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Energy Poverty in Colombia: Empirical Evidence from 2011 to 2016

by

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Declaration of Authorship

I, Jhon Jairo Pérez Gelves, declare that this monograph titled, 'Energy Poverty in Colombia: Empirical Evidence from 2011 to 2016' and the work presented in it are my own. I confirm that:

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Abstract

Most existing multidimensional indexes such as: the Human Development Index (HDI); the Multidimensional Poverty Index (MPI) and the GINI coefficient allow for the identification of gaps in development. Since energy plays an important role in economic growth and human development, the measurement of energy poverty makes it possible to determine the origin of inequalities in developing countries.

Currently, Colombia is Latin America's fourth largest economy by GDP (Constant 2010, USD), accounting for 372.31 billion dollars in 2017. Hence it is an important energy producer. In 2014 it accounted for 5.06 quadrillion British Thermal Units (BTU), placing it 25^{th} worldwide and making it one of the world's largest coal producers.

This work makes two contributions. First, the Multidimensional Energy Poverty Index (MEPI) is calculated in rural and urban areas for the periods of 2011 and 2016 at the national and regional level. Second, this thesis contributes to the literature by calculating and analyzing the correlations between socioeconomic factors in rural and urban areas with respect to energy intensity using two recognized techniques: Ordinary Least Square (OLS) and Pooled Cross-Section.

The results show remarkable differences between rural and urban areas in Colombia. The regression model applied based on pooled cross-section showed the existence of statistically significant correlations between the energy intensity and socioeconomic factors. The understanding of socioeconomic relations through the use of energy will make it possible to propose better energy policies for the development of the regional and national states.

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Dedicatory*: This work is dedicated mainly to my daughter Alejandra and my brothers/cousins Alvaro, Sergio (Niño), Fede (Papa) and Pedro (Menino).*

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Abbreviations

DANE	**N**ational **A**dministrative **D**epartment of **S**tatistics
EI	**E**nergy **I**ntensity
HDI	**H**uman **D**evelopment **I**ndex
GDP	**G**ross **D**omestic **P**roduct
MEPI	**M**ultidimensional **E**nergy **P**overty **I**ndex
MPI	**M**ultidimensional **P**overty **I**ndex
NQLS	**N**ational **Q**uality of **L**ife **S**urvey
OLS	**O**rdinary **L**east **S**quares
PCS	**P**ooled **C**ross **S**ection
PPP	**P**urchasing **P**ower **P**arity
TPES	**T**otal **E**nergy **P**rimary **S**upply
SDGs	**S**ustanaible **D**evelopment **G**oals
UN	**U**nited **N**ations
WB	**W**orld **B**ank

Chapter 1

INTRODUCTION

According to the Sustainable Development Goals (SDGs) put forth by the United Nations (UN), the main challenges facing humanity approaching the year 2030 are as follows: poverty, inequality, and environmental degradation [Nations, 2015]. The stated goals relating to these challenges are: Goal 1 *"No poverty"*; Goal 7 *"Affordable and Clean Energy"*; and Goal 10 *"Reduced Inequalities"*[1]. These aspects are concerned with economic growth, human development and environmental sustainability. Energy plays an important role in economic growth and human development, and hence is known as the *"golden thread"* [Daly and Walton, 2017].

There are several useful indicators which serve as proxies to measure development. The Human Development Index (HDI) is an index that contains three dimensions: life expectancy; knowledge; and standard of living [Anand and Sen, 1994]. The Multidimensional Poverty Index (MPI) is an indicator usually applied in developing countries and includes three dimensions: education; health; and living standards [Alkire et al., 2016]. Finally, the World Bank (WB) uses the Gross Domestic Product (GDP) per capita as a measure of the prosperity of a nation. Nevertheless, the WB also defines the global line of extreme poverty at 1.90 USD per day [Group, 1978].

Several authors consider poverty using a multidimensional approach, which includes social, political, cultural and economic aspects [Bourguignon and Chakravarty, 2003] [Alkire and Foster, 2011] [Atkinson, 2003] [Minujin et al., 2012] [Gordon et al., 2000]. Nobel Laurate Amartya Sen[2] defines poverty as a deprivation not limited to low income, but including also mortality, morbidity, illiteracy and malnutrition [Anand and Sen, 1997] [Miletzki and Broten, 2017]. Further, the link between energy and development have been widely researched in the literature [Van Ruijven et al., 2008] [Yu and

[1] Sustainable Development Goals.`http://www.undp.org/content/undp/en/home/sustainable-development-goals.html`

Choi, 1985] [Toman and Jemelkova, 2003] [Goldemberg and Lucon, 2010]. Table 1.1 shows a summary of development indicators such as: HDI, GDP at purchasing power parity (PPP), MPI and energy consumption per capita for Latin America. The indicators illustrate the close link between development and energy consumption. Bolivia, El Salvador and Guatemala have a very close HDI score, as well as GDP (PPP), HDI, MPI and energy consumption. By contrast, at the top of the list Chile and Argentina have similar HDI, GDP (PPA), and energy consumption. These indicators could suggest a strong link between development and energy poverty.

TABLE 1.1: Development indicators and energy consumption in Latin America

Country	**HDI (1) (2017)**	**GDP-PPP (2) (2016)**	**MPI (3) (2018)**	**Energy (kg oil per capita -2014)**
Chile	0.843	24,085	—	2,049
Argentina	0.825	20,787	—	2,015
Uruguay	0.804	22,563	—	1378
Costa Rica	0.794	17,044	—	1031
Panama	0.789	24,446	—	1079
Cuba	0.777	—	—	1022
Mexico	0.774	18,149	0.063	1513
Venezuela	0.761	—	—	—
Brazil	0.759	15,484	0.063	1484
Equador	0.752	11,617	0.070	891
Peru	0.750	13,434	0.126	767
Colombia	0.747	14,552	0.060	711
Dominican Republic	0.736	—	0.055	—
Paraguay	0.702	9,691	0.070	788
Bolivia	0.693	7,560	0.168	788
El Salvador	0.674	8,006	0.089	647
Nicaragua	0.658	5,842	0.146	609
Guatemala	0.650	8,150	0.225	830
Honduras	0.617	4,986	0.181	607
Haiti	0.498	1,815	0.316	392

(1) HDI. Statistical annex - Human Development Reports - UNDP.

(2) GDP-PPP. World Development Indicators.

(3) MPI. The Global Multidimensional Poverty Index (MPI) [Alkire et al., 2018].

There are many definitions of energy poverty. The International Energy Agency (IEA) defines energy poverty as *"a lack of access to modern energy services. These services are defined as household access to electricity and clean cooking facilities"* [Daly and Walton, 2017]. For Reddy, energy poverty is *"the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development"* [Reddy et al., 2000].

[2] The Nobel Prize.https://www.nobelprize.org/prizes/economic-sciences/1998/sen/facts/

1.1 Brief review of literature on energy poverty

The literature presents two approaches to energy poverty: (i) Economic-based. These analyses include, for instance, prices of energy and the application of multidimensionality energy poverty index [Pachauri and Spreng, 2011] [Birol et al., 2007] [Nussbaumer et al., 2012]; and (ii) Engineering-based, which takes into account the selection of energy by households or communities and the quantification of the energy necessary for development [Heltberg, 2004] [Khandker et al., 2012]. Table 1.2 provides a brief review of the literature focused on economic and physical approaches.

On the other hand, there are some authors who have focused on measure of the energy poverty using different metrics such as: access to different energy resources; statistical household energy consumption; and decomposition analysis [Nussbaumer et al., 2012] [Pachauri et al., 2004] [Papada and Kaliampakos, 2016] [Okushima, 2016b]. Nussbaumer et al. [2012] developed an index related to energy poverty known as MEPI based on the deprivation of the use of modern energy. The MEPI contains five dimensions: cooking; lighting; services provided by means of household appliances; entertainment; and education.

1.2 Motivation

This work proposal seeks to apply the MEPI to Colombia in rural and urban areas, in the two periods of 2011 and 2016. The MEPI can be considered as a proxy indicator of poverty and inequality. The assessment will allow us to know and understand the current state of Colombia in relation to energy poverty with respect to: use of fuels for cooking; access to electricity; home appliances; training and communication. Another contribution of this paper consists in establishing socioeconomic statistical correlations between MEPI per household and socioeconomic variables such as: income, education, social status and head of household from empirical evidence in Colombia.

Research Questions

Calculate the MEPI in Colombia at a national and regional level for Colombia in the years of 2011 and 2016, in rural and urban areas.

What correlation exists between socioeconomic factors in energy poverty in Colombia for rural and urban areas?

1.3 Objectives

To apply the MEPI indicator to determine the evolution of energy poverty and its distribution in Colombia from 2011 to 2016.

Specific objectives

1. To determine the MEPI from of the National Quality of Life National Survey Methodology (QLNSM) for the period between the years of 2011 and 2016.

