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Regional analysis across Colombian departments: a non-parametric study of energy use

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A R T I C L E I N F O

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A B S T R A C T

The analysis of energy use is important in emerging economies and especially in the manufacturing industries, as energy is a key factor of sustainable development. This research analyses and evaluates the features of regional energy use and efficiency across Colombian departments in the manufacturing industries for the period between 2005 and 2013 by applying two Malmquist data envelopment analysis models. The results indicate significant difference in energy use and efficiency across Colombian departments in the manufacturing industries. The results of the Malmquist indexes determine that various manufacturing industries across Colombian departments have a high potential to increase energy efficiency. Several manufacturing industries across Colombian departments have experienced gains in productivity, a growth in efficiency, an improvement in the relationship between inputs and outputs and scale production and advances in innovation through new technologies. This technique allows to make comparisons and improves energy policies to increase energy efficiency and decrease CO_2 emissions. The application of panel data models indicate that increases in energy prices, exports and productivity lead to better energy use, while a higher presence of energy intensive sectors and small and medium enterprises across Colombian departments reduce energy efficiency. The methods selected in this research generated consistent, robust and reliable estimates related to energy use and CO_2 emissions for regional studies. The findings of this study indicate that diverse energy policies should implement in the industrial sector across Colombian departments and that they should contribute to improvements in energy use, especially in small and medium companies and energy intensive sectors.

1. Introduction

Energy is used in large quantities to run industrial units, process materials and mine, transport goods and people and carry out the activities of daily life. This energy use is causing substantial environmental and social impacts, both in the form of local environmental damage as well as at the global climate scale (Gottschalk, 1996). Currently, the challenge is to reduce energy use while maintaining industrial and individual activities, with the aim of increasing development and living standards in an economically, environmentally and socially sustainable way (UNIDO, 2011).

Energy use is a vital input in the production of goods and services in the manufacturing industries, which account for a third of global energy demand (IEA, 2010). It is among the manufacturing industries where improvements in energy efficiency are among the least-cost options to decrease greenhouse gas (GHG) emissions today and in the coming decades. Moreover, improving energy efficiency has other benefits for achieving industrial and commercial competitiveness and energy security (Worrell et al., 2009) and the coverage of energy efficiency regulation worldwide extended to more than a quarter of global energy consumption, which is key to limit world energy demand growth (IEA, 2015).

Energy use can be measured with different techniques. The traditional measurement is energy intensity indicators that measure the quantity of energy required to perform an activity in monetary or physical units several studies have used these indicators e.g., Fiorito (2013) in the context of modern economies, and Hasanbeigi et al. (2012) for the textile industry in Iran.

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Decomposition analysis is used in energy studies to determine the independently features affecting energy use e.g., Shao et al. (2014) used this technique to analysis industrial energy consumption in Tianjin, China, and Robaina-Alves et al. (2015) applied this technique to evaluate change in energy-related CO_2 emissions in Portuguese tourism. Econometric models are used to evaluate the effects of different variables on energy efficiency performance e.g., Wang et al. (2015) applied an econometric model based on panel data techniques to analysis the relationship between urbanization and energy use in Association of Southeast Asian Nations (ASEAN) countries, and Hashem et al. (2011) used econometric models to evaluate energy use patterns in canola production in Iran. In the last decades, Data Envelopment Analysis (DEA) has been utilized as a technique that allows to evaluate energy efficiency within a framework with inputs and outputs. These techniques have allowed increase the knowledge on energy trends and features from different approaches.

Data Envelopment Analysis (DEA) is used in this study taking into account its advantages to determine the role of input substitution in achieving energy efficiency and compare relative efficiency across of Decision Making Units (DMUs). This is a non-parametric technique to assess the performance or relative efficiencies of various entities or Decision Making Units (DMUs) on the basis of multiple energy inputs and gross production or carbon dioxide emissions as outputs, where the models are CCR (Charnes, Cooper and Rhodes) (Charnes et al., 1978) and BBC (Banker, Charnes and Cooper) (Banker et al., 1984).

This method has been conducted to analyse performance in energy sectors in many countries and to compare countries, regions and sectors. For example, Sözen and Alp (2009) used DEA to compare GHG emissions between Turkey and European Union countries, establishing that the trends of greenhouse and other harmful emissions is affected by combustion conditions, fuel sources, technology, and emission control policies and instruments. Hu et al. (2011) calculated the energy efficiency of 23 regions in Taiwan using a four-stage DEA procedure, and determined a worsening trend in the nation's energy efficiency over 1998–2007, with urban areas usually more efficient in energy use than rural areas. Wang et al. (2013) studied total-factor energy and environmental efficiency in 29 regions of China for the period 2000–2008, applying DEA techniques to assess the energy and environmental efficiency, showing that the eastern area of China has the best energy and environmental efficiency whereas in the western area the efficiency was the poorest. Suzuki et al. (2013) used a DEA model to evaluate energy-environment efficiency for ten regions in Japan, determining that the efficiency index of all DMUs reduces meaningfully in comparison with base period as a consequence of the negative effect of the Fukushima disaster and related efforts to increase thermal power generation with associated higher fuel costs and CO_2 emissions. Wang and Wei (2014) determined energy savings, energy efficiency and potential of emissions reduction for the industrial sector in 30 Chinese cities over 2006–2010 through DEA, concluding that energy use and CO_2 emissions have decreased since 2006 in the cities studied and that cities with higher level of economic developed showed higher efficiency. Goto et al. (2014) used DEA to evaluate in Japanese manufacturing industries operational efficiency, unified efficiency under natural disposability or natural and managerial disposability, finding that environmental regulation has been effective for improving the performance of Japanese manufacturing industries and that GHG emissions are a primary source of unified inefficiency in the industries analysed. Honma and Hu (2014) used DEA to determine the total-factor energy efficiency (TFEE) of industries in 14 developed countries over 1995–2005, concluding that benchmarking countries provides useful information about energy efficiency improvements among inefficient industries. They also found that to improve inefficient industries, the countries should adapt energy conservation technologies from benchmark countries with the best performance levels. These studies have demonstrated the importance of DEA to the analysis of energy and environmental efficiency from different approaches.

