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The relationship between enterprise efficiency in resource use and energy efficiency practices adoption

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ABSTRACT

The purpose of this paper is to investigate the relationship between enterprise efficiency in resource use and the adoption of energy efficiency practices recommended by the US Department of Energy (DOE) through the Industrial Assessment Center (IAC). Using non-parametric techniques such as Data Envelopment Analysis (DEA) and parametric techniques like Stochastic Frontier Analysis (SFA) and Corrected Ordinary Least Square (COLS) to measure the efficiency. The Regression Quantile (RQ) is carried out to test the hypothesis that the most efficient companies have adopted a higher level of practice. The main conclusion is that when the enterprise operates at increasing Returns-to-Scale (RTS) the impact of efficiency on adoption increases positively, inversely when the enterprise operates at decreasing (RTS) the impact of efficiency on adoption increases negatively.

1. Introduction

The study of energy efficiency is not a new area; it is the focus of the studies that has changed, it went from energy conservation (Motamen and McGee, 1986; Fawkes and Jacques, 1987) to energy efficiency (Phylipsen, et al., 1997; Worrell et al., 2003), to the impact of energy use on sustainability (Gutowski et al., 2005; DelRio and Burguillo, 2008) and energy management (Bunse et al., 2011; Backlund et al., 2012; Negai et al., 2013). The studies have identified various benefits of energy efficiency management in companies: Increased productivity, reduced pollution, reduced noise, low cost of maintenance, savings in water, reduced waste, among other benefits (Worrell et al., 2003; Trianni et al., 2014). On the other hand, the studies have also identified what is known in the literature as the *Energy Efficiency Gap*, the paradox of the existence of this gap is explained by a series of barriers that prevent greater efficiency (Jaffe and Stavins, 1994; DeCanio, 1998; Cagno, et al., 2013). This gap exists as a result of not implementing energy efficiency or energy conservation measures even though their cost effectiveness has been evaluated by techniques like *payback*, internal return rate (IRR) or net present value (NPV) (Jaffe and Stavins, 1994; DeCanio, 1998).

In the analysis of three bibliometric studies: Yaoyang and Boeing (2013), Du et al. (2013), and Du et al. (2014) comparing more robustly the total number of publications and citations in the periods 1993–2001 to 2002–2010, results show a growing interest in some specific areas in the field of energy. In the area of biofuels, as showed by Yaoyang and Boeing (2013), there was a 1310% increase in publications and 1946% in the number of citations, in the area of energy efficiency, according to Du et al. (2013), a 278% and 396% increase, and finally in solar energy, as showed by Du et al. (2014), an increase of 103% and 187% for the same indicators. Based on these studies there is a greater relative interest in researching energy efficiency over solar energy.

Data sources for energy efficiency research are scarce. One study opportunity comes from the Department of Energy of the United States (DOE), through the energy efficiency audit program for small and medium enterprises (*SMEs*), sponsored by the American government (US DOE-IAC, 2011). Participating in the study are 24 *Industrial Assessment Centers* (IAC) together with 32 American universities.

Many studies have used the information provided by the DOE-IAC for investigating impacts such as cost, price of energy, time of return on investment and other factors, on the implementation of energy management and energy efficiency practices (Tonn and Martin, 2000; Anderson and Newell, 2004; Abadie et al., 2012;

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Therkelsen and McKane, 2013; Blass et al., 2014). The main contribution of our work is to look at how prior enterprise efficiency has had an influence on the adoption of practices, in other words: What is the relationship between enterprise efficiency and the adoption of energy efficiency practices? The efficiency is measured by three different techniques: Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA) and Corrected Ordinary Least Square (COLS). DEA, SFA and COLS provide methods for estimating the best practice production frontiers and evaluating the relative efficiency of different entities (enterprise). The efficiency is measured by the distance between the enterprises that are on the frontier and below it (Bogetoft and Otto, 2010). The Regression Quantile (RQ) is carried out to test the hypothesis that the most efficient companies, measured by DEA, SFA and COLS, have adopted a higher level of practice. A second question is raised: Considering the practices, is there a difference in efficiency among the enterprises that adopted certain practices and those that did not?

The idea behind the first question is to generate evidence demonstrating that the most efficient companies are also those more concerned with environmental issues, since the use of less energy results in fewer harmful gas emissions into the environment (CO_2, CH_4, N_20). The second question seeks to determine whether or not more efficient companies have a preference for any particular practices.

This study uses the model proposed in Perroni et al. (2015), including the year 2013 in the model. A specific set of objectives was used to deal with the large body of information, approximately 17,000 cases and 130,000 recommendations, broken down into the following sections: literature review of the determinants of energy efficiency; research design, which describes the treatment of data, construction of models for calculating the efficiency, model to examine the research question, and application and test methodology; calculations of efficiency and the model which investigated the relationship between the enterprise efficiency and the adoption of energy efficiency practices; and at the last two sections discussion and conclusion are presented.

2. Literature review of the determinants of energy efficiency

Enterprise efficiency can be analyzed in various ways, the most widely known are technical efficiency and allocative efficiency. Technical efficiency is related to the use of adequate or optimal procedures and allocative efficiency takes into consideration the costs of these procedures for optimal allocation (Farrel 1957; Bogetoft and Otto, 2010).

According to Patterson (1996) efficiency in the context of energy is a generic term, where there is no single measure. Efficiency is related to the use of less input (energy), maintaining a constant output. For Patterson (1996) the energy efficiency indicator comes from the output/input ratio, classified in four groups: *Thermodynamic, Physical-thermodynamic, Economic-thermodynamic, Economi*c.

The link between the concept of energy efficiency and energy management can be interpreted according to the definition put forth by Bunse et al. (2011, p. 668) “*In our research we define ‘energy management in production’ as including control, monitoring, and improvement activities for energy efficiency*”. Based on the research of Backlund et al. (2012) both the policy documents and the academic literature recognize the existence of the so-called *energy efficiency gap*, which is related to the non-implementation of measures for energy management and energy efficiency, despite their cost effectiveness.

Studies evaluating the extent to which energy management has been adopted by industrial companies have revealed a low rate of adoption. For 304 industrial companies in Denmark, Christoffersen et al. (2006) concluded that between 3% and 14% of the companies practiced energy management. In analyzing intensive Swiss industries like paper and foundry Thollander and Ottosson, 2010 found that 40% and 25% respectively, practiced energy management. Studies in Italy found that in small and medium-sized companies the *energy efficiency gap* can be explained by a series of barriers such as: *High investment costs, hidden costs, intervention not sufficiently profitable, information issues on energy contracts, information not clear by technology suppliers and lack of information on costs and benefits* (Trianni and Cagno, 2012; Trianni et al., 2013).

Concerns over barriers to implementing *Energy Efficiency Measures (EEMs)* culminated in the development of a model for identifying the barriers proposed by Cagno et al. (2013). This model proposes a taxonomy for the study of barriers, separating them into external factors (market, government, technology, suppliers of technology and financing system) and factors internal to the company (economic, behavioral, organizational, competence and awareness).

Various studies have looked at the relationship between energy efficiency variables and internal and external variables, the main results have been summarized in Table 1. The work of Kounetas and Tsekouras (2010) used the *Stochastic Frontier Analysis* (SFA) for manufacturers in Greece where they found a positive relationship between energy efficient technologies and the productive performance of manufacturers, but they found a negative relationship when the deterministic part of the frontier was analyzed. For productive performance, energy efficient technologies have a different effect when considering industrial sectors and company size. When the industries are intensive users of energy, the adoption of *Energy Efficient Technologies* (EETs) has a positive impact on performance, but the opposite occurs when the industries are not intensive users of energy.

In the survey by Suk et al. (2013), in energy intensive Korean companies, using a factorial analysis and logistic regression, no relationship was found between the external factors (regulation, competitors and associations) and energy savings. The energy saving practices are determined by upper management as well as training and economic incentives. Medium and large-sized companies adopt the best practices in EETs. Liu et al. (2013) in a survey in China using econometric techniques (multiple regression) a negative relationship was found between the price of energy and the acceptance of carbon tax costs and a positive relationship between energy management strategies and these same costs. The acceptance of higher carbon taxes by industries are determined by subjective perceptions as well as self-motivation, likely due to the lack of training of internal management.

In another study in Spain and Slovenia using data from the (*European Manufacturing Survey*) through linear and ordinal regression, Pons et al. (2013) found no relationship between economic performance and energy efficiency, instead they found a positive relationship between environmental performance and energy efficiency. Also for Chinese companies Zhang and Wang (2014) using multiple, logistic and ordinal linear regression demonstrated that collaboration for reducing carbon emissions (*Industrial Symbiosis*) has a positive relationship with economic performance. These authors found that for this study in China environmental regulations have no effect on the reduction of carbon emissions.