2. To establish the socioeconomic variables that are related to energy poverty in rural and urban areas.

TABLE 1.2: Brief summary of energy poverty approach literature

	Economic approach		
Author	Title	Topic	Method
Burlinson et al. [2018]	The elephant in the energy room: Establishing the nexus between housing poverty and fuel poverty.	This paper quantifies fuel costs for low-income households in England.	Multinomial logistic regression
Farzanegan and Habibpour [2017]	Resource rents distribution, income inequality and poverty in Iran.	This work analyzes the distribution of revenues from oil and gas sales through investments in public policies.	Gini coefficient
Legendre and Ricci [2015]	Measuring fuel poverty in France: Which households are the most fuel vulnerable?	This paper studies the prices of energy in France, establishing the impacts and determining which households are the most vulnerable.	Logistic regression
Martey [2019]	Tenancy and energy choice for lighting and cooking: Evidence from Ghana.	This research presents how from the possession of goods, its influences on the selection of energy for lighting and cooking.	Probit regression
Troncoso and da Silva [2017]	LPG fuel subsidies in Latin America and the use of solid fuels to cook.	This study analyzes the impact of subsidies for reducing the use of solid fuels.	Review and discussion
Han and Wu [2018]	Rural residential energy transition and energy consumption intensity in China.	This article examines the impact of the energy transition, from a rural society based on biomass to a society that uses market fuels.	Panel data
	Engineering approach		
Joshi and Bohara [2017]	Household preferences for cooking fuels and inter-fuel substitutions: Unlocking the modern fuels in the Nepalese household.	This paper studies the transition in Nepal towards cleaner fuels.	Binomial and multinomial regression.
[Alem et al., 2016]	Modeling household cooking fuel choice: A panel multinomial logit approach.	This paper analyzes the determinants for the selection of energy for cooking.	Multinomial logistic regression
Karimu [2015]	Cooking fuel preferences among Ghanaian Households: An empirical analysis.	This paper evaluates the key factors for the selection of energy such as income, infrastructure and location.	Probit multinomial regression
Romero et al. [2018]	The policy implications of energy poverty indicators.	This paper compares different types of methods for to measure energy poverty.	Measure of energy poverty
Acharya and Marhold [2019]	Determinants of household energy use and fuel switching behavior in Nepal.	This paper analyzes the energy selection behavior of Nepalese households, using an Annual Household Survey (AHS) from multiple discrete continuous extreme value (MDCEV) model.	Multiple discrete continuous extreme value (MDCEV model.

Chapter 2

METHODS AND MATERIALS

In this section the methods are presented. These methods correspond to the theoretical model related to MEPI; econometric and empirical models; as well as data and descriptive statistics.

2.1 The MEPI index

The MEPI captures relative weights in five dimensions according to Table 2.1 related to energy deprivations of a person. Equation 2.1 presents a matrix nxd that contains d variables for n individuals. The rows of the matrix represent the individuals i and each column contains the distribution of achievements (dimensions) in the j variable. The MEPI is a index based on The MPI which includes three dimensions: education; health; and living standards [Alkire et al., 2016].This last dimension has the variables related to energy poverty.

$$y_{i,j} = \begin{bmatrix} y_{1,1} & y_{1,2}\cdots & y_{1,d} \\ y_{2,1} & y_{2,2}\cdots & y_{2,d} \\ \cdots & \cdots & \cdots \\ y_{n,1} & y_{n,2}\cdots & y_{n,d} \end{bmatrix} \tag{2.1}$$

This methodology can be explained thus according to Nussbaumer et al. [2012]: A weighting vector is built across the j variable, where $\sum_{j=1}^{d} w_j = 1$. Z_j is the deprivation cut-off in variable j, and $g_{i,j}$ is defined as the matrix of deprivation according to the weights as follows in Equation 2.1:

$$g_{i,j} = w_j \quad when \quad y_{i,j} < z_i \quad and \quad g_{i,j} = 0 \quad when \quad y_{i,j} \geq z_j$$

Table 2.1: Dimensions, indicators and variables of MEPI index. Adapted from Nussbaumer et al. [2012]

Dimension	**Indicator (Weight - w)**	**Variable**
Cooking	Modern cooking fuel (0.2)	Type of cooking
	Indoor pollution (0.2)	Food cooked (stove or open fire)
Lighting	Electricity access (0.2)	Access to electricity (yes or not)
Services provided by means of household appliances	Household appliance ownership (0.13)	Fridge (yes or not)
Entertainment/education	Entertainment/education appliance ownership (0.13)	Television (yes or not)
Communication	Telecomunication means (0.13)	Phone land line or mobile phone

(2.2)

Note that the value w_j when a person i is not deprived in variable j corresponds to zero. A vector c of deprivation counts is calculated; thus the equation $C_i = \sum_{j=1}^{d} g_{i,j}$ calculates the sum weighted deprivations in the person i. q is the number of energy individuals $c_i > k$ and n the individuals. H is defined as the headcount ratio of individuals $\frac{q}{n}$ that are multidimensionally energy poor. The intensity of multidimensional energy poverty is written as: $\sum_{j=1}^{n} \frac{C_i(k)}{q}$. Finally, the MEPI corresponds to multiplication between H x A [Nussbaumer et al., 2012].

2.2 Theoretical framework

2.2.1 Ordinary Least Squares

The Ordinary Least Squares (OLS) regression is a recognized statistical model, where the coefficient estimators are obtained by applying a linear regression model for continuous and ordinal variables according to Equation 2.2.1. The OLS linear model makes the assumptions of homoskedasticity and uncorrelated errors. These hypotheses are known as as the Best Linear Unbiased Estimator (BLUE) [Verbeek, 2008]:

$$y = X\beta + \epsilon_t$$

$$\widehat{\beta}_i = \left(X'X\right)' X'Y$$

$Assumptions: \quad E[\epsilon \mid X] = 0 \quad and$

$Var[\epsilon \mid X] = \sigma^2 I_n$

$Where:$

β: estimator

X: be a N k matrix of the observations on K variables for N units

Y: a n-vector of observations on the dependent variable

(2.3)

2.2.2 Pooled Cross Section

Cross-sectional data in statistics and econometrics is a kind of one-dimensional data set. This method consists of comparing the differences among the subjects. Pooled Cross Section (PCS) data uses randomly sampled points in the time. The observations across different time periods allows for policy analysis. A pooled model can be expressed according to Equation 2.4 [Raffalovich and Chung, 2015] as follows:

$$Y_{t,i} = \alpha + \sum_k \beta_k X_{k;t,i} + \epsilon_{t,i} \tag{2.4}$$

Where: $i = 1, 2, 3, \ldots I$ indexes cross-section; $t = 1, 2, 3, \ldots T$
Indexes time; and $k = 0, 1, 2, 3 \ldots K$ indexes independent.
$Y_{t,i}$: is a vector of the dependent variable that varies over cross-section and time.
t, i: is a vector of dependent variables that vary over cross-section and time.
$X_{k,t,i}$: are the k independent variables that vary over cross-section and time.
β_k: are the coefficients on the k independent variables.
$\epsilon_{t,i}$: are the stochastic errors that vary over cross-section and time.

2.3 Empirical model

The literature presents several approaches to the study of energy poverty. One is focused on energy use and energy access, and takes the amount of energy consumed as a measure of access to affordable and adequate energy services [Pachauri and Spreng, 2004] [Davis, 1998]. The authors, however, developed techniques based on the measurement of energy poverty and the application of methodologies to determine indexes which may indicate deprivation or access to modern energy systems [Nussbaumer et al., 2012] [Okushima, 2016a] [Okushima, 2017]. This latter approach relies on the relationships between energy poverty, economic development and socioeconomic variables. This type of study is more recent and seeks to determine which are the economic and social variables that have an effect on energy poverty. These works apply econometric techniques using household level data and include socioeconomic indicators such as: income, education, health and type of housing among others indicators [Acharya and Sadath, 2019] [Espinoza-Delgado and Klasen, 2018] [Prykhodko, 2006]. Nevertheless, in this topic the literature is scarce. This work proposes to study correlational effects between energy poverty and socioeconomic factors.

Equation 2.5 is the basic econometric model employed for estimation, proposed in this paper. The dependent variable is Energy Intensity (EI) which corresponds to the vector of weights w_j per household and independent variables correspond with a matrix of socioeconomic aspects such as: status (low, middle and high); income (USD in constant dollars, 2018); head of household (male or female); and education (basic, secondary, and tertiary).

$$EI_i = \beta_0 + \beta_1 Income_i + \beta_2 Status_i + +\beta_4 Head_i + \beta_4 Education_i + e_i \tag{2.5}$$

Where:
EI_i: is the energy intensity per household.
$Income_i$; is the income per household.
$Status_i$: is the socioeconomic status per household.
$Head_i$: is the household head.
$Education_i$: is the level of education of the household head.