This background shows that considerable research has been conducted on energy efficiency using DEA. However, studies on the performance of energy efficiency in manufacturing industries across regions in developing countries are limited. Therefore, the main contribution of this research is in using data envelopment analysis (DEA) and Malmquist indices to evaluate energy use, efficiency and CO_2 emissions in the manufacturing industry across Colombian departments.[1] Different variables related to energy and development from particular to each department are considered, which has rarely been considered in this field. In second-stage, the Malmquist-DEA indices are included as independent variables in different regression models applying panel data analysis to establish that independent variables should affect the results of energy efficiency and CO_2 emissions in the manufacturing sector of Colombian departments. Thus, this study provides a more truthful measurement of energy efficiency and CO_2 emissions in industrial sector across regions and compares traditional measurement with relative efficiencies from DEA to determine its reliability and robustness, and contributes to the literature of regional energy efficiency and CO_2 emission measurements especially in the Colombian context as a case of Latin-American, where studies of energy efficiency and CO_2 emission performance and their determinants is quite new. The study also contributes to the limited empirical evidence on energy efficiency and CO_2 emission as a comparative analysis across regions and factors and variables that determine their trends in the industrial sector over time. The research question that guides this study is the following: *What are the factors that determine better performance as energy efficiency in the manufacturing sector across Colombian departments?*

This paper is structured into five sections. The methods and data used in this study, such as Malmquist-DEA, Wilcoxon rank-sum test, data panel model and data construction, to analyse and compare the energy efficiency performance of manufacturing industries across Colombian departments are explained in the second section. The next section includes results and the fourth section shows discussion and implications of this study. The fifth section concludes and provides some policy suggestions.

2. Methods and data construction

2.1. The Malmquist-DEA

Fig. 1 illustrates the framework applied in this research, following Caves et al. (1982), Fare et al. (1990, 1993). The production frontiers shown as non-parametric distance functions implies the efficient grade of output (y) that can be generated from a given grade of input (x), and the supposition is made that this frontier can have variation in a period time Caves et al. (1982), Hjalmarsson and Veiderpass (1992). Fig. 1 describes the frontiers where the present (t) and future $(t+1)$ time periods are measured subsequently. In the presence of inefficiency, the relative movement of any given Colombian department in a period time will therefore differ on both its position relative generating technical efficiency and the location of the frontier itself denominated technical change. If inefficiency is unobserved, the productivity

[1] In Colombia, departments are sub-national political territories.

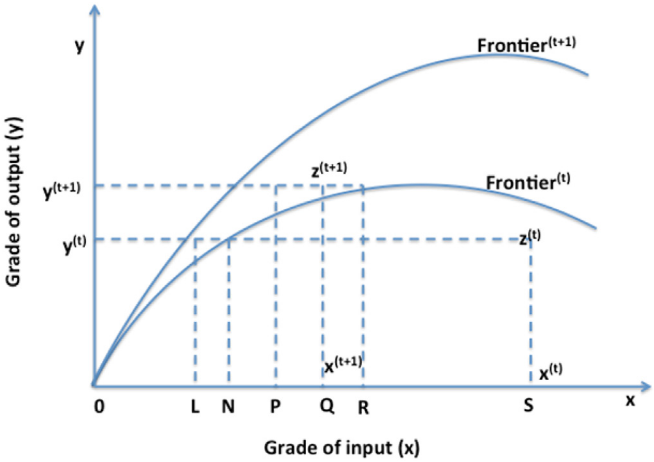

Fig. 1. Explanation of Malmquist index and productivity changes in a period time.

growth in the period time will be incapable of differentiating between enhancements that derive from a Colombian department "catching up" to its own frontier, and the result from the frontier itself changing in the period time (Price and Weyman, 1996).

For example, in this case, a Colombian department in period t is explained by the input/output bundle z(t), and an input-based measure of efficiency is assumed by the horizontal distance ratio 0N/0S. This denotes that inputs can be reduced with the aim of generating production in a technically efficient manner in period t (i.e., movement against the efficient frontier). By association, in period $t + 1$, inputs should be multiplied by the horizontal distance ratio 0R/0Q with the aim of achieving a comparable technical efficiency to that found in period t. Hence, the frontier has changed and 0R/0Q exceeds unity, even though it is technically inefficient when compared to the period $t + 1$ frontier Berg et al. (1992) and Worthington (1999).