In a broad study Eccles and Serafeim (2013) conducted an econometric analysis with over 3000 companies to examine the effect of sustainable practices on the financial performance of these companies. The result showed a negative correlation between financial performance and combined improvements in social and environmental factors, when innovation is not present.

According to Kannan and Boie (2003) the objective of the

Table 1
Relationship between energy efficiency and variables internal and external to the company.

Origin	Authors/acronyms	Energy variables	Internal and external variables	Effect
Greece	Kounetas and Tsekouras (2010)	EETs	Productive performance	+
	EETs - Energy Efficient Technologies	EETs	Productive performance (deterministic model)	−
		EETs	Size of firms	+
		EETs	Intensive firms	+
		EETs	Not intensive firms	−
Korea	Suk et al. (2013)	ESA	Regulation, competitors and association	‡
	ESA - Energy Saving Activities	ESA	Top management, training and economic incentives	+
		ESA	Large firms	+
China	Liu et al. (2013)	CBP	Energy price	−
	CBP - Carbon Price Polices	CPB	Energy management strategies	+
		CPB	Subjective perception and self-motivation	+
Spain	Pons et al. (2013)	EST	Economic performance	‡
	EST - Energy saving technologies	EST	Environmental performance	+
USA	Eccles and Serafeim (2013)	SUS	Financial Performance	−
	SUS - Sustainability INO- Innovation	SUS-INO	Financial Performance	+
China	Zhang and Wang (2014)	IS-CER	Environmental regulations	−
	IS-CER Industrial Symbiosis Carbon Emission Reduction	IS- CER	Economic performance	+
USA-IAC	Tonn and Martin (2000)	A-EEMs	Energy efficiency decision making	+
	A-EEMs - Adoption of Energy Efficiency Measures			
USA-IAC	Anderson and Newell (2004)	A-EEMs	Payback and project cost	−
		A-EEMs	Annual savings and price of energy	+
		A-EEMs	Energy prices squared	−
USA-IAC	Abadie et al. (2012)	A-EEMs	Payback time	−
		A-EEMs	Natural gas	−
		A-EEMs	Higher emissions	+
		A-EEMs	Higher gross domestic product (GDP)	+
USA-IAC	Therkelsen and McKane (2013)	A-EEMs	Payback and Implementation cost	−
USA-IAC	Blass et al. (2014)	A-EEMs	Top operations management	+
		A-EEMs	Top general management	±

+ positive; − negative; ‡ no effect; ± weak effect.
Note: Energy variables: adoption of energy efficient technologies, energy saving, pollution reduction measures or adoption of measures to increase energy efficiency.

energy audit is to scan the areas in order to find the gaps in energy efficiency. The aim of the DOE-IAC program is to find these gaps for small and medium-sized enterprises (SMEs), proposing the recommendations to be adopted. The result of whether or not they are adopted is recorded in a public database,[1] revealing a source of valuable information, according to the perceptions of the various researchers listed in Table 1.

Studies that have used the information in the DOE-IAC database are listed in the lower part of Table 1. Tonn and Martin (2000) collected data on before and after the companies participated in the DOE-IAC program, they found through descriptive statistics that the benefits of the IAC are positively associated with later energy efficiency decisions. In one of the most cited studies in the literature, Anderson and Newell (2004), in the period from 1981 to 2000, found that only half of the recommended energy efficiency projects were implemented. Using logistic regression panel data they found that the rate of adoption is higher for projects with smaller paybacks, lower cost, higher savings/conservation of energy and prices. The companies are more motivated by the implementation costs than energy savings.

A more recent study by Abadie et al. (2012) also using logistic regression for the period from 1984 to 2009, confirmed the results of Anderson and Newell (2004), adding that the recommendation for natural gas has a lower probability of implementation. Companies located in states with higher Greenhouse Gas (GHG) emissions have a greater probability of adoption. Companies located in states with a higher Gross Domestic Product (GDP) have a lower probability of adoption. Therkelsen and McKane (2013) focus on the industrial vapor systems using 1165 cases, finding that the implementation is primarily determined by cost metrics. The main reasons for non-adoption are (%): Economic 41; Facility/Production 25; Behavioral 19; Other 8; Organizational 7. The work of Blass et al. (2014) using logistic regression techniques, investigated the role of upper management in adopting energy efficiency practices, finding that when upper management is involved in operations there is a significant improvement in the adoption rate. For management in general the impact on adoption is low.

3. Research design

The methodological approach is presented in four subsections according to the objectives of our study: Selection and gathering of data, models for estimation of enterprise efficiency, model for testing the relationship between the adoption or implementation of energy efficiency practices and estimated enterprise efficiency, finally a brief subsection describing the application methodology. There was a need to include the subsection selection and gathering of data due to the complexity of the database, which called for delimitations and further clarification. In the subsection estimated efficiency, both parametric and non-parametric models were used under varying conditions of return to scale aiming to test the influence of efficiency on the level of implementation of practices in different ways. For the test approach the quantile regression model was used for modeling all of the conditional distribution of the dependent variable (level of implementation).

3.1. Selection and gathering of data

The DOE-IAC project has 24 IAC centers together with 31 American universities. There are some rules in place for the companies to qualify for the program: sales lower than 100 million; cost of energy between 100 thousand and 2.5 million; up to 500 employees and the firm cannot have a dedicated energy

[1] https://iac.university/download.

Table 2
Energy efficiency practices more recommended.
Source: (US DOE-IAC_ARC, 2007; US DOE-IAC, 2011).

Status	Recommended	Implemented			Not Implemented		
(ARC) Energy efficiency practices more recommended	%Q	%QI	%cost	%save	%NQI	%cost	%save
27,142 Utilize higher efficiency lamps and/or ballasts	11.7	6.4	4.3	2.6	5.3	4.1	2.2
24,236 Eliminate leaks in inert gas and compressed air lines/ valves	7.8	6.3	0.5	2.6	1.5	0.2	0.6
24,221 Install compressor air intakes in coolest locations	5.6	2.5	0.1	0.3	3.1	0.1	0.4
24,133 Use most efficient type of electric motors	5.3	3.4	2.0	1.1	1.8	1.1	0.5
27,135 Install occupancy sensors	4.6	1.7	0.2	0.3	2.9	0.3	0.4
22,511 Insulate bare equipment	3.5	1.6	0.3	1.0	1.8	0.4	1.0
27,143 Use more efficient light source	3.3	1.7	1.2	0.7	1.6	0.9	0.6
24,231 Reduce the pressure of compressed air to the minimum required	3.0	1.5	0.1	0.3	1.5	0.2	0.4
24,111 Utilize energy-efficient belts and other improved mechanisms	2.7	1.4	0.2	0.3	1.3	0.3	0.3
24,141 Use multiple speed motors or afd for variable pump, blower	2.0	0.6	0.8	0.7	1.4	1.8	1.6
22,434 Recover heat from air compressor	1.9	0.6	0.1	0.2	1.3	0.2	0.5
21,233 Analyze flue gas for proper air/fuel ratio	1.8	1.2	0.2	0.9	0.6	0.2	0.6
27,261 Install timers and/or thermostats	1.5	0.8	0.1	0.3	0.8	0.1	0.2
27,111 Reduce illumination to minimum necessary levels	1.5	0.8	0.1	0.3	0.8	0.1	0.2
24,232 Eliminate or reduce compressed air used for cooling	1.4	0.6	0.1	0.3	0.8	0.2	0.4
22,131 Insulate steam/hot water lines	1.3	0.8	0.1	0.3	0.5	0.1	0.2
21,311 Replace electrically-operated equipment with fossil fuel equipment	1.2	0.3	0.8	0.6	0.9	2.1	1.8
22,411 Use waste heat from hot flue gases to preheat combustion air	1.2	0.2	0.3	0.4	1.0	2.2	3.2
27,134 Use photocell controls	0.9	0.4	0.0	0.1	0.5	0.1	0.1
26,218 Turn off equipment when not in use	0.8	0.4	0.1	0.3	0.4	0.2	0.2
Total partial	62.9	33.1	11.6	13.8	29.8	14.9	15.7

Note: This table shows only the 20 most recommended practices in a total of 504, calculated by Excel® pivot table. a) %: (percentage of 62,263 recommendation aggregate by 504 ARC code in 10,448 companies audited); b) (%Q=%QI+%NQI) where %Q (% of quantity); %QI (% of quantity Implemented); %NQI (% of quantity not implemented), c) % cost: (% of sum of client reported implementation cost in dollars); d) %save: (% of sum for primary resource's dollar savings for recommendation).

management specialist (US DOE-IAC, 2011). The database covers the period from 1981 to 2015, containing a table with the data from the 16,859 companies evaluated and a second table with the 127,479 recommendations made, generating an average of seven recommendations per company (case). The recommendations are classified under three larger categories, according to the table *Assessment Recommendation Code* (ARC): *Energy Management, Waste Minimization/Pollution Prevention and Direct Productivity Enhancement* (US DOE-IAC_ARC, 2007).