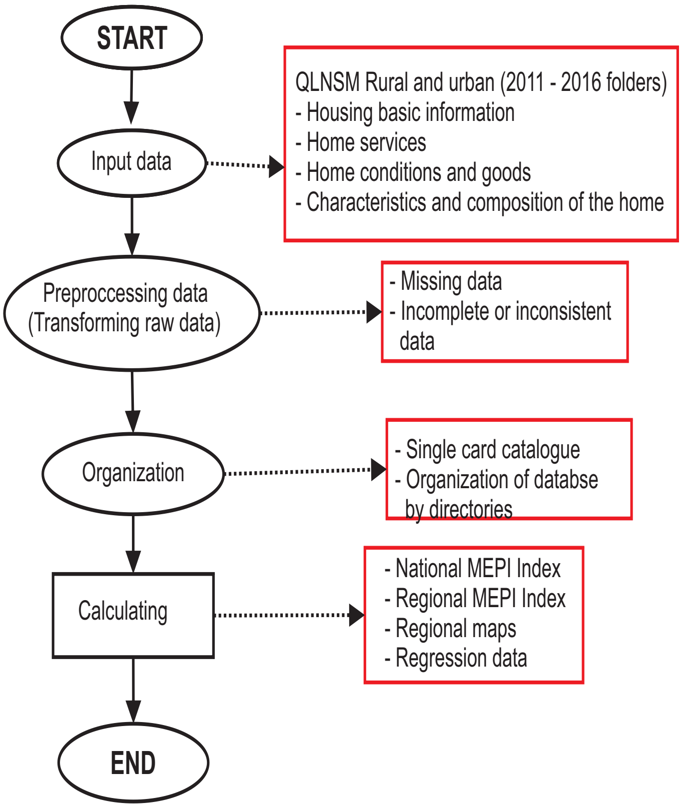
2.4 Data and descriptive statistics

The data used here are taken from of the National Quality of Life Survey (NQLS) collected by The National Administrative Department of Statistics DANE [2016] at the national level for rural and urban households in 2011 and 2016. There are two NQLSs that were used in this paper. These surveys contain data related to living standard as well as: public facilities; characteristics of housing; health services; demographic characteristics; workforce; ownership of goods and so on. Each survey is divided into urban areas, intermediate areas and rural areas of Colombia. The NQLS 2011 sample consists of 25,364 households divided into: 14,624 for urban; 3,325 for intermediate cities; and 7,415 for rural. The NQLS 2016 sample corresponds to 22,454 households divided into: 13,900 for urban; 3,066 for intermediate cities; and 5,488 for rural. Nevertheless, this work only includes rural and urban areas of Colombia.

Figure 2.2 illustrates the general algorithm developed to calculate: National MEPI; Regional MEPI and econometrical regressions. The algorithm was developed in Matlab R2014a (The Mathworks, Inc) and, is divided into:

(i) preprocessing data
(ii) organization of the data
(iii) calculated indexes
(iv) data to apply regressions

Figure 2.1: General algorithm



The data used in this paper are continuous, binary and categorical. The specific information for each data parameter used is described as follows:
(i) Energy intensity (EI) per household: this variable is calculated based on the MEPI for each household. EI comprises a range between 0 to 1 from the weight matrix w_j and corresponds to a continuous variable.
(ii) Socioeconomic status: is divided into three segments: low (Status 1 and 2); middle (Status 3 and 4); and high (Status 5 and 6). The reference corresponds to low status.
(iii) Income: corresponds to the income per household, expressed in constant dollars (USD) of 2018.

(iv) Household head: classified into male and female head of household. The reference corresponds to Male head.
(v) Education: the level of education was selected according to the last year of schooling of the household head: illiterate, basic, secondary and tertiary. Nonetheless, in the study only the levels basic, secondary and tertiary were considered (Tertiary is considered any study above secondary education). The reference corresponds to basic education.

2.5 Descriptive statistics

This section provides a summary of statistics related to samples used in regressions models that corresponds to the Tables 2.2 and 2.3. In Figures 2.2 and 2.3 the relationship between socioeconomic status and income for rural and urban areas is presented.

2.5.1 Rural statistics

According to Table 2.2, the NQLS 2011 sample, 96.4% correspond to low income households; 3.3% to middle income; and 0.2% to high income. For the NQLS 2016 sample, 97.7% represent low income households; 1.9% for middle income; and 0.2% for high income. The income in rural areas experienced a considerable change from 2011 to 2016, going from 212 USD to 404 USD monthly.

Figure 2.2 illustrates a summary box-plot of the monthly income distribution in rural areas of Colombia. The income distribution is divided into three socioeconomic status: low, middle and high. In NQLS 2011 for low status the median is roughly 190 USD; in middle status the median is almost 285 USD; and high status is approximately 280 USD. With respect to NQLS 2016 for low status the median corresponds to 292 USD; middle status is 529 USD; and high status is approximately 595 USD. The inflation-adjusted values were converted to constant dollar values of 2018[2].

2.5.2 Urban statistics

Table 2.3 presents summary statistics for the NQLSs 2011 and 2016 in urban samples. For NQLS 2011 96.3% correspond to low income households; 3.3% to middle income; and 0.2% to high income. For NQLS 2016 sample, 81.6% represent low income households; 18.0% middle income; and 0.2% high income. The income in urban areas experienced a

[2]Index Consumer Prices (IPC) of Colombia.http://www.banrep.gov.co/es/estadisticas/indice-precios-consumidor-ipc

considerable change from 2011 to 2016, going from 253 USD to 542 USD monthly. The remaining summary statistics are presented in Table 2.3.

Figure 2.2 presents a summary box-plot of the monthly income distribution in rural areas of Colombia. This figure illustrates the income distribution divided into three socioeconomic statuses: low, middle and high. In NQLS 2011 for low status the median corresponds to 256 USD; in middle status the median is almost 388 USD; and high status is approximately 360 USD. With respect to NQLS 2016 for low status the median corresponds to 292 USD; middle status is 529 USD; and high status is approximately 595 USD. The inflation-adjusted values were converted to constant dollar values of 2018 [2].

TABLE 2.2: Socioeconomic characteristics of the rural samples

Sample	NQLS 2011(1)		NQLS 2016(2)	
Variable	Mean (3)/ Count (4)	Std (5)/ Freq (6) (%)	Mean/ Count	Std/ Freq (%)
EI per household	0.47	0.24	0.37	0.24
Low	5,467	96.4	4,338	97.7
Middle	191	3.3	87	1.9
High	13	0.2	11	0.2
Income (USD)	212.1	357.2	404.3	617.5
Male head	4,425	78.0	2,405	54.2
Female head	1,243	21.9	2,031	45.7
Illiterate	2,256	39.7	3,690	83.1
Basic	3,101	54.6	438	9.87
Secondary	237	4.1	281	6.33
Tertiary	77	1.3	27	0.6

(1) Rural sample 2011 (5,671 Households).

(2) Rural sample 2016 (4,436 Households).

(3) Mean: if is continuous variable.

(4) Count: if is counting variable.

(5) Std: standard deviation if is continuous variable.

(6) Freq: Percentage in frequency if is counting variable.

TABLE 2.3: Socioeconomic characteristics of the urban samples

Sample	NQLS 2011(7)		NQLS 2016(8)	
Variable	Mean(9)/ Count(10)	Std(11)/ Freq (%) (12)	Mean/ Count	Std/ Freq (%)
EI per household	0.16	0.16	0.13	0.13
Low	5,462	96.3	9,439	81.6
Middle	191	3.3	1,704	18.o
High	13	0.2	25	0.2
Monthly income (USD)	253.8	427.6	542.3	695.3
Male head	4,425	78.0	4,760	50.4
Female head	1,241	21.9	4,679	50.4
Illiterate	2,251	39.7	2,729	28.9
Basic	3,101	54.7	1,566	16.5
Secondary	237	4.1	1,594	16.8
Tertiary	77	13.0	3,550	37.6

(7) Urban sample 2011 (10,902 Households).

(8) Urban sample 2016 (9,940 Households).