Following Färe et al. (1994) and Färe and Grosskopf (1996), Table 1 shows Malmquist indexes calculated and the alternative results according to improvement or deterioration of the index measured from Equation (1) for productivity change index, (2) for technical efficiency and (3) for technical change.

Moreover, in Malmquist indices, Färe and Grosskopf (1996) described total factor productivity change (TFPC) in the one-input and one-output case the following manner (see Equation (4)):

$$TFPC = \frac{y^{t+1}/x^{t+1}}{y^t/x^t} \tag{4}$$

These indices are resolved through various series of linear programming models. The assumption indicates that in N Colombian departments each one uses variable amounts of K diverse inputs to generate M outputs. The vectors x_i y_i and the $(K \times N)$ input matrix X denote the features of the i_{th} department. The $(M \times N)$ output matrix Y contains the data of all departments in the example. The objective is to make a nonparametric envelopment frontier over the data following to Farrell (1957) as an input-orientated technical efficiency measures.

This analysis suggests two DEA models to assess energy efficiency, with the industrial sector of a Colombian department producing a vector of n outputs y from a vector of n inputs $x = (x_1, x_2,\ldots, x_n)$, and specifying that the vector y_i signifies the output package and the vector x_i signifies the input package of the i_{th} DMU, $i = 1 \ldots m$. For the DEA model that includes an undesirable output, the different studies suggest various alternatives (Zhou and Ang, 2008). In this research, we use reciprocal value of the undesirable output according to Ramanathan (2006) and Zhou and Ang (2008). In the model (1) proposed, the input–output package is (x_0, y_0), where the input package (x_{ji}) is the amount of input j (capital, labour, materials, energy) of DMU n, and the output package (y_{ji}) is the amount of output j (gross production and CO_2 emissions) of each department. The second model assesses efficiency achievements through a joint production framework that considers desirable and undesirable outputs simultaneously. The input vector includes energy (E), labour (L), capital (C), and materials (M), and the output vector contains as desirable and undesirable outputs gross production and carbon dioxide emissions, respectively.

2.2. Energy intensity and DEA scores of technical efficiency

Following Banker and Natarajan (2004), the Wilcoxon rank-sum test was assessed as a non-parametric alternative to establish whether the differences between the two sets are significant. In this study, this test was used to determine whether empirical distributions of DEA scores and energy efficiency measured as energy intensity (EI = energy per gross production) are different or equal, to establish if the technical efficiency of DEA is adequate to assess energy efficiency in the manufacturing industries of Colombian departments.

2.3. What aspects define energy efficiency in the manufacturing industries of Colombian departments?

To define that aspects influence or should explain different results of energy efficiency in Colombian department in the sample period different panel models are used. As dependent variable

Table 1
Possible results of three Malmquist indices.

Index	Result	Implication
Productivity change index:	>1	Productivity improvement
$\left[\left(\frac{D_o^t(x^{t+1},y^{t+1})}{D_o^t(x^t,y^t)}\right)\left(\frac{D_o^{t+1}(x^{t+1},y^{t+1})}{D_o^{t+1}(x^t,y^t)}\right)\right]^{1/2}$ (1)	=1	Unchanged productivity
	<1	Productivity deterioration
Technical efficiency:	>1	Technical efficiency improvement
$\frac{D_o^{t+1}(x^{t+1},y^{t+1})}{D_o^t(x^t,y^t)}$ (2)	=1	Unchanged technical efficiency
	<1	Technical efficiency deterioration
Technical change:	>1	Technical progress
$\left[\frac{D_o^t(x^{t+1},y^{t+1})}{D_o^{t+1}(x^{t+1},y^{t+1})} X \frac{D_o^t(x^t,y^t)}{D_o^{t+1}(x^t,y^t)}\right]^{1/2}$ (3)	=1	Unchanged technology
	<1	Technical regress

technical efficiency and energy efficiency (EI) are used and log transformed by the skewness and to improve normality. The model proposed is the following (see Equation (5)):

$$DV_{i,t} = \alpha_0 + \alpha_1 \, EP_{i,t} + \alpha_2 \, Exp_{i,t} + \alpha_3 \, EIS_{i,t} + \alpha_4 \, LPR_{i,t} + \alpha_5 \, SC_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $DV_{i,t}$ is dependent variable (defined as the DEA index or energy intensity); $EP_{i,t}$ defines the energy price for every Colombian department i in the industrial manufacturing sector in period t; $\mathrm{Exp}_{i,t}$ represents exports; $EIS_{i,t}$ represents the share of a department's manufacturing output generated from the most energy-intensive 2-digit sectors; LPR_{it} is labour productivity; and $SC_{i,t}$ represents company size in period t for each department i. The panel data method requires the following stages:

- To establish the adequate panel model the following tests are applied: The *F test* determines between the pooled the Ordinary Least Squares Model (OLS) and the fixed effects model (see Greene (2011)); *the Breusch-Pagan test* selects between the pooled OLS and the random effects model (see Breusch and Pagan (1980), Baltagi and Li (1990) and Baltagi and Wu (1999)); and the Hausman test determines between the fixed effects model and the random effects model (see Hausman (1978)).
- To establish the reliability and robustness of results these tests are applied: The *test for heteroskedasticity* uses a likelihood ratio test (for more details see Nair et al. (2009)) and the *Wooldridge test* to establish serial autocorrelation (see Drukker (2003) and Wooldridge (2010)).
- To correct the estimations, for the random effects is used maximum likelihood estimation (MLE) (see Calzolari and Magazzini (2012) and Karlsson and Skoglund (2004)) and for fixed effect model is used Driscoll and Kraay standard errors (see Driscoll and Kraay (1998)).