This study is an update of the model developed by Perroni et al. (2015) for the period 1990–2012. This updated work for the period 1990–2013 applies the same rules, but adds the year 2013 to the analysis. The beginning of the period was chosen due to a certain stability in the price of energy, 2014–2015 was excluded as the evaluations are conducted for a period of up to two years and many of the evaluations are still pending. For the period of analysis 13,796 assessments were carried out, but for a variety of reasons approximately 30% of the data were omitted, which is similar to the rate of 25% found in the work of Anderson and Newell (2004) for similar reasons such as: the exclusion of questionable data, incomplete data, status of implementation pending or excluded, did not include at least two sources of energy (*Electrical, Natural Gas*). Companies with 10 or more employees and sales over U $10,000 were selected as cases. After refining the data 10,448 companies remained, with 62,263 recommendations.

Table 2 describes the twenty (20) most recommended practices of the 10,448 selected cases and 62,263 recommendations, considering that the ARC table contains 676 possible practices for the recommendation, 504 practices (ARC) were recommended to the selected data that cover 10,448 cases. The most recommended practice was (*Utilize higher efficiency lamps and/or ballasts*) meaning 11.7% of the recommendations, 8.5% of the cost and 4.8% of savings, where, 6.4% were implemented and 5.3% were not implemented.

The twenty recommendations in Table 2 represent 62.9% (33.1%+29.8%) of the recommendations, 26.5% (11.6%+14.9%) for cost and 29.5% (13.8%+15.7%) for savings, in other words, 4% (20/504) of practices is responsible for 63% of recommendations, 30% of cost and 16% of savings.

Different from the work of Anderson and Newell (2004) and Abadie et al. (2012) that used the table of recommendations, our work uses the table with the data from the companies (cases), adding the recommendation information (i to j). The data on recommendation of cost of implementation (*impcost*) was added to the variable IC, resources saved (*psaved*) was added to the variable PS and resource conservation (*pconserved*) generated the variable PC as demonstrated in Eqs. (1)–(3). An IL variable was created (*implementation level*), which is the proportion of recommendations implemented, varying from 0% to 100%, the IL is the sum of recommendations implemented by the companies QI divided by the total recommendations (implemented QI plus not implemented NQI), as shown in Eq. (4).

$$IC_k = \sum_{i=1}^{j} IMPCOST_{ARC_i} \tag{1}$$

$$PS_k = \sum_{i=1}^{j} PSAVAD_{ARC_i} \tag{2}$$

$$PC_k = \sum_{i=1}^{j} PCONSERVD_{ARC_i} \tag{3}$$

$$IL_k = \sum_{i=1}^{j} QI_{ARC_i} \Big/ \left(\sum_{i=1}^{j} QI_{ARC_i} + \sum_{i=1}^{j} NQI_{ARC_i} \right) \tag{4}$$

The added recommendations were handled in two ways, first by including all of the categories in the table: *Assessment Recommendation Code (ARC)* (*Energy Management, Waste Minimization/Pollution Prevention and Direct Productivity Enhancement*) and second by only including the category *Energy Management* of ARC (US DOE-IAC_ARC, 2007). This distinction was made to verify whether there was a difference between the impact of enterprise efficiency on adoption if only energy management actions are considered. Two points to be highlighted are that the ARC *Energy Management* represents almost 90% of the recommendations and there is also the synergy factor among the recommendations, for example the use of waste (wood) to generate energy.

3.2. Models for estimating enterprise efficiency

In the Benchmarking area, the classification of Patterson (1996) can be seen as a *Key Performance Indicator* (*KPI*) of the company, or the measuring of productivity. Based on Bogetoft and Otto (2010) efficiency, inefficiency and enterprise effectiveness can be represented as:

$$InEfficiency = (ActualPeformance - MinimalPerformance) / ActualPerformance \tag{5}$$

$$Efficiency = MinimalPerformance/ActualPerformance = 1 - InEfficiency \tag{6}$$

$$Effectiveness = ActualPerformance/IdealPerformance = U(A)/\{ max_{y \in T} U(y)\} = U(A)/U(ideal) \tag{7}$$

The problem with effectiveness is that it depends on utility function U (.) which is not always known a priori. One way of overcoming this problem has been through the application of the concept of efficiency called Farrel efficiency (1957), moving the focus from effectiveness to relative efficiency.

Three different techniques have been applied to the literature to estimate relative efficiency: *Corrected Ordinary Least Squares* (COLS) (Azadeh et al., 2009), *Stochastic Frontier Analysis* (SFA) (Boyd et al., 2008, Boyd, 2014) and *Data Envelopment Analysis* (DEA) (Olanrewaju et al., 2013; Olanrewaju and Jimoh, 2014). The origin of the first two methods is from the econometric approach and the latter from mathematical programming and management science (Bogetoft and Otto, 2010). In a bibliometric study Lampe and Hilgers (2015) confirm a growing number of publications, both DEA and SFA for measuring performance, finding that DEA is more widely used in operations while SFA is used in the area of finance. In another literature review Zhou et al. (2008) found that there has been an emphasis on the area of energy efficiency in the use of DEA.

Eq. (8) shows the COLS and the Eq. (9) the SFA, where (x) is a n dimensional input vector, (y) is the m=1 dimensional output and β are unknown vector of parameters. COLS (Eq. (8)) is attributed to Aigner and Chu (1968), classified as parametric-deterministic, it can be estimated by the traditional method of *ordinary least squares* (OLS). COLS is deterministic because it takes into consideration the error term (u) fully as inefficiency (the deviation from frontier is always inefficiency). The N_+ denotes a half-normal distribution $N_+(0,\sigma^2)$ of the (u) in the interval [0,∞]. SFA (Eq. (9)) is attributed to Aigner et al. (1977), considered a parametric-stochastic method, assuming that errors are divided into noise (v), normally distributed $N(0,\sigma^2)$ and inefficiency (u), half-normal distributed $N_+(0,\sigma^2)$ (the deviation from frontier not only reflects inefficiencies, but noise as well), and can be estimated by the *maximum likelihood* principle, estimating the parameters (β,σ^2,λ) [2](Bogetoft and Otto, 2010).

$$y^k = f(x^k, \beta) - u^k,\ u^k \sim N_+(0,\sigma^2) k=1, \dots, K \tag{8}$$

$$u^k = f(x^k, \beta) - y^k$$

$$y^k = f(x^k, \beta) + v^k - u^k,\ v^k \sim N(0,\sigma^2),\ u^k \sim N_+(0,\sigma^2) k=1, \dots, K \tag{9}$$

$$u^k = f(x^k, \beta) - y^k + v^k$$

The DEA approach can be attributed to Charnes et al. (1978), it is a non-parametric deterministic method that uses mathematical programming to estimate the frontier of best practices. DEA can be represented in different return systems, like CRS (*constant returns to scale*), VRS (*variable returns to scale*), DRS (*decreasing returns to scale*) and IRS (*increasing returns to scale*) as shown in Eq. (10), where θ is the measure of efficiency, x_{ij} and y_{rj} are the *i*th input and *r*th output of the problem, x_{io} and y_{ro} are the *i*th input and *r*th output under evaluation and λ_j are the weights to be determined by the solution (Zhu, 2009). Based on Bogetoft and Otto (2010) DEA is more flexible in terms of the economic properties of production, while SFA is more flexible in terms of the quality of data.