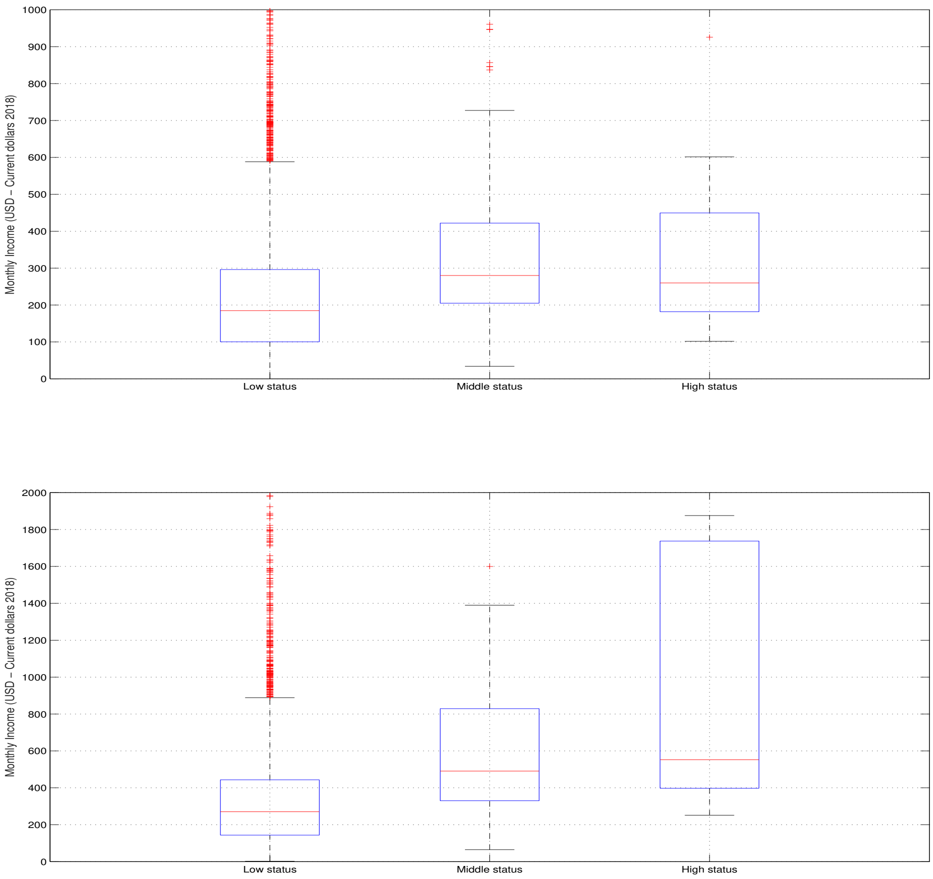
(9) Mean if is continuous variable.

(10) Count: if is counting variable.

(11) Std: standard deviation if is continuous variable.

(12) Freq: Percentage in frequency if is counting variable.

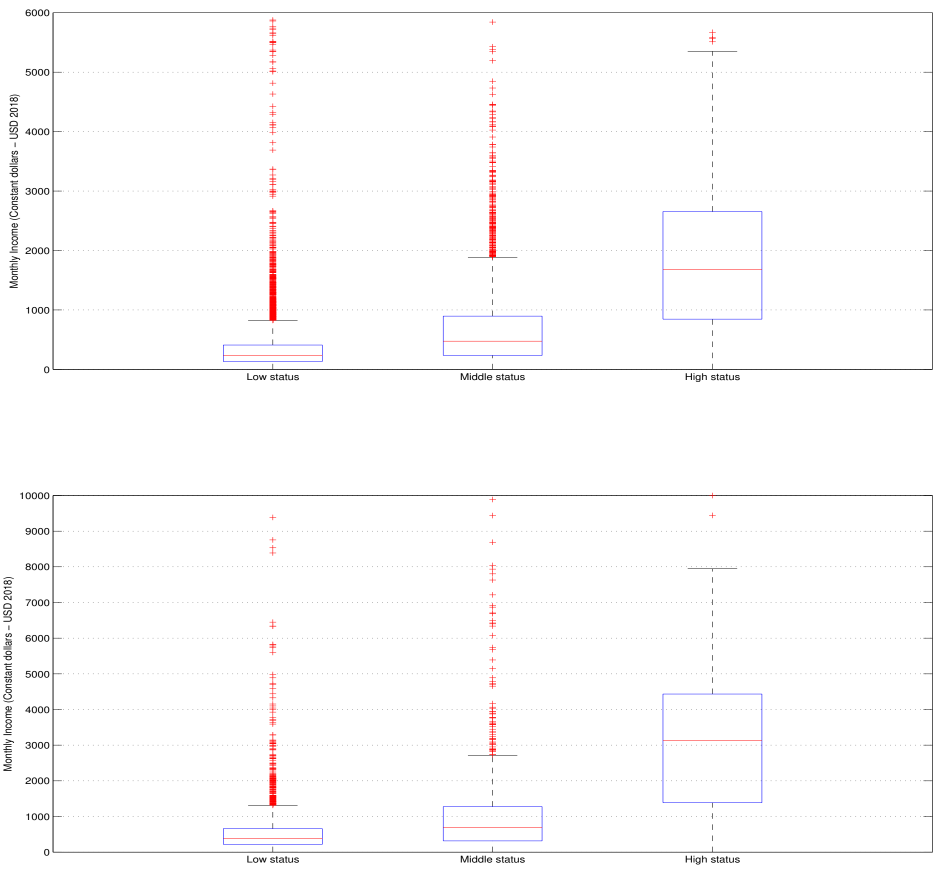
FIGURE 2.2: Boxplot distribution of income in rural areas of Colombia from 2011 and 2016.



a. Income monthly 2011.

b. Income monthly 2016.

Figure 2.3: Boxplot distribution of income in urban areas of Colombia from 2011 to 2016.



a. Income monthly 2011. b. Income monthly 2016.

Chapter 3

RESULTS AND FINDINGS

Using the general algorithm developed in chapter 2, this section provides detailed results as follows: the MEPI for Colombia (rural and urban national level); MEPI maps from Colombian regions (rural and urban regional level); and pooled cross-sections.

3.1 MEPI for Colombia

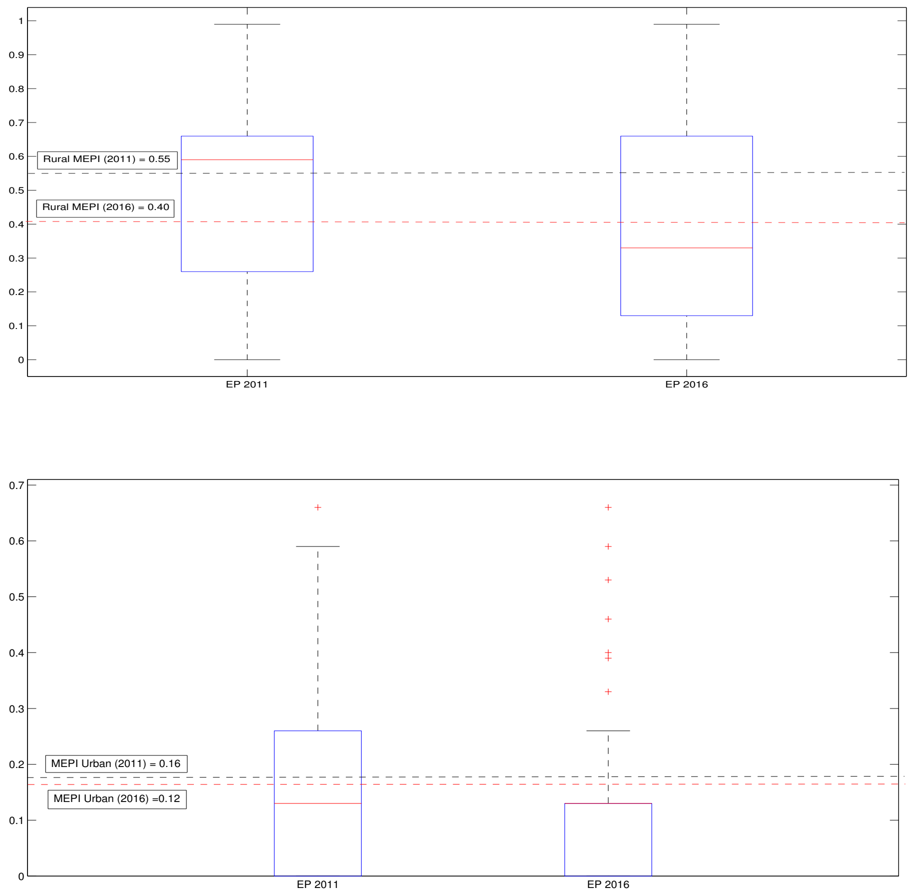
This section presents the results relating to the MEPI for Colombia. These results provide remarkable information about the evolution of energy poverty per person in the surveys. The NQLSs 2011 and 2016 are household level surveys. Eventhough, the number of persons per household was included, according to MEPI methodology.

Figure 3.1 illustrates the results concerning rural samples. The MEPI was calculated using the NQLS 2011 for 27,244 persons, of which 26,857 had a numeric multidimensionally energy poverty greater than zero. The head ratio (H) was calculated as 0.98. The MEPI for rural areas of Colombia in 2011 was 0.55. Regarding the NQLS 2016, the sample contains 18,489 persons and 18,097 persons with any value different from zero related to energy poverty. For this sample, the head ratio (H) corresponds to 0.97 and the MEPI corresponds to 0.40.