These estimations should generate restrictions and the results should be analysed carefully. For this reason, in this study, to compare the results of DEA and traditional measurements, different statistical tests are applied in every regression model to guarantee its robustness and reliability of outcomes.

2.4. Data construction

This empirical analysis examines department-level data from the Colombian manufacturing industries at 2-digit levels of aggregation from the Colombian International Standard Economic Classification (ISEC) for the years 2005–2013. The data are distributed by the Departamento Nacional de Estadística (Colombian Department of Statistics, DANE), and energy data are published by Superintendencia de Servicios Públicos (the Public Utility Superintendence, SSPD) through the SUI system and Unidad de Planeación Minero Energética (Unit of Mines and Energy Planning, UPME). The research covers 20 major departments with similar conditions in terms of manufacturing production, by their process, technologies, inputs and outputs. This guarantees the main requirements of DEA, that DMUs are evaluated under similar conditions through a set of comparable entities such as the manufacturing sector of primary departments, taking into account that all selected inputs and outputs are positive. These departments together accounted for 99.3% of the manufacturing production and 99.82% of the industrial energy consumption in Colombia in 2012–2013. Table 2 shows the variables used in DEA models and panel data techniques.

3. Results of the application to the manufacturing industry of Colombian departments

3.1. Results of the Malmquist indices

The first index of Malmquist DEA-model denominated technical efficiency is shown in Fig. 2. The average results for the manufacturing industries of Colombian departments are 0.886 for model (1) and 0.550 for model (2) suggesting possibilities to improve energy efficiency and decline CO_2 emissions in manufacturing industries across the country. In the case of model (1), the objective is to decrease all inputs to the largest extent possible by the same amount to accommodate any potential complementarity between energy and other inputs. The results suggest that it would be possible to decrease the inputs proportionately by 11.4% and still generate the given level of output. The results were different across departments and across years, showing that while Bogotá, Antioquia and Santander demonstrated 100% technical efficiency or achieved technical efficiency close to 100% each year, departments such as Cauca, Meta and Tolima could have decreased their inputs use proportionally by as much as 30% and still generated the given production level.

In contrast, the objective of model (2) is to reduce energy use without raising any other inputs or decreasing outputs, suggesting that Colombian manufacturing could decrease energy inputs by nearly 45% on average and continue to the same ranks of output and decrease CO_2 emissions without requiring additional inputs. Although the results of this model on average are low, states such as Bogotá, Santander and Antioquia emerge as 100% efficient or achieved technical efficiency close to 100% each year, whereas Cesar, Caldas and Magdalena are the worst performers by this model.

Table 3 shows the Malmquist indices for the sample. Results are similar for both models. The Malmquist index presented in column 1 as the total productivity change score (TFP) is on average close for both models (0.981 for model (1) and 1.007 for model (2)), suggesting that various manufacturing industries across Colombia achieved gains in productivity during the sample period, especially Antioquia, Bogotá, Meta and Valle. On average, for model (1) 45% and for model (2) 35% of departments decreased their productivity.

Column 2 shows the trends in the total efficiency index that implies the dissemination of best technologies and process in the administration of the organization as investment, strategies, administration, technical experience and management in the manufacturing industries across Colombian departments. We can see that this index it is closer to one in the DEA model (1), indicating an advance in efficiency during the sample period in the following departments: Antioquia, Atlántico and Risaralda. In model (1), 35% of departments decreased technical efficiency whereas for model (2) 35% improved their technical efficiency.

In column 3 (pure efficiency) and 5 (scale efficiency change) indicate diverse results, where some areas saw simultaneous improvements in both efficiencies and others saw improvements in one but losses in the other; the departments with the best performances were Antioquia, Atlántico, Huila, Risaralda and Santander. A better balance between inputs and outputs demonstrates improvements in pure efficiency. A growth of size in several manufacturing industries is the result of better scale efficiency during the sample period. In column 4, it is shown the index denominated technological change that implies innovation by application of new technologies. In model (2), this index is higher than in model (1), specifying that innovation grew, especially in the energy use and decreased CO_2 emissions, in the majority of departments. These results indicates that several Colombian departments have achieved improvements and progress in the Malmquist indices, which have allowed for a constant or growing

Table 2
Variables used in the analysis of industrial sector of Colombian departments.