After preliminary studies the multiplicative model (Eqs. (11) and (12)) was adopted for calculating the parametric efficiency. Eq. (11) represents COLS and Eq. (12) SFA, where Y(annual sales); L(employees); pH(annual production hours); UE(annual use of electricity); UN(annual use of natural gas); CE(annual cost of electricity); CN(annual cost of natural gas); e^{v_k} (error); e^{-u_k} (estimation of the efficiency). The variables cost of gas and cost of electricity act as control variables.

$$CRS \left| \begin{array}{c} \theta^* = \min \theta \\ subject\ to \\ \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{i0 i=1,2,\dots,m}; \\ \sum_{j=1}^{n} \lambda_j y_{rj} \le y_{r0 r=1,2,\dots,s}; \\ \lambda_j \ge 0 \end{array} \right| VRS - \sum_{j=1}^{n} \lambda_j = 1 \Bigg| IRS - \sum_{j=1}^{n} \lambda_j \le 1 \Bigg| DRS - \sum_{j=1}^{n} \lambda_j \ge 1 \tag{10}$$

$$Y_k = \beta_1 L_{2K}^{\beta_2} pH_{3k}^{\beta_3} UE_{4k}^{\beta_4} UN_{5k}^{\beta_5} CE_{6k}^{\beta_6} CN_{7k}^{\beta_7} e^{-u_k} \tag{11}$$

$$Y_k = \beta_1 L_{2K}^{\beta_2} pH_{3k}^{\beta_3} UE_{4k}^{\beta_4} UN_{5k}^{\beta_5} CE_{6k}^{\beta_6} CN_{7k}^{\beta_7} e^{v_k} e^{-u_k} \tag{12}$$

DEA modeling does not require a functional form, using Eq. (10) as a basis, the X_j are the inputs and the Y_j are the output, the variables *L*, pH, UE, UN, CE, CN and Y are the same as in Eqs. (10) and (11), but in logarithm form.

$$X_j = \{ \ln(L_i), \ln(pH_i)\ln(UE_i), \ln(UN_i), \ln(CE_i), \ln(CN_i)\}; Y_j = \{\ln(Y_r)\} \tag{13}$$

3.3. Test model: implementations verses enterprise efficiency

To reach our main objective, which is to investigate the relationship between enterprise efficiency and the adoption of energy efficiency practices, a quantile regression model is proposed. Quantile regression was developed by Koenker and Bassett (1978), having the advantage of modeling the complete conditional distribution of the independent variable, instead of just the average as in OLS, thus generating more robust results. Represented as a linear program, the quantile regression can be estimated at 14, where θ is the quantile in the interval $0 < \theta < 1$, the term $'y_t - x_t\beta'$ is an error term in the linear regression

[2] The log-likelihood function can be written: $l(\beta,\sigma^2,\lambda) = -\frac{1}{2}Klog\left(\frac{\pi}{2}\right) - \frac{1}{2}Klog\sigma^2 + \sum_{k=1}^{K} log\Phi\left(-\frac{\lambda\left(y^k - f\left(x^k;\beta\right)\right)}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2}\sum_{k=1}^{K}\left(y^k - f\left(x^k;\beta\right)\right)^2$ where $\sigma^2 = \sigma_v^2 + \sigma_u^2$, and $\sigma_v^2 = \frac{1}{1+\lambda^2}\sigma^2; \sigma_u^2 = \frac{\lambda^2}{1+\lambda^2}\sigma^2$ (implemented in R package Benchmarking, Bogetoft and Otto, 2010, p.197–231).

Table 3
Parameters of SFA and COLS - (dependent variable: annual sales).

Independent variables		(Intercept)	L	pH	UE	UN	CE	CN
SFA	**Parameters**	9.694*	0.565*	0.078*	0.141*	−0.126*	0.114*	0.205*
	Std. Error	0.199	0.014	0.028	0.018	0.020	0.019	0.022
	***t*_value**	48.513	39.923	2.809	7.864	−6.373	5.897	9.421
COLS	**Parameters**	8.965*	0.587*	0.106*	0.160*	−0.102*	0.070*	0.170*
	Std. Error	0.174	0.013	0.023	0.019	0.018	0.019	0.019
	***t*_value**	51.456	45.215	4.568	8.352	−5.766	3.644	8.777

Note: a)* significant at 1%; b) SFA ($\lambda=1.54$; $\sigma^2=1.48$; $\sigma_v^2=0.44$; $\sigma_u^2=1.04$; log likelihood = −13,623.22)[3].
c) COLS (Adjusted R-squared = 0.41); d) *t*_value ratio = (Parameters/Std. Error)[4].

'$u_t = y_t - x_t\beta$'.

$$\min_{\beta \in \mathbb{R}^K}\left[\sum_{t\epsilon\{t:y_t\geq x_t\beta\}}\theta\left|y_t - x_t\beta\right| + \sum_{t\epsilon\{t:y_t<x_t\beta\}}(1-\theta)\left|y_t - x_t\beta\right|\right] \tag{14}$$

The values $b\theta$ can modify as they advance in the quantiles. The proposed quantile regression is 15.

$$(IL)_k = b_{0\varnothing} + b_{1\theta}u_k^{Eff} + b_{2\theta}\ln\left(\frac{IC}{PS}\right)_k + b_{3\theta}\ln\left(\frac{PS}{PC}\right)_k + b_{4\theta}\ln\left(\frac{UE}{Y}\right)_k + b_{5\theta}\ln\left(\frac{UN}{Y}\right)_k + u_k \tag{15}$$

where IL and the proportion of implemented projects; u_k^{Eff} represents the estimated efficiency of the parametric and non-parametric models presented previously; IC/PS cost of project implementation ratio by the potential for energy savings, since the two values are monetary this variable can be interpreted as a simple payback; PS/PC as the potential ratio for savings and potential for conservation. Energy savings is in a monetary value and conservation in Kilowatt-hour (KWh) or British Thermal Unit (BTU), making this variable the average price of energy for each project. The variables payback and average price of energy were computed in a similar manner in the work of Anderson and Newell (2004). UE/Y energy intensity of electricity; UN/Y energy intensity of natural gas.

3.4. Application methodology

The application is designed to attend the proposed research objective, which is to investigate the relationship between enterprise efficiency and the adoption of energy efficiency practices, using the data treated in Section 3.1 (selection and gathering of data). In the first stage (Section 4.1) it was calculated the efficiency using the regression method SFA and COLS, as shown in Eqs. (11) and (12) respectively, then the efficiency was calculated using the approach of mathematical programming, data envelopment analysis (DEA), assuming the hypothesis of four different systems of return to scale: decreasing (DRS), constant (CRS), increasing (IRS) and variable (VRS). In the second stage (Section 4.2) the quantile regression model of Eq. (15) was used to test the relationship between the level of energy efficiency adoption (dependent variable) and the efficiency calculated by the regression and mathematical models (independent variable).

4. Application of models

Based on the description of the application methodology, this section is divided into two subsections: The Section 4.1 presents the estimation of enterprise efficiency using SFA, COLS and DEA (Eqs. (8)–(13)). The calculation of efficiency and the implementation level (Eq. (4)) are aggregated based on the industrial sectors that enterprises belong to check the concordance between the efficiency estimation, and the level of implementations by sectors. The Pearson correlation matrix also shows the calculated efficiencies and the level of implementation. The Section 4.2 shows the relationship between enterprise efficiency and the adoption of energy efficiency practices (Eq. (15)). Efficiency of recommendation equivalent to 10,448 enterprise efficiency was aggregate by 504 ARC code to verify the difference in efficiency between the enterprises that adopted certain practices and those that did not. To investigate the relationship between enterprise efficiency and the adoption of energy efficiency practices, 120 models of quantile regression (15 quantile *versus* 8 efficiency calculations) are proposed, changing the quantile and the variable of efficiency.

4.1. Estimation of enterprise efficiency for the DOE-IAC cases

For estimating the efficiency, the methodological model developed in Eqs. (8)–(13) was used. Table 3 presents the SFA (estimated by R package Benchmarking and tested in R package Frontier) and COLS coefficient (estimated in R), where the dependent and independent variables were defined Eqs. (11) and (12) (Coelli and Henningsen, 2013; Bogetoft and Otto, 2014). The interpretation of SFA parameters is made easier, since it is a logarithmic model, therefore, 1% of variation in annual sales (dependent variable, Y) results in an increase of 0.14% in the annual use of electricity (UE) or curiously, a reduction of 0.12% in the annual use of natural gas (UN). The interpretation of COLS parameters is similar. From Table 3 it is possible to note that all of the SFA and COLS estimations are significant at 1%. The *t*_value ratio in SFA and COLS indicates that the parameters are statistically different from zero, since the *t*_value belong to critical region (Student's t-distribution), the null hypothesis that the parameters are in fact zero are rejected (see footnote 2). Considering the SFA lambda value ($\lambda = 1.54$) informs that the percentage variation in inefficiency is 70%, therefore 30% is random variation (see footnote 2 and 3). An important observation is about the return to scale, both in the SFA and COLS estimations, the returns to scale are decreasing, as the sum of the coefficients is lower than 1. but closer to the unit with 0.98 for SFA and 0.99 for COLS.