Figure 3.2 presents the results with respect to MEPI for urban areas. From the NQLS 2011 of 51,145 persons, 37,638 had a numeric multidimensionally energy poverty greater than zero. The head ratio (H) was calculated as 0.73 and the MEPI for urban areas of Colombia in 2011 was 0.16. Meanwhile, for NQLS 2016 of 44,589 persons, there were 31,661 with any value different from zero for energy poverty. The head ratio (H) was 0.71 and the MEPI was reduced to 0.12.

Figures 3.1 and 3.2 show various box-plots that correspond with energy poverty distribution and MEPI according to NQLSs. This plot contains ve types of information: minimum, rst quartile, median, third quartile, and maximum of the EI by household of the samples. Additionally the MEPI indexes are presented.

FIGURE 3.1: Energy poverty distribution in rural and urban areas in Colombia per households and MEPI from 2011 to 2016



a. MEPI Index rural in Colombia.

b. MEPI Index urban in Colombia.

3.2 MEPI maps from Colombian regions

Two maps were elaborated with information about MEPI by region of Colombia. These maps were programmed in R software [R Development Core Team, 2008] based on shape files in digital vector format for storing geometric location. The maps provide remarkable information about the evolution of the MEPI from Colombian regions between 2011 and 2016 and the maps are a symbolic representation of the MEPI methodology. The maps are shown in a 0-1 scale, where light and darkness level is an indication of energy deprivation.

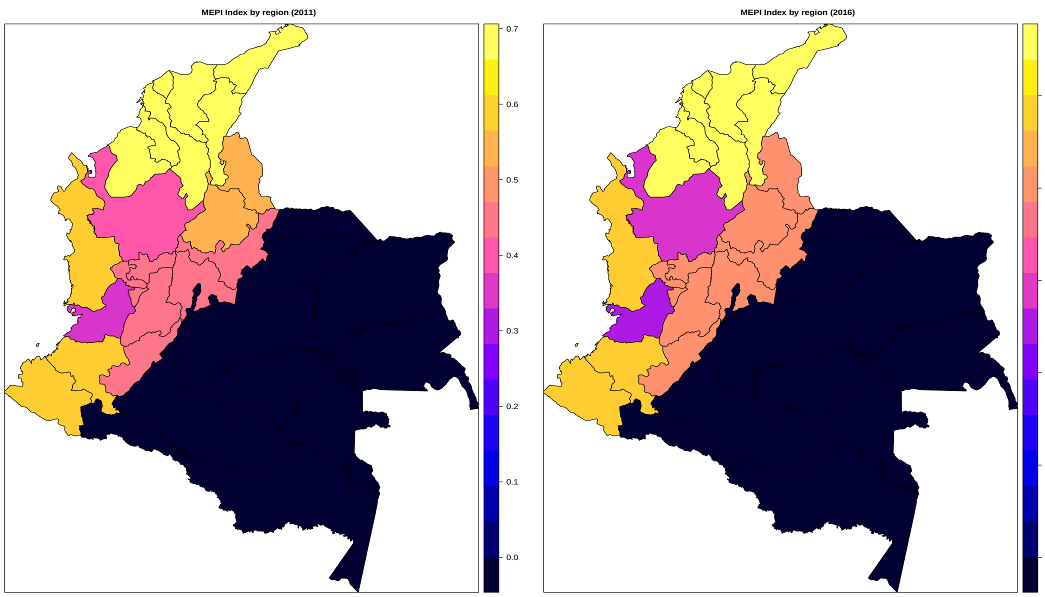
Figure 3.2 presents general information of the main regions of Colombia as follow: Caribbean; Antioquía; Central; ; Pacific, the Cauca Valley, Orinoquía and Amazon regions. Colombia is divided into 31 departments, each with urban, intermediate and rural areas, as well as the capital district of Bogotá D.C (BOG). The Caribbean region is divided into: Atlántico (ATL), Bolívar (BOL), César (CES), Córdoba (COR), La Guajira (GUA), Magdalena (MAG), and Sucre (SUC). The Central region into Boyacá (BOY), Caldas (CAL), Cundinamarca (CUN), Huila (HUI), Quindío (QUI), Risaralda (RIS), and Tolima (TOL). The Eastern into Norte de Santander (NSD) and Santander (SAN). The Pacific into Cauca (CAU), Chocó (CHO), and Nariño (NAR). Orinoquía and the Amazon region into Amazonas (AMA), Arauca (ARA), Casanare (CAS), Caquetá (CAQ), Guainía (GUA), Guaviare (GUV), Meta (MET),Putumayo (PUT), Vaupés (VAU), and Vichada (VIC). Antioquía (ANT), and Cauca Valley regions.

FIGURE 3.2: Map of Colombia: Capital district and departments of Colombia

Source: Adapted from Free Software Foundation GNU

Figure 3.3 and Table 3.1 provide the maps and MEPI by rural regions from 2011 and 2016. The rural samples do not contain information of Orinoquía and Amazon regions. Table 3.1 contains a detailed summary indicating the size of each sample and the MEPI obtained for each rural region respectively. The results show important differences between the regions. For instance, Caribbean and Pacific present the highest MEPI (2011) of 0.66 and 0.59 respectively, with an MEPI (2016) of 0.54 and 0.47. In contrast, the Cauca Valley and Antioquía have an MEPI (2011) corresponding to 0.34 and 0.42 respectively, and an MEPI (2016) of 0.25 and 0.30.

FIGURE 3.3: MEPI in rural areas of Colombia by region from 2011 to 2016.



a. MEPI 2011. b. MEPI 2016.

TABLE 3.1: Detailed summary of MEPI in rural areas by region of Colombia from 2011 to 2016

Region	Sample 2011 (Households level)	MEPI 2011	Sample 2016 (Households level)	MEPI 2016
Caribbean	1,400	0.66	545	0.54
Antioquía	612	0.42	871	0.30
Central	695	0.43	1,101	0.41
Eastern	1,900	0.52	1,194	0.39
Pacific	2,317	0.59	1,079	0.47
Cauca Valley	375	0.34	696	0.25

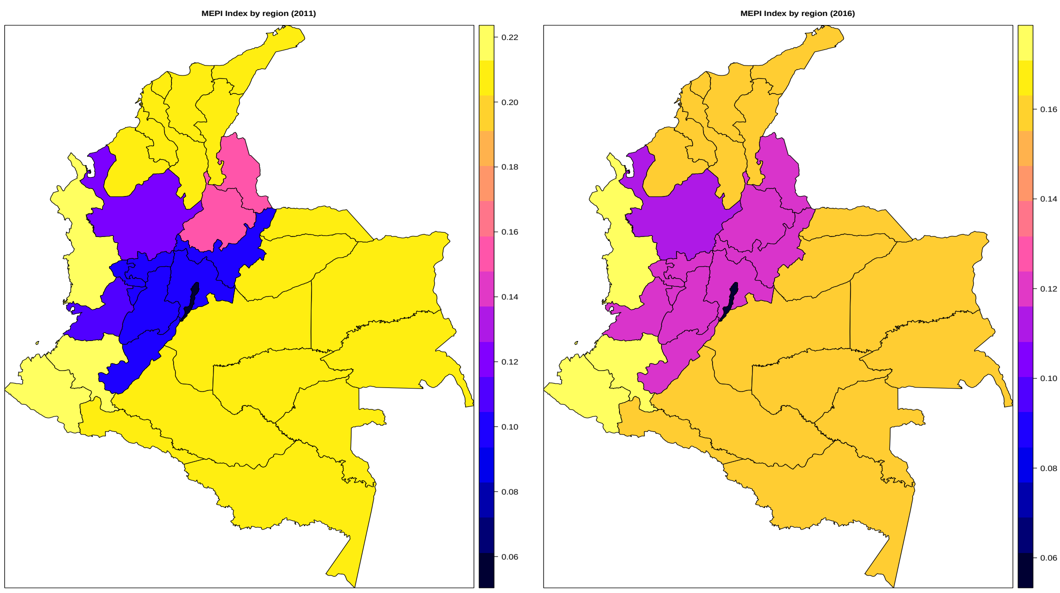
Figure 3.4 and Table 3.2 show the maps and MEPI for urban regions. Table 3.1 presents the results obtained for each urban region respectively. The highest MEPI was obtained in the Pacific region from 0.21 to 0.17 between 2011 and 2016. A similar result was found in the Caribbean region from 0.20 to 0.15 in the same period. The lowest MEPI

was achieved in the city of Bogotá D.C.

TABLE 3.2: Detailed summary of MEPI in urban areas by region of Colombia from 2011 to 2016

Region	Sample 2011 (Households level)	MEPI 2011	Sample 2016 (Households level)	MEPI 2016
Caribbean	3,216	0.20	1,522	0.15
Metropolitan Medellín	1,116	0.11	1,694	0.10
Central	696	0.10	1,492	0.12
Eastern	2,103	0.15	1,498	0.11
Metropolitan Cali	1,240	0.11	2,981	0.12
Bogotá D.C.	1,185	0.06	1,824	0.06
Pacific	3,034	0.21	1,711	0.17
Orinoquía and Amazonia	645	0.20	507	0.15
San Andrés islands	574	0.14	534	0.14

FIGURE 3.4: MEPI in urban areas of Colombia by region from 2011 to 2016.



a. MEPI 2011. b. MEPI 2016.