DEA models		
Variables	Measurement	Source
Capital – input	A stock measured as the value of gross fixed value in dollars	Dane, the annual manufacturing survey
Labour – input	Total number of persons employed in industrial sector	Dane, the annual manufacturing survey
Material – input	Expenditure on materials in dollars	Dane, the annual manufacturing survey
Energy – input	Final energy consumption by industrial sector in Terajoules (TJ)	UPME, Energy balances
Gross production – output	Gross value of manufacturing production in dollars	Dane, the annual manufacturing survey
CO_2 emissions – output	Tonnes of CO_2 emissions (carbon emission factors come from Resolution 181401/2004, where natural gas is 56.1 tCO_2/TJ and electricity is 59.14 tCO_2/TJ)	UPME, Energy balances

Panel data model			
Variables	Measurement	Source	Hypothesis
Energy price	Energy price in dollar per TJ	UPME, Energy balances	A higher energy price to be related to more efficient use of energy and lower CO_2 emissions.
Exports	Value of exports per year in dollars	Dane, the annual manufacturing survey	Higher exports related to more efficient use of energy and lower CO_2 emissions.
Energy Intensive sectors	Percentage of the manufacturing production of a department generated from the five most energy-intensive 2-digit sectors (textiles, coke and refined oil products, rubber and plastic products, glass and glass products, and basic metals) following recommendations of DANE (2013) and Pardo Martínez, (2015).		It expects this variable to have an unfavourable effect on energy efficiency.
Labour productivity	Labour quality expressed as labour productivity (gross production per worker)	Dane, the annual manufacturing survey	A higher quality labour force is related to more efficient use of energy.
Size of companies	Percentage of the gross production in medium and small companies, according to the classification established by Colombian statistics office from the number of workers and output levels for every industrial sector	Dane, the annual manufacturing survey	Higher levels of output in SMEs are related to with lesser energy efficiency.

Note: The series were transformed as follows. First, the variables were deflated according to the respective wholesale price index. Second, all monetary variables are standardized in 2005 dollars.

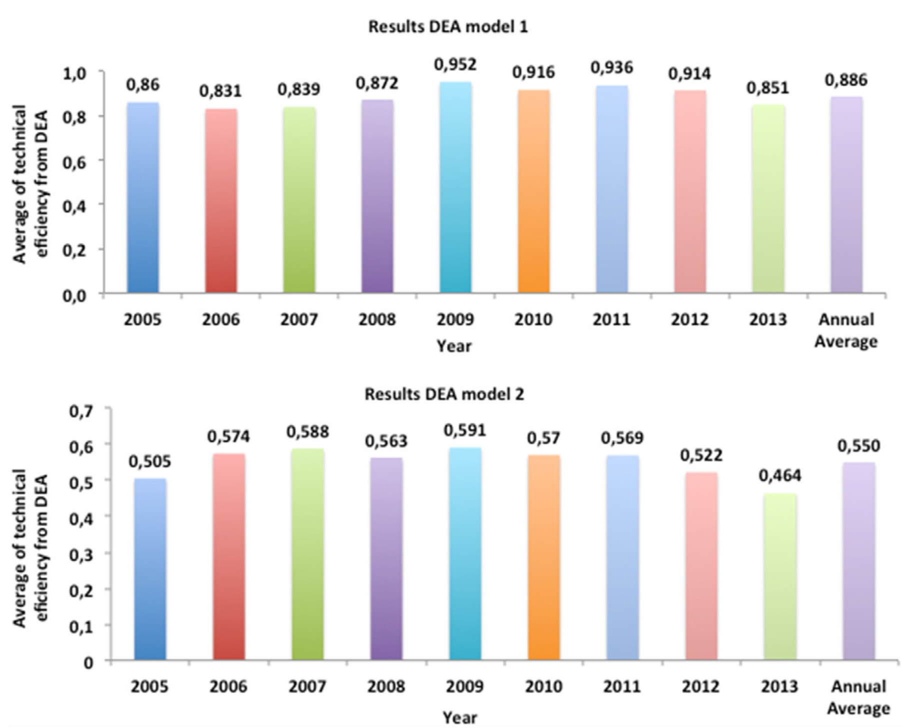

Fig. 2. Technical efficiency in the manufacturing industry of Colombian departments from Malmquist DEA models.

Table 3
Results of Malmquist indices in the Colombian industrial sector (2005–2013).

	DEA Malmquist Indices Model 1					DEA Malmquist Indices Model 2				
	TFP	EC	PE	TC	SEC	TFP	EC	PE	TC	SEC
05–06	1.012	0.935	0.966	1.082	0.968	1.099	0.930	1.200	1.182	0.775
06–07	1.040	1.043	1.014	0.997	1.029	0.782	1.306	1.024	0.598	1.275
07–08	0.900	1.085	1.049	0.829	1.034	1.175	0.990	0.951	1.188	1.041
08–09	1.048	1.083	1.102	0.968	0.982	1.066	1.122	1.061	0.950	1.057
09–10	0.974	0.978	0.955	0.996	1.024	1.114	0.930	0.959	1.199	0.970
10–11	1.079	1.018	1.026	1.059	0.992	1.246	0.543	0.947	2.293	0.574
11–12	1.025	0.934	0.974	1.097	0.959	1.239	1.105	0.917	1.121	1.204
12–13	0.804	0.886	0.892	0.907	0.994	0.570	0.847	0.821	0.672	1.032
Annual Average	0.981	0.993	0.996	0.9880	0.997	1.007	0.945	0.980	1.065	0.965

Note: TFP: Total Factor Productivity, EC: Total efficiency, PE: Pure Efficiency, TC: Technological Change, and SEC: Scale Efficiency Changes.

industrial sector across Colombia, which is a key factor in achieving sustainable development from an energy perspective. In summary, Colombian industrial sectors across departments have experienced gains in productivity, a growth in efficiency, an improvement in the relationship between inputs and outputs and scale production and advances in innovation through new technologies, which indicate that various regions of Colombia is key to improve energy efficiency and decrease CO_2 emissions.