Table 4 presents a summary (class of efficiency) of the calculation for the DEA, with input oriented efficiency, estimated by R package Benchmarking and tested in Excel® OpenSolver (Zhu, 2009; Bogetoft and Otto, 2014). The input and output variables are the same as defined for regression models (Table 3) using the same data set (10,448 enterprise) treated in Section 3.1.

The efficiency estimation using DEA is done assuming the hypothesis of four systems of return to scale: decreasing (DRS), constant (CRS), increasing (IRS) and variable (VRS), as shown in Eq. (10). Considering constant or decreasing returns the efficiency average was 0.75 with 16 enterprises considered efficient respectively. For the hypothesis of variable or increasing return the efficiency average was 0.88 with 73 enterprises considered efficient. The estimation of constant and decreasing returns are very similar,

Table 4
Class of efficiency of DEA models.

Efficiency class		0.00–0.59	0.60–0.79	0.80–0.99	1	Total
DRS	**Number of enterprises**	86	8735	1611	16	10,448
	%	0.82	83.60	15.42	0.15	100
CRS	**Number of enterprises**	86	8735	1611	16	10,448
	%	0.82	83.60	15.42	0.15	100
IRS	**Number of enterprises**	0	51	10,324	73	10,448
	%	0.00	0.49	98.81	0.70	100
VRS	**Number of enterprises**	0	51	10,324	73	10,448
	%	0.00	0.49	98.81	0.70	100

Note: Average efficiency (CRS=DRS=0.75; IRS=VRS=0.88)

the same occurring with variable and increasing returns. Regarding the distribution of efficiency, 83% of the enterprises belong to efficiency class (0.60–0.79) assuming returns DRS and CRS, and 98% for efficiency class (0.80–0.99), assuming IRS and VRS.

Table 5 shows the average value of enterprise efficiency (aggregated by industrial sectors) for examine the concordance between the efficiency estimation, and between the efficiency estimation and level of implementations by the 20 industrial sectors of the *Standard Industrial Code* (SIC), the darker brown color is associated with lower efficiency and white with greater efficiency.

In Table 5 the classification is made in relation to SFA, which means that the position of the other efficiency calculations is relative to SFA. Three other variables appear in Table 5: Implementation level of recommendations IL (Eq. (4)), GMI and GMD. The GMI variable is the geometric average of (SFA, CRS and DRS) and the GMD variable is the geometric average of (VRS, IRS). According to Azadeh et al. (2009) the geometric average is an approach used to consolidate the average efficiency from different perspectives. The choice to separate these variables for calculating the geometric average was not by chance, it is possible to note in Table 5 that even when efficiency is added by sectors, the colors of SFA, CRS and DRS which have constant or decreasing returns are in

Table 6
Matrix of Pearson correlation of efficiency and implementation level.

	SFA	DRS	CRS	COLS	GMD	IRS	VRS	GMI	IL
SFA	–	**0.697***	**0.697***	0.145*	**0.956***	0.216*	0.217*	0.217*	0.000
DRS	–	–	**1.000***	0.148*	**0.852***	**0.663***	**0.664***	**0.664***	0.016
CRS	–	–	–	0.148*	**0.852***	**0.664***	**0.665***	**0.664***	0.016
COLS	–	–	–	–	0.143*	0.067*	0.068*	0.067*	−0.015
GMD	–	–	–	–	–	0.376*	0.377*	0.376*	0.011
IRS	–	–	–	–	–	–	**1.000***	**1.000***	0.036*
VRS	–	–	–	–	–	–	–	**1.000***	0.036*
GMI	–	–	–	–	–	–	–	–	0.036*

Note. Calculation: (correlation matrix between efficiency estimated by the models of the Eqs. (10)–(12) and the IL variable of the Eq. (4)).

* Significant at 1%.

agreement, on the other hand, efficiency when considering variable or increasing returns (VRS, IRS) have agreeing colors, making the GMD representative of the constant and decreasing returns and the GMI a representation of the increasing and variable returns. Regarding the variable (IL), from the sectoral analysis it was not possible to extract information based on the gradient of colors.

Sector 29, *Petroleum and Coal Products* were classified with the best efficiency average using SFA with no significant discrepancy in relation to other methods. In sector 26 *Paper and Allied Products*, there is a clear divergence between the parametric and non-parametric methods. In sector 22 *Textile Mill Products* there is an agreement of less efficiency for all methods. From a general perspective there is an agreement of methods for estimation of enterprise efficiency, given that the lower part of Table 5 is almost all dark brown. Regarding the variable (IL), as an addition or through a sectoral analysis it is not possible to extract information based on the color gradient, as the implementation level of the practices, speaking in terms of sectors, seems not to have a clear relationship with the calculated enterprise efficiency.

Table 6 shows the coefficients of the Pearson correlation between the calculated efficiencies and the level of implementation, confirming the strongest correlations between (SFA, CRS, DRS) and (VRS, IRS).

Based on the correlation coefficients of Table 6, it can be affirmed that the degree of linear association between the

Table 5
Aggregation of efficiency and implementation level by industrial sectors.

SIC - Industrial sectors	SFA	DRS	CRS	COLS	GMD	IRS	VRS	GMI	IL
29 Petroleum and Coal Products	0.615	0.781	0.781	0.004	0.716	0.885	0.886	0.885	0.517
21 Tobacco Products	0.608	0.831	0.828	0.011	0.739	0.904	0.908	0.906	0.433
28 Chemicals and Allied Products	0.584	0.759	0.759	0.003	0.689	0.872	0.872	0.872	0.458
20 Food and Kindred Products	0.567	0.754	0.754	0.003	0.679	0.874	0.874	0.874	0.486
26 Paper and Allied Products	0.555	0.736	0.736	0.002	0.667	0.859	0.859	0.859	0.463
38 Instruments and Related Products	0.554	0.777	0.777	0.002	0.686	0.899	0.899	0.899	0.469
37 Transportation Equipment	0.547	0.762	0.762	0.002	0.676	0.885	0.885	0.885	0.485
35 Industrial Machinery and Equipment	0.546	0.759	0.759	0.002	0.675	0.891	0.891	0.891	0.492
24 Lumber and Wood Products	0.537	0.769	0.769	0.002	0.678	0.898	0.898	0.898	0.480
39 Miscellaneous Manufacturing Industries	0.533	0.761	0.761	0.002	0.671	0.901	0.901	0.901	0.446
25 Furniture and Fixtures	0.532	0.775	0.775	0.002	0.681	0.916	0.916	0.916	0.477
36 Electronic and Other Electric Equipment	0.526	0.761	0.761	0.002	0.668	0.887	0.887	0.887	0.473
31 Leather and Leather Products	0.511	0.775	0.775	0.001	0.671	0.920	0.920	0.920	0.506
34 Fabricated Metal Products	0.502	0.742	0.742	0.002	0.646	0.883	0.883	0.883	0.486
27 Printing and Publishing	0.500	0.743	0.743	0.001	0.646	0.871	0.871	0.871	0.456
30 Rubber and Miscellaneous Plastics Products	0.486	0.734	0.734	0.001	0.635	0.861	0.861	0.861	0.465
32 Stone, Clay, And Glass Products	0.481	0.738	0.738	0.001	0.635	0.866	0.866	0.866	0.492
33 Primary Metal Industries	0.479	0.734	0.734	0.002	0.630	0.865	0.865	0.865	0.443
23 Apparel and Other Textile Products	0.475	0.764	0.764	0.001	0.644	0.916	0.916	0.916	0.517
22 Textile Mill Products	0.468	0.725	0.725	0.001	0.621	0.856	0.856	0.856	0.477
Mean	0.526	0.750	0.750	0.002	0.661	0.879	0.879	0.879	0.476

Note: a) Aggregation of the 10,448 enterprise efficiency estimated by the models of the Eqs. (10)–(12) and the IL variable of the Eq. (4), taking into account the sector in which each of the enterprise belong: (*sum of efficiency or IL of the enterprises belonging to the sector/number of enterprise in the sector*), (classified by SFA). b) Darker color (Percentile 30% less efficient); Lighter color (Percentile 70% more efficient).

Table 7
Aggregation of efficiency by ARC practice implemented and not implemented.
Source: (US DOE-IAC_ARC, 2007; US DOE-IAC, 2011).