3.3 Correlation analysis of variables

As a robustness check of the empirical model specifications, tests related to the existence of serial correlation and heteroskedasticity were performed on the residuals. The assumption of the linear regression model are errors of zero; hence they are uncorrelated and have equal variances. This model is known as the Best Linear Unbiased Estimator

(BLUE). The first step was to apply tests related to serial correlation (Durbin-Watson [Savin and White, 1977], correlogram and serial correlation test [Durbin and Watson, 1951]) and Heteroskedasticity test (Jarque-Bera [Jarque and Bera, 1980] and Breusch-Pagan-Godfrey [Waldman, 1983]). Tables 3.3 and 3.4 present the results for the normality, serial correlation and homocedasticity.

Table 3.3: Serial correlation and heteroskedasticity tests on the all sample

All sample			
Rural (2011)		**Rural (2016)**	
Test	Value/Stat	Test	Value/Stat
Durbin-Watson	1.292	Durbin-Watson	1.057
Serial Correlation	0.000	Serial Correlation	0.000
Jarque_Bera	0.000	Jarque_Bera	0.000
Breusch-Pagan-Godfrey	0.000	Breusch-Pagan-Godfrey	0.000
Urban (2011)		**Urban (2016)**	
Test	Value/Stat	Test	Value/Stat
Durbin-Watson	0.703	Durbin-Watson	0.972
Serial Correlation	0.000	Serial Correlation	0.000
Jarque_Bera	0.000	Jarque_Bera	0.000
Breusch-Pagan-Godfrey	0.000	Breusch-Pagan-Godfrey	0.000

Table 3.4: Serial correlation and heteroskedasticity tests on the low status sample

Low status sample			
Rural (2011)		**Rural (2016)**	
Test	Value/Stat	Test	Value/Stat
Durbin-Watson	1.275	Durbin-Watson	1.558
Serial Correlation	0.000	Serial Correlation	0.000
Jarque_Bera	0.000	Jarque_Bera	0.000
Breusch-Pagan-Godfrey	0.000	Breusch-Pagan-Godfrey	0.000
Urban (2011)		**Urban (2016)**	
Test	Value/Stat	Test	Value/Stat
Durbin-Watson	0.697	Durbin-Watson	0.949
Serial Correlation	0.000	Serial Correlation	0.000
Jarque_Bera	0.000	Jarque_Bera	0.000
Breusch-Pagan-Godfrey	0.000	Breusch-Pagan-Godfrey	0.000

3.4 Ordinary Least Squares (OLS)

Table 3.5 presents the estimation results for NQSLs 2011 and 2016 in rural samples reflecting the empirical model, which is based on Least Squares which is corrected by cross-correlation. The results in Equations 3.4 and 3.4 show that all variables have the expected sign, with the exception of a few cases that were not statistically significant. Therefore, most variables were statistically significant. This sections presents all results in average terms due to OLS regression method.

The results indicated that income is a significant factor in determining the correlations with EI. For instance, income indicates a statistically significant (at least at the 0.1 percent level) and strong negative correlation with IE. For the full sample, in NQSL 2011 the elasticity corresponds to (-0.06); and in 2016 to (-0.140). This result means that in 2011 a household income increase of 100% meant the reduction of EI by 6% and in NQSL 2016 an income increase of 100% meant the reduction of EI by 14%. These results correspond to the decrease of the MEPI between 2011 to 2016.

Low status is the reference category and is the lowest level of socioeconomic status. The middle status is statistically significant (at least at the 0.1 percent level); the difference between low and middle status is -0.878%, indicating that for every 1% increase in middle status energy poverty is reduced by -0.878%. This interpretation is the same for high status -1,572%. Both middle and high status are statistically significant (at least at the 0.1 percent level). Related to head of household, where: *0 = Female head and 1 = Male head*, the regression coefficients in NQSL 2011 of 0.027%; and in NQSL 2016 of 0.007% reflect that men have an average higher EI than women. Nevertheless these results are not significant. In regard to education the reference category is basic education. The difference between basic and secondary education represents -0.769% in NQSL 2011, and between basic and tertiary education -0.612% in NQSL 2016. These results suggest that secondary and tertiary education have a strong negative correlation with EI.

Finally, with respect to the regressions of low status the results are statistically significant (at least at the 0.1 percent level). In NQSL 2011 the result is inelastic (-0.000) and in NQSL 2016 it is (-0.138). In the first sample the result might suggest a poverty trap and as expected in NQSL the elasticity is higher; this result agrees with the increase of the MEPI.

The equations 3.4 and 3.4 for NQSL 2011 and NQSL 2016 in rural areas respectively can be written as:

$$EI_{2011} = -0.640 - 0.060\, Income^{***}_{2011} - 0.238\, Middle\,stat^{***}_{2011} - 0.887\, High\,stat^{***}_{2011}$$

$$+\, 0.027\,\mathrm{Head}_{2011} - 0.129\, Sec\,educ^{**}_{2011} + 0.028\, Ter\,_{2011} + 0.284\, AR(1) + 0.228\, AR(2) \quad (3.1)$$

$$EI_{2016} = -0.765 - 0.140\, Income^{***}_{2016} + 0.342\, Middle\,stat^{***}_{2016} - 0.260\, High\,stat_{2016}$$

$$+\, 0.007\,\mathrm{Head}_{2016} - 0.051\, Sec\,educ_{2016} - 0.229\, Ter\,educ^{***}_{2016} + 0.667\, AR(1) - 0.120\, AR(2) \quad (3.2)$$

Table 3.5: Correlations between EI and socioeconomic variables in rural areas of Colombia from 2011 to 2016

	All		**Low status**	
Variables	Rural (2011) 5,675 Hh	Rural (2016) 4,436 Hh	Rural (2011) 5,467 Hh	Rural (2016) 4,338 Hh
Intercept	-0.640***	-0.765***	-0.848***	-0.430***
	(0.000)	(0.000)	(0.000)	(0.000)
Income	-0.060***	-0.140***	-0.000***	-0.138***
	(0.000)	(0.000)	(0.000)	(0.000)
Middle status	-0.238***	0.342***	—	—
	(0.000)	(0.000)		
High status	-0.887***	-0.260	—	—
	(0.000)	(0.319)		
Male head	0.027	0.007	0.001	0.008
	(0.159)	(0.570)	(0.929)	(0.525)
Sec educ	-0.129**	-0.051	-0.120*	-0.017
	(0.005)	(0.113)	(0,011)	(0.110)
Ter educ	0.028	-0.229***	0.018	-0.048*
	(0.735)	(0.009)	(0.830)	(0.032)
AR(1)	0.284***	0.667***	0.283***	0.660***
	(0.000)	(0.000)	(0.000)	(0.000)
AR(2)	0.228***	-0.120***	0.233***	-0.122***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.226	0.483	0.213	0.478
Adjusted R-squared	0.225	0.482	0.212	0.477
F-statistic	184.04	414.93	211.51	496.28

Where *p<0.05; **p<0.01; ***p<0.001 Significant.

Table 3.6 shows the estimation results for NQSLs 2011 and 2016 in urban samples reflecting the empirical model; this model is corrected by cross-correlation. The results in Equations 3.4 and 3.4 illustrate that all variables have the expected sign. Therefore, most variables were statistically significant.

The results demonstrate that income is a significant factor in determining the correlations with EI. In particular, income indicates a statistically significant (at least at the 0.1 percent level) and strong negative correlation with IE. As expected the elasticity is lower compared to rural areas. For the full sample, in NQSL 2011 the elasticity corresponds to -0.04; and in 2016 represents -0.09 roughly. These results mean that in 2011 a household income increase of 100% meant the reduction of EI by 4% and in NQSL 2016 an income increase of 100% meant the reduction of EI by 9%. These results correspond to the decrease of the MEPI between 2011 to 2016 in urban areas.

In NQSL 2011, the middle status is statistically significant (at least at the 0.1 percent level); the difference between low and middle status is -1.577%, indicating that for every 1% increase in middle status energy poverty is reduced by -1.577%. This interpretation is the same for high status -1,583%. Both status middle and high are statistically significant (at least at the 0.1 percent level). In NQSL 2016 the elasticities correspond for middle status to -1321%, and for high status to -1.33%. As in the rural sample, the results for the regressions of low status are statistically significant (at least at the 0.1 percent level) for income and this may suggest the existence of a poverty trap.