3.2. Results of the Wilcoxon rank-sum test for the Malmquist DEA model, energy intensity and CO_2 emission intensity

Energy intensity and CO_2 emission intensity for the manufacturing industries across Colombian departments were 0.88 TJ/US$ and 51.35 ton/US$, respectively. The majority of the manufacturing industries across departments showed reduced energy intensity and CO_2 emission intensity per dollar of gross production during the sample period.

Results of DEA analysis in Colombian departments varied across years and have similar trends with traditional energy intensity indicators. The Wilcoxon test is used to determine if results of DEA analysis and traditional indicators have the equivalent distribution. In this case, the test reveals similar distribution for both measurements (see Table 4). These results indicate that DEA models proposed in this research are a suitable possibility to evaluate eco-efficiency from energy and CO_2 emissions perspective.

3.3. Determinants of energy use and CO_2 emissions in manufacturing industries of Colombian departments applying panel data techniques

Panel data models are applied to explain the difference in energy use and CO_2 emissions across Colombian departments during the sample period. Dependent variables in the regression models are defined as technical efficiency from DEA models, energy intensity and CO_2 emission intensity.

Results of regression analysis from two DEA models and energy intensity and CO_2 emission intensity using gross production have similar results (see Table 5). The adequate panel data model for all cases is a MLE for random effects model taking into account the presence of serial correlation and heteroskedasticity. This estimation is adequate for a distribution the endogenous variables given the exogenous variables (Wooldridge, 2010).

The results indicate that higher energy prices, exports and productivity drive to higher energy efficiency and decrease CO_2 emissions, while a higher presence of energy intensive sectors and small and medium companies reduces energy efficiency and increases CO_2 emission. Moreover, the signs of the coefficients for technical efficiency from DEA models are the inverse to energy intensity and CO_2 emission intensity as the two results are inverses of one another—energy intensity is the inverse of energy efficiency (U.S. Department of energy, 2008).

Table 4
Results of the Wilcoxon test.

Pairs	Wilcoxon test	
	Z	P-value
DEA Model 1 vs. EI (energy consumption/gross production)	3.767	0.000
DEA Model 1 vs. COI (CO_2 emissions/gross production)	−11.635	0.000
DEA Model 2 vs. EI (energy consumption/gross production)	−3.439	0.000
DEA Model 2 vs. COI (CO_2 emissions/gross production)	−11.635	0.000

Notes: EI: energy intensity, COI: CO_2 emission intensity.

4. Discussion and implication

4.1. The Malmquist indices and energy use

The Malmquist indices allowed to analysis and evaluate energy performance and efficiency across Colombian departments. The results of these indices show that some Colombian manufacturing industries have improved energy efficiencies while reducing CO_2 emissions. Departments with the best energy use in manufacturing industries according to DEA suggest the most energy efficiency and lower CO_2 emissions and should be considered model for the other departments. Moreover, the indices obtained by DEA-Malmquist show relative efficiency across Colombian departments in a systematic and structured manner, which should help to policy makers to make comparisons and define energy performance targets. Song et al. (2015) suggested similar implications of the DEA application in the context of Chinese cities.

In Colombia, it has suggested that the industrial sector has a possibility to reduce energy use by 5.3% in 2015, and the goal of the government is achieve a reduction of 3.43% for the same year UPME (2010), which confirm the results of DEA models. To achieve this goal, eight strategic programs have been formulated such as optimization of electric motors, optimization of boilers, increasing energy efficiency in illumination, implementation of energy management systems and cleaner production, new strategies on energy efficiency in SMEs, the application of cogeneration and auto-generation, improvements in combustion processes and optimization of refrigeration systems UPME (2010). These programs should be applied with specific targets across Colombian departments taking into account results of DEA Malmquist indices and requirements of every manufacturing industrial sector and localization.

The Malmquist indices are good tool to determine energy use and performance in comparison with traditional measurement according to results of Wilcoxon test. However, DEA technique has some limitations to indicate only relative efficiency across units and the analysis is the relationship between inputs and outputs, which does not allow evaluate the effects and impacts of intermediate process where it is important to continue researching alternative to understand transformation process. Despite this limitation, DEA is a good technique to make comparisons and improve energy policies from the indices calculated with the aim to increase energy efficiency and decrease CO_2 emissions.