Status	Recommended	Implemented		Not Implemented	
(ARC) Energy efficiency practices more recommended	Q	Eff	QI	Eff	NQI
27,142 Utilize higher efficiency lamps and/or ballasts	7284	0.7386	4010	0.7359	3274
24,236 Eliminate leaks in inert gas and compressed air lines/ valves	4883	0.7425	3942	0.7391	941
24,221 Install compressor air intakes in coolest locations	3465	0.7336	1558	0.7362	1907
24,133 Use most efficient type of electric motors	3273	0.7356	2126	0.7305	1147
27,135 Install occupancy sensors	2865	0.7413	1052	0.7395	1813
22,511 Insulate bare equipment	2149	0.7278	1027	0.7271	1122
27,143 Use more efficient light source	2053	0.7425	1069	0.7386	984
24,231 Reduce the pressure of compressed air to the minimum required	1856	0.7420	913	0.7479	943
24,111 Utilize energy-efficient belts and other improved mechanisms	1680	0.7319	854	0.7295	826
24,141 Use multiple speed motors or afd for variable pump, blower	1225	0.7285	347	0.7325	878
22,434 Recover heat from air compressor	1184	0.7451	379	0.7413	805
21,233 Analyze flue gas for proper air/fuel ratio	1105	0.7349	725	0.7243	380
27,261 Install timers and/or thermostats	961	0.7472	492	0.7351	469
27,111 Reduce illumination to minimum necessary levels	949	0.7419	478	0.7359	471
24,232 Eliminate or reduce compressed air used for cooling	859	0.7379	365	0.7391	494
22,131 Insulate steam/hot water lines	805	0.7293	473	0.7316	332
21,311 Replace electrically-operated equipment with fossil fuel equipment	777	0.7318	195	0.7315	582
22,411 Use waste heat from hot flue gases to preheat combustion air	725	0.7246	115	0.7213	610
27,134 Use photocell controls	547	0.7434	222	0.7459	325
26,218 Turn off equipment when not in use	505	0.7297	257	0.7399	248
Total Implementations	39,150	–	20,599	–	18,551
Mean of Efficiency		0.7365	–	0.7351	–
t-test - Eff Implemented *versus* Eff Not Implemented		*p*-value = 0.5236			

Note: This table shows only the 20 most recommended practices in a total of 504, calculated by Excel® pivot table. a) (Q=QI+NQI) where Q: (62,263 efficiency of recommendation equivalent to 10,448 enterprise efficiency aggregate by 504 ARC code); QI (quantity Implemented); NQI (quantity not Implemented) c) Eff =geometric mean (SFA. CRS. DRS. VRS. IRS); d) Shaded area (percentile 40% more efficient); e) *t*-test presuming equivalent variances.

estimations of efficiency and the adoption of energy efficiency practices is low (less than 3%), requiring an alternative approach for modeling the entire distribution of the dependent variable (quantile regression).

4.2. Relationship between enterprise efficiency and the adoption of energy efficiency practices

Table 7 shows the aggregated enterprise efficiency by 20 most recommended practices. The efficiency of practices is equivalent to the efficiency of enterprise that did and did not adopt the recommended practices in Table 2, remembering that the 39,150 recommendations represent 62.9% of the total practices where 20,599 were implemented and 18,551 not implemented (see Table 2 in %).

The calculated efficiency values of the companies that adopted and did not adopt the practices are very close in all of the 20 practices. Also coinciding with the percentile of 40% greater efficiency values. The testing for differences in the efficiency averages also was not significant. These data show that there is no preference for practices by more efficient companies, when the most recommended practices are analyzed.

To investigate the level of efficiency of the audited companies and the adoption of energy efficiency practices the quantile regression model (Eq. (15))[3] was developed. Based on Eq. (15) the dependent variable is the implementation level (IL). The main independent variable is the value of enterprise efficiency u_k^{Eff} estimated by the various methods (SFA. COLS. CRS. DRS. VRS. IRS. GMD and GMI). The auxiliary independent variables are: Energy Intensity of electricity (UEY); Energy Intensity of gas (UNY); Simple Payback (ICPS); Average energy price of the project (PSPC).

Table 8 presents the estimations made considering the different efficiency measurements in 15 different quantiles (0.20–0.90) of the (IL) variable generating a total of 120 regression models (the coefficients of the GMI and GMD variable regressions are not presented in Table 8).

The supposition of these models in quantile regression is that the level of implementation of the practices depends on the efficiency present in the company, which is different in the various quantiles. Therefore, payback, average price of energy and energy intensity are control variables. Analyzing it another way, once the price of the project, payback and energy intensity are controlled, what is the relationship between enterprise efficiency and the level of implementation of the practices?

Table 8 can be analyzed in two ways: (a) Taking the type of return to scale into consideration for estimating efficiency; (b) Considering the quantile of the dependent variable implementation level (IL). Firstly, when analyzing the returns to scale what stands out is that in all of the quantiles, the sign of the coefficients of the models in constant or decreasing returns (SFA, COLS, CRS, DRS) are negative and the signs of the models in variable or increasing returns (VRS, DRS) are positive. Another factor to be considered is the magnitude of these coefficients, as the measure of the higher quantiles are achieved the strength of the relationship increases, either positively or negatively. This factor means that the companies that have higher rates of implementation in energy efficiency are more tuned in to their previous level of efficiency. Taking as an example the quantile 0.90 of SFA, the coefficients can be interpreted in the following manner: An increase of one percentage point (1.0%) in enterprise efficiency lowers implementation to (0.28%). Considering (IRS and VRS) also in quantile 0.90 the interpretation is the inverse: An increase of one percentage point (1.0%) in enterprise efficiency increases the implementation of practices by (0.43%).

One issue to be resolved, related to the main objective of this work is interpreting the sign, using the models under different hypotheses of return to scale. When the sign is positive it means

[3] Estimated by pacote R quantreg (Koenker, 2015) and tested in Gretl (Gnu Regression, Econometrics and Time-series Library - gretl.sourceforge.net). The (Std. Error and *t*_value) was omitted for reasons of space.

Table 8
Parameters of quantile regression (dependent variable: implementation level).