TABLE 3.6: Correlations between EI and socioeconomic variables in urban areas of Colombia from 2011 to 2016

	All		**Status low**	
Variables	Urban (2011) 10,902 Hh	Urban (2016) 9,439 Hh	Urban (2011) 9,198Hh	Urban (2016) 7,710Hh Hh
Intercept	-1.387***	-1.274***	-1.342***	-1.262
	(0.000)	(0.000)	(0.000)	(0.000)
Income	-0.041***	-0.089***	-0.000***	-0.090***
	(0.000)	(0.000)	(0.000)	(0.000)
Middle status	-0.183***	-0.047***	—	—
	(0.000)	(0.000)		
High status	-0.196	-0.056	—	—
	(0.099)	(0.594)		
Male head	-0.014	0.000	0.001	0.002
	(0.156)	(0.984)	(0.919)	(0.672)
Sec educ	-0.015**	0.013	-0.120	0.003
	(0.003)	(0.205)	(0.011)	(0.324)
Ter educ	-0,016*	0.024***	0.018	0.006***
	(0.034)	(0.000)	(0.830)	(0.000)
AR(1)	0.181***	0.430***	0.283***	0.439***
AR(2)	0.147***	0.195***	0.233***	0.246***
R-squared	0.11	0.38	0.10	0.40
Adjusted R-squared	0.11	0.38	0.10	0.40
F-statistic	157.21	546.50	152.20	577.87

Where *p<0.05; **p<0.01; ***p<0.001 Significant.

The equations 3.4 and 3.4 for NQSL 2011 and NQSL 2016 in urban areas respectively can be written as:

$$EI_{2011} = -1.387 - 0.041\, Income^{***}_{2011} - 0.183\, Middle\, stat_{2011} - 0.196\, High\, stat_{2011}$$

$$\text{- } 0.014\, \text{Head}_{2011} - 0.015\, Sec\, educ^{**}_{2011} - 0.016\, Ter\, educ^{*}_{2011} + 0.181\, AR(1) + 0.430\, AR(2)(3.3)$$

$$EI_{2016} = -1.274 - 0.089\, Income^{***}_{2016} - 0.047\, Middle\, stat^{***}_{2016} + 0.013\, Sec\, educ_{2016}$$

$$+ 0.024\, \text{Ter educ}^{***}_{2016} + 0.147\, AR(1) - 0.195\, AR(2)(3.4)$$

3.4.1 Pooled Cross-Sections

Pooled cross-section takes random samples in different time periods and different units; and each sample can be populated by different individuals (this can range from two periods to any large number). Among the advantages of this econometric technique are the following: time dummy variables can be used to capture structural change over time, and observations across different time periods allow for policy analysis [Mundlak, 1978]. In this subsection a robustness test was also applied on the residuals for the existence of serial correlation and heteroskedasticity. Table 3.7 shows the results for normality, serial correlation and homocedasticity.

Table 3.7: Serial correlation and heteroskedasticity tests on the pooled cross-section

Full sample			
Rural(2011 and 2016)		**Urban (2011 and 2016)**	
Test	Value/Stat	Test	Value/Stat
Durbin-Watson	1.002	Durbin-Watson	1.342
Serial Correlation	0.000	Serial Correlation	0.000
Jarque_Bera	0.000	Jarque_Bera	0.000
Breusch-Pagan-Godfrey	0.000	Breusch-Pagan-Godfrey	0.000

Table 3.8 illustrates the estimation results for NQSLs 2011 and 2016 in rural and urban samples, reflecting the empirical model using pooled cross-section focused on Least Squares which is corrected by cross-correlation. This sections presents all results in average terms due to OLS regression method applied to pooled cross-sections. The results are presented in Equations 3.4.1 and 3.4.1. The results are robust, all variables have the expected sign, and most variables were statistically significant.

Income was statistically significant (at least at the 0.1 percent level) for NQSLs rural and urban; the elasticities are -0.072 and -0.049, higher for rural areas as expected. The interpretation is that a 1% increase of income corresponds to a reduction of 0.072% and 0.049% in rural and urban samples. Low status is the reference category and is the lowest level of socioeconomic status. Middle status and high status are statistically significant (at least at the 0.1 percent level). The difference between low and middle status is -0.779% and -1.561% for rural and urban respectively. This indicates that a 1% change of status provides a reduction on energy poverty in 0.779% and 1.561%. The differences for high status correspond to -1.466% and -1.586% in rural and urban areas respectively. These results are consistent and show that socioeconomic status changes in the urban area have a higher effect than in the rural area. With respect to head of household, however, the results are not statistically significant. For secondary and tertiary education the results are statistically significant for secondary education (at least at the 0.1 percent level). In secondary education the elasticities are -0.692% and

-0.623%, which means that an increase of 1% will reduce energy poverty by 0.692% and 0.623% for rural and urban respectively. This result suggests that education plays a fundamental role in reducing energy poverty.

TABLE 3.8: Correlations between EI applying the pooled cross-section in full sample (2011 and 2016)

All sample (Pooled Cross Section; 2011 and 2016)			
Variables	**Rural Pooled**	**Variables**	**Urban Pooled**
Intercept	-0.613***	Intercept	-1.427***
	(0.000)		(0.000)
Income	-0.072***	Income	-0.049***
	(0.000)		(0.000)
Middle status	-0.166***	Middle status	-0.134***
	(0.000)		(0.000)
High status	-0.853***	High status	-0.159**
	(0.000)		(0.039)
Male head	0.019	Male head	-0-001
	(0.106)		(0.755)
Sec education	-0.079**	Sec education	-0.010**
	(0.009)		(0.008)
Ter education	-0.072	Ter education	-0.008
	(0.263)		(0.110)
AR(1)	0.427***	AR(1)	0.267***
AR (2)	0.163***	AR (2)	0.196***
R-square	0.33	R-square	0.194
Adjusted R square	0.33	Adjusted R square	0.193
F.statistic	575.54	F.statistic	543.93

Where *p<0.05; **p<0.01; ***p<0.001 Significant.

$$EI_{rur} = -0.613 - 0.072\, Income^{***}_{rur} - 0.166\, Middle\, stat^{***}_{rur} - 0.853\, High\, stat^{***}_{rur}$$

$$+\, 0.019\, \mathrm{Head}_{2011} - 0.079\, Sec\, educ^{**}_{2011} - 0.072\, Ter\, euc_{rur} + 0.427\, AR(1) + 0.163\, AR(2) \quad (3.5)$$

$$EI_{urb} = -1.427 - 0.049\, Income^{***}_{urb} - 0.134\, Middle\, stat^{***}_{urb} - 0.159\, High\, stat^{**}_{urb}$$

$$-\ 0.001\ \mathrm{Head}_{urb} - 0.010\, Sec\, educ^{**}_{urb} - 0.008\, Ter\, educ_{urb} + 0.267\, AR(1) - 0.196\, AR(2) \quad (3.6)$$

Combinations of Pooled Cross-Sections

In this subsection is presented the results related to combinations of pooled cross-sections with the year of reference 2011. This quantitative analysis allows to research relationship of variables between the years 2011 to 2016 by comparing observations across space or observations over time years 2011 to 2016. This econometric method can be suitable for analysis of energy policy.

Table 3.9 presents the combination time estimation results for NQSLs 2011 and 2016 in rural and urban samples, reflecting the empirical model using pooled cross-section based on Least Squares which is corrected by cross-correlation. Also, This sections presents all results in average terms due to OLS regression method applied to pooled cross-sections. The results show that most of the variables are statistically significant in rural areas as follows: Y16, income, income*Y16, high status and secondary education. Urban as follows: income, middle status, secondary education and tertiary education.

The results allow to study the evolution of the year 2011 to 2016. In rural, as expected, the variables statistically significant are a strong negative correlation with respect to EI. The income has a changed by 5.8% between the year 2011 to 2016 in the reduction of IE. For high status a reduction of 77.8% and secondary education the reduction was in 7.1%. The effect cross shows for income between the year 2011 to 2016 $(-0.058 + (-0.093)) = 0.151$, is in 15.1%. With respect to urban results, also the variables statistically significant are a strong negative correlation with respect to EI. The income has a changed by 4.0% between the year 2011 to 2016 in the diminishing of IE. Middle status has a reduction of 17.7%, secondary education the reduction was in 1.5% and tertiary education was in 1.9%.