4.2. Panel data techniques and factors that determine energy use and CO_2 emissions

Results of panel data techniques indicate as different factors affect energy use and CO_2 emissions in the manufacturing industries across Colombian departments in the case of energy price, this has a positive sign and significant effect on better energy use and decreasing CO_2 emissions. These results concur with Cornellie and Fankhauser (2004) that demonstrated that a rise in prices over time drives to a reduction in energy intensity. In general, it is supposed that energy use in manufacturing is influenced by the behaviour of energy prices, in the industrial sector progresses in the process or suitable substitution of other inputs for energy is motivated by high energy prices (McKane et al., 2008; Mukherjee, 2008a,b; Cotte and Pardo Martínez, 2013).

Moreover, a good strategy to promote adequate energy use in the industrial sector is energy price, which have been use successfully of different countries (Mure-Odyssee, 2006; Halpern et al., 2007) because the economic agents respond to the price indicator leading their efforts to decrease the effects of higher energy price on their earnings through a better energy use (Flues et al., 2015). For this reason, it is important to consider this when developing an adequate energy price policy across Colombia aimed at increasing energy efficiency, decreasing CO_2 emissions and improving growth, productivity and sustainable development through best practices and process and technological change in energy use.

Exports likely have a positive effect on better energy use and decreasing CO_2 emissions but are not significant in some models, probably because this variable has not primarily attempted to improve energy use or decrease CO_2 emissions. Forslid et al. (2014) suggested that exports could be favourable for the environment to promote investments making production cleaner. According to Copeland and Taylor (2004), exports could generate three types of effects on countries: i) growth in technology and incomes due to the consumption of environmental goods; ii) the scale effect, which could lead to increases in exports and outputs and which can in turn deteriorate the environment; and iii) the composition effect, which could lower pollution depending on the relative size of the technology and application of cleaner process. These effects require more research especially in developing countries to promote sustainable development and open trade.

Another factor that determines inter-department difference in energy use and CO_2 emissions is the manufacturing industry mix that changes across Colombian departments. Some departments have a greater percentage of their manufacturing output produced from energy-intensive industries than others. The variable energy intensive sectors have a negative influence on energy use and CO_2 emissions, and this factor is significant in the majority of models, indicating that departments with a higher presence of energy manufacturing industries have higher energy intensity and CO_2 emission intensity. These results coincide with Mukherjee (2008) in the context of India. Moreover, in the Colombian context, it is important to incentive and prioritises the application of energy management practices in energy intensive sectors to obtain a better energy use and cleaner production in the manufacturing industries (Thollander and Ottosson, 2010).

Table 5
Results of panel data models.

Parameters	Technical efficiency				EI (energy/gross production)		COI (CO_2 emissions/gross production)	
	DEA model 1		DEA model 2					
	Random effects	MLE	Random effects	MLE	Random effects	MLE	Random effects	MLE
Constant	0.664* (1.707)	0.720 (1.688)	−1.895 (2.845)	−1.903 (2.799)	1.591 (2.311)	1.589 (2.283)	5.714** (2.320)	5.713** (2.292)
Energy Price	0.078*** (0.030)	0.076*** (0.030)	0.324*** (0.052)	0.324*** (0.051)	−0.937*** (0.042)	−0.938*** (0.042)	−0.940*** (0.042)	−0.941*** (0.042)
Exports	0.021 (0.013)	0.022* (0.012)	0.029 (0.028)	0.029 (0.027)	−0.041* (0.023)	0.042* (0.022)	−0.040* (0.023)	−0.041* (0.022)
Energy intensive sectors	−0.012 (0.023)	−0.011 (0.021)	−0.133** (0.060)	−0.131** (0.061)	0.143*** (0.049)	0.148*** (0.049)	0.147*** (0.050)	0.152*** (0.049)
Labour Productivity	0.012 (0.031)	0.013 (0.030)	0.011 (0.050)	0.011 (0.050)	−0.066 (0.041)	−0.066 (0.040)	−0.065 (0.041)	−0.065 (0.041)
Size of Companies	−0.309 (0.390)	−0.323 (0.386)	−0.044 (0.643)	−0.045 (0.633)	0.451 (0.522)	0.451 (0.516)	0.434 (0.524)	0.434 (0.518)
F-test statistic	F(18, 138) = 4.66 0.000 *Reject OLS*		F(18,138) = 29.56 0.000 *Reject OLS*		F(18, 138) = 29.30 0.000 *Reject OLS*		F(18, 138) = 29.25 0.000 *Reject OLS*	
LM test Prob > $chibar^2$	$chibar^2$(01) = 47.45 0.000 *Reject OLS*		$chibar^2$(01) = 328.77 0.000 *Reject OLS*		$chibar^2$(01) = 325.73 0.000 *Reject OLS*		$chibar^2$(01) = 326.96 0.000 *Reject OLS*	
Hausman test Prob > chi^2	chi^2(5) = 3.68 0.595 *Reject FE*		chi^2(5) = 5.81 0.325 *Reject FE*		chi^2(5) = 3.87 0.568 *Reject FE*		chi^2(5) = 3.74 0.587 *Reject FE*	
Test for heteroskedasticity[a] Prob > chi^2	LR chi^2(18) = 186.58 0.000		LR chi^2(18) = 60.53 0.000		LR chi^2(18) = 100.24 0.002		LR chi^2(18) = 99.13 0.000	
Wooldridge test for autocorrelation[b] Prob > F	F(1, 18) = 16.727 0.000		F(1, 18) = 21.841 0.000		F(1, 18) = 12.96 0.002		F(1, 18) = 13.50 0.001	
No. Obs	162	162	162	162	162	162	162	162

Notes: Figures in the parentheses are standard errors. *** Significant at the 1% level, **Significant at the 5% level, * Significant at the 10% level.
[a] If Prob > $chibar^2$ < 0.05, indicate heterokedasticity.
[b] If Prob > F > 0.05, indicate no serial correlation.