Quantile θ	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
SFA	**−0.027**	**−0.077**	**−0.104**	**−0.088**	**−0.083**	**−0.098**	**−0.071**	**−0.118**	**−0.139**	**−0.168**	**−0.190**	**−0.153**	**−0.167**	**−0.217**	**−0.280**
UEY	−0.016	−0.023	−0.025	−0.021	−0.019	−0.022	−0.016	−0.019	−0.022	−0.024	−0.026	−0.022	−0.026	−0.031	−0.036
UNY	0.003	0.004	0.003	0.003	0.003	0.004	0.001	0.000	0.001	0.001	−0.001	−0.001	−0.001	−0.004	−0.002
ICPS	−0.034	−0.033	−0.029	−0.027	−0.027	−0.030	−0.025	−0.032	−0.030	−0.028	−0.028	−0.025	−0.028	−0.022	−0.024
PSPC	−0.005	−0.006	−0.005	−0.007	−0.008	−0.009	−0.008	−0.011	−0.012	−0.012	−0.013	−0.011	−0.012	−0.014	−0.016
COLS	**−0.262**	**−0.348**	**−0.401**	**−0.442**	**−0.467**	**−0.512**	**−0.535**	**−0.559**	**−0.600**	**−0.637**	**−0.284**	**−0.328**	**−0.383**	**−0.474**	**−0.505**
UEY	−0.015	−0.018	−0.016	−0.014	−0.013	−0.015	−0.010	−0.009	−0.011	−0.012	−0.011	−0.011	−0.012	−0.014	−0.010
UNY	0.003	0.005	0.004	0.003	0.004	0.005	0.001	0.001	0.002	0.003	0.001	0.000	−0.001	−0.002	−0.002
ICPS	−0.034	−0.032	−0.031	−0.026	−0.026	−0.031	−0.024	−0.032	−0.029	−0.028	−0.028	−0.025	−0.028	−0.023	−0.023
PSPC	−0.005	−0.005	−0.005	−0.007	−0.008	−0.009	−0.008	−0.010	−0.012	−0.011	−0.012	−0.010	−0.011	−0.013	−0.014
CRS	**−0.047**	**−0.107**	**−0.111**	**−0.081**	**0.004**	**−0.007**	**−0.030**	**0.003**	**−0.051**	**−0.003**	**0.015**	**−0.002**	**−0.108**	**−0.005**	**−0.107**
UEY	−0.015	−0.019	−0.018	−0.015	−0.012	−0.015	−0.010	−0.009	−0.011	−0.011	−0.009	−0.011	−0.014	−0.013	−0.013
UNY	0.003	0.004	0.003	0.003	0.004	0.005	0.001	0.001	0.002	0.003	0.001	0.001	−0.001	−0.003	−0.002
ICPS	−0.034	−0.032	−0.031	−0.026	−0.026	−0.031	−0.025	−0.032	−0.028	−0.028	−0.028	−0.025	−0.028	−0.023	−0.023
PSPC	−0.005	−0.004	−0.006	−0.007	−0.008	−0.009	−0.008	−0.010	−0.012	−0.011	−0.012	−0.010	−0.010	−0.013	−0.013
DRS	**−0.047**	**−0.112**	**−0.111**	**−0.087**	**0.003**	**−0.007**	**−0.030**	**0.002**	**−0.052**	**−0.003**	**0.015**	**−0.004**	**−0.108**	**−0.006**	**−0.107**
UEY	−0.015	−0.019	−0.018	−0.015	−0.012	−0.015	−0.010	−0.009	−0.011	−0.011	−0.009	−0.011	−0.014	−0.013	−0.013
UNY	0.003	0.004	0.003	0.003	0.004	0.005	0.001	0.001	0.002	0.003	0.001	0.001	−0.001	−0.003	−0.002
ICPS	−0.034	−0.032	−0.031	−0.026	−0.026	−0.031	−0.025	−0.032	−0.028	−0.028	−0.028	−0.025	−0.028	−0.023	−0.023
PSPC	−0.005	−0.004	−0.006	−0.007	−0.008	−0.009	−0.008	−0.010	−0.012	−0.011	−0.012	−0.010	−0.010	−0.013	−0.013
VRS	**0.037**	**0.059**	**0.090**	**0.118**	**0.130**	**0.177**	**0.177**	**0.247**	**0.326**	**0.373**	**0.354**	**0.283**	**0.399**	**0.370**	**0.428**
UEY	−0.013	−0.015	−0.014	−0.010	−0.010	−0.012	−0.006	−0.005	−0.004	−0.004	−0.005	−0.005	−0.006	−0.007	−0.002
UNY	0.003	0.004	0.004	0.003	0.004	0.005	0.002	0.002	0.003	0.003	0.003	0.002	0.000	0.000	0.001
ICPS	−0.034	−0.032	−0.029	−0.027	−0.028	−0.030	−0.026	−0.032	−0.030	−0.031	−0.029	−0.025	−0.028	−0.023	−0.025
PSPC	−0.005	−0.005	−0.005	−0.007	−0.008	−0.009	−0.009	−0.011	−0.012	−0.013	−0.014	−0.011	−0.012	−0.014	−0.016
IRS	**0.041**	**0.065**	**0.091**	**0.121**	**0.135**	**0.180**	**0.177**	**0.247**	**0.326**	**0.373**	**0.357**	**0.283**	**0.400**	**0.370**	**0.428**
UEY	−0.013	−0.015	−0.014	−0.010	−0.010	−0.012	−0.006	−0.005	−0.004	−0.004	−0.005	−0.005	−0.006	−0.007	−0.002
UNY	0.003	0.004	0.004	0.004	0.004	0.005	0.002	0.002	0.003	0.003	0.003	0.002	0.000	0.000	0.001
ICPS	−0.033	−0.032	−0.030	−0.027	−0.028	−0.030	−0.026	−0.032	−0.030	−0.031	−0.029	−0.025	−0.028	−0.023	−0.025
PSPC	−0.005	−0.005	−0.005	−0.007	−0.008	−0.009	−0.009	−0.011	−0.012	−0.013	−0.014	−0.011	−0.012	−0.014	−0.016

Note: a) Independent variables are defined in quantile regression model of Eq. (15): (*SFA, COLS, CRS, DRS, VRS, IRS*=u_k^{Eff}; *UEY*=$\frac{UE}{Y}$; UNY = $\frac{UN}{Y}$; ICPS=$\frac{IC}{PS}$; PSPC = $\frac{PS}{PC}$). b) Shaded area (Coefficients statistically significant by at least 5%).

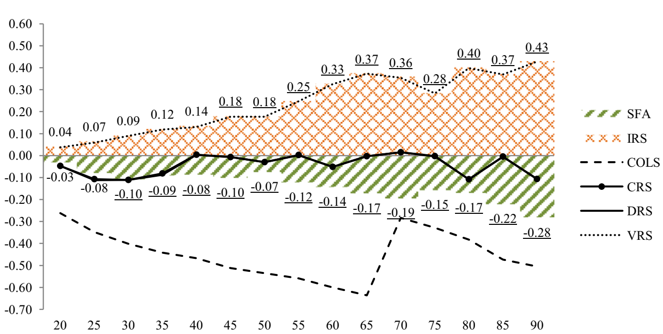


Fig. 1. Quantile coefficients (all three categories of recommendations).

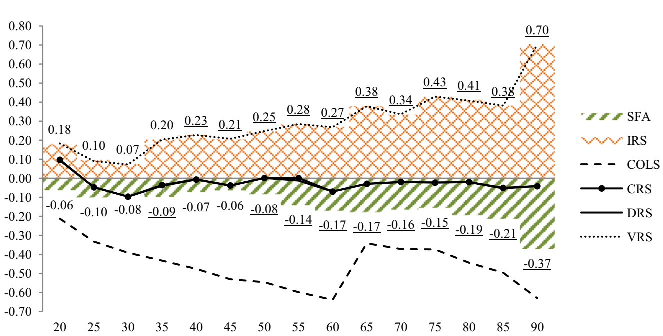


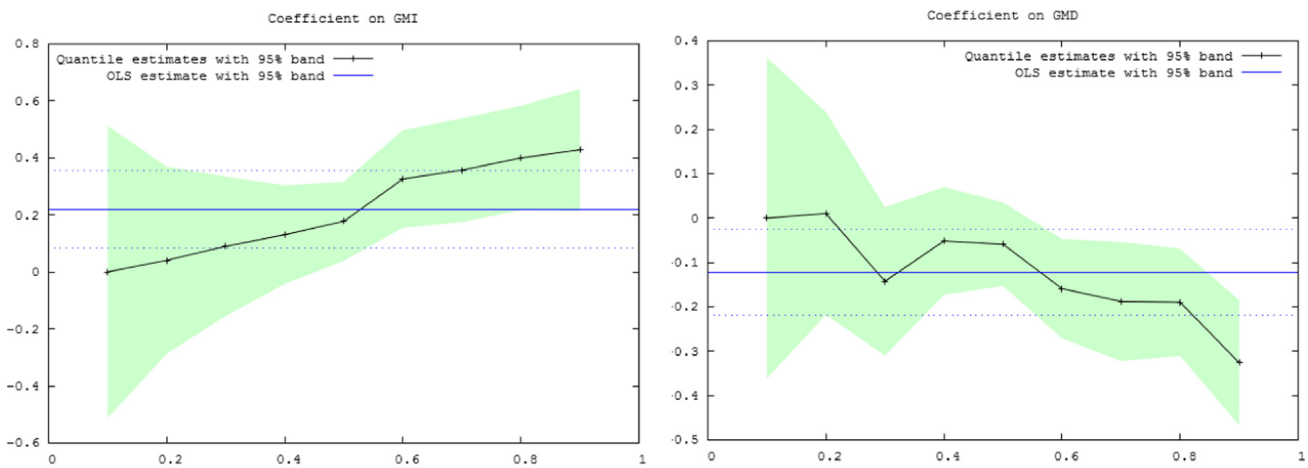
Fig. 2. Quantile coefficients (energy management recommendations).

that a more efficient company adopts more energy management practices and the opposite is true when the sign is negative. Fig. 1 shows the graph of the estimated coefficients of Table 8 (underlined values significant at 5% for SFA and IRS), which consider the practices in all of the recommended categories, (*Energy Management. Waste Minimization/Pollution Prevention and Direct Productivity Enhancement)* and Fig. 2 only the recommendations of energy management which represent 88% of the recommendations.[4]

Fig. 2 was included to demonstrate that even if only the energy management category is considered, the behavior or tendency of the graph does not change, possibly because the majority of the recommendations (88%) are for energy management practices or in synergy with other categories such as: waste minimization/pollution prevention and direct productivity enhancements.

