an observation is added or subtracted from the sample, all values should be recalculated due to changes in the mean of the sample.