These results also should indicate that Colombian energy-intensive industries have an important potential for both the energy saving and reduction of carbon dioxide emissions, which concurs with Lu et al. (2013) in the context to the industrial sector of Taiwan and Alfonso and Pardo Martínez (2014) in the context of Bogotá.

Labour productivity has a positive sign, indicating that departments with better labour quality have better energy efficiency and lesser CO_2 emissions. These results concur with Grott and Mulder (2004), which found labour productivity improves to be higher on average than energy productivity performance and that technology changes contributed to the better energy-efficiency. It also concurs with Metz and Worrel (2007), who demonstrated that the diminution of GHG emissions in the manufacturing industry is directly related to productivity due to increased production and quality, better maintenance and operating costs and an better working environment, among other benefits.

The variable size of companies is included in the analysis because implies the amount of capital and investments in manufacturing, which generate improvements in energy consumption and decrease CO_2 emissions Schön and Kander (2007). The results of the four models indicate a negative coefficient, suggesting that departments with higher small and medium enterprises have lower energy efficiencies and higher CO_2 emissions. These results concur with DEFRA (2006), that determined that in small and medium enterprises (SMEs) management and staff resources are more reduced than in large enterprises and SMEs generally do not have a budget for energy or facilities, which generate higher energy and CO_2 emissions intensities. Moreover, Cagno and Trianni (2014) determined that main barriers to increase energy efficiency in SMEs are related to size, production complexity and innovativeness where it is key to develop specific programs for SMEs. This finding is key to develop a programme and strategies to improve energy use and decrease CO_2 emissions according to requirements of SMEs across Colombia where jointly participate policy makers and industrial decision makers.

Results of panel data analysis demonstrated that DEA indexes have similar results compared with traditional measurements on energy intensity and CO_2 emission intensities, which allows for adequate analysis according to Banker and Natarajan (2008). This is despite the recommendation of Simar and Wilson (2011) to not use second-stage regressions involving DEA efficiency scores, and if they are used, then the results should be analysed with caution. In this paper the second stages apply different tests with the aim of obtaining consistent results and as several researchers have used two stages in different studies.

Findings of this analysis allow to design suitable energy policies and instruments to improve energy use and reduce CO_2 emissions in manufacturing industries across Colombian departments. The design and application of various plans, programmes and policy instruments are important especially in those departments with higher energy intensive sectors and SMEs. Different strategies should be used such as formulation of energy efficiency indicators, application of energy management systems according to ISO 50001, improvements in decision-making procedures, training and control improvements on energy efficiency, promote energy innovation in the industrial sector and formulate energy strategies and programs jointly between policy makers and industrial decision makers.

5. Conclusions

This study evaluated energy use and CO_2 emissions in manufacturing industries across Colombian departments over 2005–2013 using the two Malmquist DEA models, a comparison between results of DEA models, energy intensity and CO_2 emission intensity, and panel data models. These applied tests demonstrated that the methods selected in this research generated consistent, robust and reliable estimates related to energy use and CO_2 emissions in the case study selected.

The results of the DEA Malmquist models, energy intensity and CO_2 emission intensity varied across years and manufacturing industry in Colombia. Several departments have improved energy use and decreased CO_2 emissions. The Malmquist indices indicate that several industries have experienced gains in productivity, a growth in efficiency, a better balance between inputs and outputs and scale production and improvements in innovation through new technologies. However, the country has the possibility to further increase energy efficiency and decrease CO_2 emissions in the manufacturing sector. The results of the panel data regression models imply that increased energy prices, exports, company size and productivity generate improvements in energy use and falling CO_2 emissions, while a higher presence of energy intensive sectors generates lower efficiency related to energy use and CO_2 emissions.

The techniques used in this study as DEA Malmquist indices indicate the possibilities to make regional studies related to energy use and CO_2 emissions from relations between inputs and outputs, which allows to compare relative efficiency and performance in the manufacturing industries of every Colombian Department. The second stage applying panel data techniques define some factors that determine energy performance, which it is important to design adequate and suitable energy policies according to requirements of regions and specific industrial sectors.

These findings allow an adequate development of effective energy policies across Colombia, with the aim of improving energy saving and management. The energy sector is private, and efficiency gains may not be strong incentives compared to the motivation to sell energy. For this reason, it is fundamental to design instruments that increase awareness in the industrial sector on the importance of energy saving and decreased CO_2 emissions as key variables to improve productive and sustainable development.

Further research is needed especially in developing countries, to determine the main barriers to adopt new technologies, adequate practices and process to decrease energy consumption and environmental problems to achieve sustainable development in the manufacturing sector across Colombia.

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