According to Figs. 1 and 2 the implementation of energy efficiency practices depends on two factors related to enterprise efficiency: The returns to scale of the company and the actual level of implementation of practices. Considering a situation of increased returns to scale, controlling factors such as price, payback and energy intensity, the companies will tend to implement a greater number of practices (IRS area of the graphs in Figs. 1 and 2). On the other hand, if there are decreased returns, fewer practices will be implemented (SFA area in the graphs Figs. 1 and 2). The degree of advancement, whether positive or negative depends on the number of implementations executed, otherwise, if the number of implementations increases (higher quantile), when the company operates on increasing returns, the efficiency has a greater positive impact on implementations, on the other hand when the company operates on decreasing returns, the efficiency

[4] The ARC table (Assessment Recommendation Code - https://iac.university/technicalDocuments) has 357 recommendations of 5 digits recorded for energy management, 243 for waste minimization/pollution prevention and 76 for direct productivity enhancements. The majority of the recommendations (88%) in the sample used for this work (10.448 cases) are for energy management.



a – Coefficients GMI *versus* OLS **b** – Coefficients GMD *versus* OLS

Fig. 3. a – Coefficients GMI *versus* OLS, b – Coefficients GMD *versus* OLS.

has a greater negative impact on implementations.

Fig. 3 uses the estimated efficiency values on increasing or variable returns (GMI) and constant or decreasing returns (GMD). The behavior of the graph in Fig. 3a is similar to the IRS coefficients in Figs. 1 and 2, in turn, the graph for Fig. 3b is similar to the SFA coefficients for the same figures, generating proof of the existence of dominant behavior of increasing and decreasing returns.

5. Discussion

Table 1 presents the main results found in the literature review regarding the implementation of technologies for energy efficiency/savings. These works can be classified into two different groups. Those that want to know the determinants for more effective energy efficiency, considering energy efficiency as an effect (Christoffersen et al., 2006; Thollander and Ottosson, 2010; Suk et al., 2013; Liu et al. 2013; Zhang and Wang, 2014; Tonn and Martin, 2000; Anderson and Newell, 2004; Abadie et al., 2012; Therkelsen and McKane, 2013; Blass et al., 2014) and the articles that want to measure the impact of efficiency on the company's performance, considering energy efficiency as a cause (Kounetas and Tsekouras, 2010; Pons et al., 2013; Eccles and Serafeim, 2013). The objective of our work more closely resembles that of the first group. In other words, it sought mainly to find out if prior efficiency in the companies is a determinant for the implementation of energy efficiency measures or technologies.

Table 2 reveals that among the most recommended energy efficiency practices, the proportion of implementations (33.15%) is almost equal to the non-implementations (29.8%). Even more simple practices like (Utilizing higher efficiency lamps and/or ballasts; Turning off equipment when not in use) are not fully adopted. The 20 most recommended practices have a rate of adoption similar to that found in Anderson and Newell (2004) and is in agreement with the results of Christoffersen et al. (2006) and Thollander and Ottosson, 2010 as the energy management practices still are not a priority for the majority of industrial enterprises. The data in Table 7 indicates that there is no preference for practices by more efficient companies when considering the practices most recommended in audits, as the average individual values are very close and the general average shows no significant difference.

In terms of sectors, Table 5 shows a certain level of agreement for estimated enterprise efficiency, considering the different models, although there are differences, especially among the models under different conditions of return to scale for sectors such as Chemicals and Allied Products, Food and Kindred Products and Paper and Allied Products. A correspondence can be found in the literature for the results in Table 5, as the petroleum sector was also considered more efficient in the work of Azadeh et al. (2007) and the literature identifies resource efficiency problems in the Textile sector, which was found to be the least efficient sector (Negai et al., 2013; Moon et al., 2013; Alkaya and Demirer, 2014). According to the correlation matrix of Pearson in Table 6 it was not possible to draw conclusions regarding the main problems of the research (relationship between enterprise efficiency and the adoption of practices), which calls for a more sophisticated approach such as quantile regression.

The application of the quantile regression model in Eq. (15) was more satisfactory, as summarized in Table 8 and in Figs. 1–3, revealing that there is both a positive and negative relationship between enterprise efficiency and the adoption of energy efficiency practices. The energy intensity of electricity (UEY) had a negative relationship, in other words, more intensive companies implemented fewer practices possibly due to the fact that these companies have already adopted simpler practices, as only the number of recommendations was considered in the (IL) variable. The energy intensity variable for natural gas (UNY) in the majority of estimations showed a positive relationship to implementation, but without significance. In the work of Abadie et al. (2012) the implementations related to natural gas had a lower probability of implementation. The ICPS variable or simple payback obtained statistical significance in all of the models and shows a negative relationship, confirming the results of Anderson and Newell (2004) and Abadie et al. (2012) that the greater the payback the fewer practices will be implemented. The variable average price of energy of the project (PSPC) shows a negative relationship with implementation. The price of energy in the work of Anderson and Newell (2004) has a positive relationship with implementation but when the variation was increased raising the price to the square the relationship was also negative, similar to the findings in our work.

Regarding the various models of enterprise efficiency, it was found that the sign of relationship depends on the return to scale of the companies, negative for decreasing and positive for increasing. Clearly Figs. 1–3 reveal that the strength of the relationship depends on the quantile of implementations. This result shows that in addition to cost, the payback of the project and price of energy found by Anderson and Newell (2004) and Abadie et al. (2012) and also in our work, the implementations also depend

Returns to Scale		Level of Implementation: Low — **Less Conscious**	Level of Implementation: High — **More Conscious**
Increasing	**High Return on investment**	α LOW RATE OF ADOPTION	β HIGH RATE OF ADOPTION
Decreasing	**Low return on investment**	λ LOW RATE OF REJECTION	Θ HIGH RATE OF REJECTION

Fig. 4. Quadrant of the categories of adoption of energy efficiency practices.

both on prior efficiency and returns to scale of the company and the strength of the relationship depends on whether the company has already adopted many or few of the practices. Fig. 4 summarizes the behavior of the companies translated in Figs. 1–3 into four categories: Low rate of adoption, high rate of adoption, low rate of rejection, high rate of rejection. The interpretation of the categories indicates that the same variation in efficiency can stimulate behaviors that depend both on returns to scale of the company (low or high return on investments) as well as whether the company adopts many or few practices (being more conscious or less conscious).

The practical interpretation of the quadrant adoption of energy efficiency practices in Fig. 4 is that for a certain level of efficiency the adoption will be higher if the company has a higher return on investments and is still initiating the adoption process (β). The policymakers can take this into consideration since in the other three cases of Fig. 4(α. λ and θ) the result is going to be lower than desired. Also the literature review in Table 1 informs that other factors are determinants for the implementation of energy efficiency practices like: Energy management strategies, self-motivation, support of upper management, trainings, economic incentives, innovation strategies, industrial symbiosis, involvement of operations manager. The quadrant in Fig. 4 does not negate these other determinants in the literature, but raises the hypothesis that these factors can be happening in companies with a greater return on investment that are already started on the process of adopting practices.

6. Conclusion

The literature identifies various barriers to industrial energy efficiency and energy management, an understanding of these barriers is needed to make the necessary corrections, both for internal company issues and external policies. Our work sought to answer the following question: What is the relationship between enterprise efficiency and the adoption of energy efficiency practices? To answer the question, we proposed models for the estimation of efficiency as well as a model to test the question. These models were idealized to use the cases from energy efficiency audits for small and medium-sized DOE-IAC companies. The main result found in our work was that projects do not depend only on cost and payback, they also depend on the current level of efficiency of the company and whether or not the company has already started some energy efficiency projects. This dependence occurs in two ways, if the company operates with increasing returns, it will probably incorporate more energy management and energy efficiency projects, on the other hand, if the returns are decreasing, more projects will be put aside. This result generates evidence that it is not necessarily the most efficient companies that are concerned with environmental issues. Since according to our study if a company is more efficient, but is operating with decreasing returns to scale, it will adopt a lower number of practices for energy savings.

A second issue raised was if there is a difference in efficiency between the companies that adopted certain practices and those that didn't? When the efficiency was added to more recommended practices we did not find significant evidence that there is a preference for practices by the more efficient companies. Our work suggests that policies for stimulating sustainable behaviors in the area of energy efficiency can have unintended results. This fact can be seen in the quadrant of categories for adopting energy efficiency practices, since, for example, a more conscious company can have a high level of rejection if it operates with decreasing returns.

The main limitation of our work is related to the creation of the dependent variable in the test model, implementation level (IL), since this variable measures the number of recommendations adopted and not the quality of the recommendations related to the energy savings potential. Another limitation is that the extrapolation of the results has to be analyzed with care since the sample of IAC cases is made up of small and medium-sized companies.

For future work we suggest including the quality of the recommendations as well as additional variables such as innovation, in other words, how innovation has influenced the implementations of the IAC-DOE project. Do the more innovative companies have higher rates of implementation? If it is found that the companies with higher return to scale are also more innovative, thus this work can conclude that more innovative companies also have greater rates of implementation.

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