The results are presented in Equations 3.4.1 and 3.4.1. The results are robust, all variables have the expected sign, and most variables were statistically significant.

$$EI_{rur} = -0.654 + 0.341\, Y16^{***}_{rur} - 0.058\, Income^{***}_{rur} -$$

$0.093\,\text{Income*Y16}^{***}_{rur} - 0.051\, Middle\, stat_{rur} - 0.778\, High\, stat^{***}_{rur}$
$+ 0.025\, Head_{rur} - 0.018\, Male\, head * Y16_{rur} - 0.071\, Sec\, educ^{*}_{rur}$
$- 0.076\, Ter\, euc_{rur} + 0.425\, AR(1)$
$- 0.163\, AR(2)(3.7)$

$$EI_{urb} = -1.429 + 0.028\, Y16_{urb} - 0.040\, Income^{***}_{urb}$$

- $0.177\,\text{Middle stat}^{***}_{urb} - 0.182\, High\, stat_{urb} - 0.005\, Head_{urb}$
$- 0.013\, Male\, head * Y16_{urb} - 0.015\, Sec\, educ^{*}_{urb}$
$- 0.019\, Ter\, educ^{*}_{urb} - 0.019$
$+ 0.179\, AR(1) - 0.151\, AR(2)(3.8)$

TABLE 3.9: Correlations between EI applying time combinations of pooled cross-section in full sample (2011 and 2016)

All sample (Pooled Cross Section; 2011 and 2016)			
Variables	**Rural Pooled**	**Variables**	**Urban Pooled**
Intercept	-0.654***	Intercept	-1.429***
	(0.000)		(0.000)
Y16	0.341***	Y16	0.028
	(0.000)		(0.249)
Income	-0.058***	Income	-0.040***
	(0.000)		(0.000)
Income*Y16	-0.093***	Income*Y16	0.000
	(0.000)		(0.920)
Middle status	-0.051	Middle status	-0.177***
	(0.130)		(0.000)
High status	.0.778***	High status	-0.182
	(0.000)		(0.128)
Male head	0.025	Male head	-0.005
	(0.150)		(0.675)
Male Head*Y16	-0.018	Male Head*Y16	-0.013
	(0.443)		(0.527)
Sec education	-0.071*	Sec education	-0.015*
	(0.019)		(0.006)
Ter education	-0.076	Ter education	-0.019*
	(0.238)		(0.016)
AR(1)	0.425***	AR(1)	0.179***
AR(2)	0.163***	AR(2)	0.151***
R-square	0.343	R-square	0.114
Adjusted R square	0.342	Adjusted R square	0.113
F-statistic	0.000	F-statistic	0.000
Durbin-Watson	2.03	Durbin-Watson	2.02

Where *p<0.05; **p<0.01; ***p<0.001 Significant.

Chapter 4

DISCUSSION AND CONCLUSIONS

4.1 Discussion

Colombia plays an important role in the Total Energy Primary Supply (TPES) in the world. In 2014 it accounted for 5.06 quadrillion British Thermal Units (BTU), 25^{th} in the world, similar to countries such as France and South Africa. The country's energy sector is based mainly on the production of coal, oil and natural gas, in that order. In 2016 oil production was 46.47 Mtoe; coal production was 58.83 Mtoe; and Natural gas was 9.58 Mtoe [Birol et al., 2017]. Colombia's electric power generation capacity is approximately 16,750 MW. Hydro-power accounts for 10,960 MW (about 66%) and thermal generation units for 4,850 MW (about 29%), of which 3,509 MW correspond to gas power plants and 1,341 MW correspond to coal-fired power plants[3].

Colombia is the fourth largest economy in Latin America by GDP (Constant 2010 USD) and accounts for 372.31 billion dollars [WB, 2018]. Colombian exports are mainly focused on minerals and fuels (54%); coffee, tea and spices (6.9%); gems and precious metals (5.3%); live trees, plants and cut flowers (3.8%); plastic products (3.6%) and other goods (8.4%) [IMF, 2018]. The GINI coefficient decreased from 53.5 in 2011 to 49.7 in 2017. Nonetheless, Colombia is still a country of high inequality [WB, 2018].

This paper calculates the MEPI in rural and urban areas at national and regional levels between 2011 and 2016. The results show a reduction in the level of energy poverty. In urban areas the MEPI was reduced from 0.16 to 0.11. According to this result the levels

[3]Colombia - Electric Power and Renewable Energy Systems.http://www.export.gov/article?id=Colombia-electric-power-and-renewable-energy-systemsl

of MEPI in urban areas are low. Nonetheless, Caribbean and Pacific urban areas must still reduce energy poverty levels. With respect to rural areas, the MEPI was diminished from 0.55 in 2011 to 0.40 in 2016. These indicators are high and comparable to such Asian countries as Vietnam and Pakistan [Nussbaumer et al., 2013]. Despite efforts to reduce energy poverty in rural areas, the energy policy have not been enough. The most problematic situation is in the Caribbean and Pacific regions, where levels correspond to 0.54 and 0.47 respectively.

Among the possible effects of high levels of poverty are diseases such as pneumonia, stroke, ischaemic heart disease, chronic obstructive pulmonary disease and lung cancer. According to the World Health Organization (WHO)[4], roughly 3 billion people cook in the world using polluting open fires or simple stoves fuelled by kerosene, biomass (wood, animal dung and crop waste) and coal. In Colombia the NQSL (2016) indicates as follows: 95% of rural households had electricity; 60.1% aqueduct water; 27.3% garbage collection; 17.1% sewage system; and 11.9% natural gas service. These low levels of public service coverage suggest the delay and lack of investment in rural areas, especially those areas most isolated from urban centers. In 2016 the use of cooking fuels in rural areas was given as: 44.6% firewood; 48.9 % LPG and 3.5% NG.

The regressions using pooled cross-sections showed the existence of statistically significant correlation between energy intensity and socioeconomic factors. For instances, in all cases a strong negative correlation was identified between income, socioeconomic status and head level of education. Higher status correlates to better public services, and higher level of education of household head may lead to better salaries allowing access to more goods and thus reducing energy poverty.

4.2 Conclusion

This work provides two contributions. First, the MEPI was calculated in rural and urban areas for the two periods of 2011 and 2016. Further, the MEPI was calculated for each of Colombia's regions. Additionally, maps were created based on shape files that store geometric and data location. Second, this work determined and analyzed the correlations between Energy Intensity by household and socioeconomic variables such as: income, education, social status and head of household from empirical evidence in Colombia.

The MEPI is a powerful and fitting tool to evaluate energy poverty at various levels (in this study the national and regional levels). The use of the MEPI methodology

[4]World Health Organization (WHO).https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health

demonstrates that the levels of the MEPI are higher in rural than urban areas. As expected the outcomes show that the MEPI was reduced between 2011 to 2016. Despite efforts to reduce energy poverty in rural areas between 2011 to 2016, the levels are still higher than desired, roughly equivalent to countries such as Vietnam, Pakistan and Namibia [Nussbaumer et al., 2013]. The Caribbean and Pacific rural regions have high levels of energy deprivation, 0.54 and 0.47 respectively, comparable to some countries in southern Africa such as Angola and Namibia [Nussbaumer et al., 2012]. By contrast, in urban areas the MEPI is low compared to rural areas. For the main cities of Colombia, including Bogotá D.C, Metropolitan Cali and Metropolitan Medellín the index provides scores between 0.06 and 0,12, corresponding to the lowest level of energy deprivation.

The results of the study identified statistically significant correlations between energy intensity by household and income, socioeconomic status, and education. As expected the results show that income is significant and higher in rural households than urban households. Furthermore, elasticities were reduced from NQSL (2011) to NQSL (2016). As expected, middle status had a strong negative correlation with EI, also statistically significant. Finally, the level of education of the head of household had a strong negative correlation with respect to EI.

Despite political efforts to reduce EI in rural communities, no major changes were observed in terms of the substitution of conventional for modern fuels according to empirical evidence. The Pacific and Caribbean regions have the highest levels of EI. This dissertation suggests a polarized vision of Colombia, consisting at one end of primarily urban areas with low levels of energy poverty, and at the other of rural areas with high energy poverty. Moving forward, policy makers and national authorities need to address the problem of investment in the implementation of access to cleaner cooking fuels, infrastructure and public services. The government must study the application of subsidies for the renewable sources. For instance, the pacific region has hydro energy potential as well as the Caribbean region has an important wind and solar energy resources.

This study contributes to the literature by calculating and analyzing the correlations between socioeconomic aspects in rural and urban areas with respect to EI using two recognized techniques, OLS and Pooled Cross-Section. For future work, it would be important to research other related socioeconomic factors and to expand the use of econometric tools and to determine causal relationships.

4.3 Declaration of interest

None

4.4 Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or non-profit sectors.

4.5 Appendix - All sample statistics

The appendix Table presents summary statistics for the NQLSs 2011 and 2016 in rural and urban full samples. This table allows to establish differences between the samples used for the regressions and the full sample in relation to the data removed from the rural and urban samples used in the regressions.

FIGURE 4.1: Appendix Table presents the full sample and missing data of NQSLs 2011 and 2016 for rural and urban sample

Sample	NQSL 2011 (Rural) Hh 7414	NQSL 2016 (Rural) Hh 5488	NQSL 2011 (Urban) Hh 14624	NQSL 20116(Urban) Hh 13900
Continuous variables				
Ei per household	0.54	0.41	0.16	0.13
Income	221.7	411.6	461.5	676.1
Counting variables				
Status				
Household does not know the status	236	185	1	16
Without status	305	231	1	94
Empty	1117	320	1	71
Head household				
Empty	1	964	1	1
Education				
Empty	137	920	3490	3850

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