Socio-Economic Planning Sciences 47 (2013) 120–130

Contents lists available at SciVerse ScienceDirect

Socio-Economic Planning Sciences

journal homepage: www.elsevier.com/locate/seps

An analysis of eco-efficiency in energy use and CO_2 emissions in the Swedish service industries

Clara Inés Pardo Martínez [a,b,c,*]

[a] Faculty of Administration, Universidad del Rosario, Bogotá, Colombia
[b] Faculty of Environmental Engineering, University of La Salle, Bogotá, Colombia
[c] Energy and Climate Studies, Department of Energy Technology, KTH, Stockholm, Sweden

ARTICLE INFO

Article history:
Available online 19 December 2012

JELS Classifications:
L80
Q4
C33

Keywords:
Swedish service industries
CO_2 emissions
Energy efficiency
Data envelopment analysis
The Malmquist productivity index
Panel data model

ABSTRACT

This study determines the trends in energy efficiency and CO_2 emissions of the Swedish service sector using data at the 2-digit level of aggregation for the Swedish service industry over the period 1993–2008, this empirical study examines eco-efficiency in terms of energy efficiency and CO_2 emissions based on a number of models. The results show that Swedish service industries increased energy consumption and CO_2 emissions during the sample period, whereas energy and CO_2 emission intensities have shown a decrease in recent years. Eco-efficiency models based on the Malmquist data envelopment analysis model suggest that Swedish service industries have an excellent potential to increase energy efficiency and reduce CO_2 emissions. Second-stage panel data techniques show that energy taxes, investments and labour productive have a significant and positive influence on energy and CO_2 emission intensities implying that increasing these variables lead to higher energy efficiency and lower CO_2 emission intensity. This analysis demonstrates the importance of designing and applying adequate energy policies that encourage better energy use and management in this industrial sector for the goal of achieving a low carbon economy.

1. Introduction

Service sector has become an engine of economic growth and is one of the factors used to measure an economy's progress, its development, its quality and its perspectives [18,47,73]. In the world, Service industries represent 63.2% of the gross domestic product, occupy 41.9% of the labour force, consume 12% of energy and account for 9% of CO_2 emissions (see Fig. 1). Between 1974 and 2009, due to the structural changes accompanying the migration from manufacturing to service industries, energy consumption has increased 69% and electricity as main energy source (see Fig. 2), has increased from 15% to 23% [40,43] and [11,42].

Notwithstanding these trends showing that the fastest growth in energy consumption is in the service industries, this sector has been neglected in energy analysis and the application of energy policies and programmes. Some causes for this neglect may be the heterogeneity of the segment, the complexity of its statistical valuation (which requires detailed and disaggregated information), and the sector's low energy intensity relative to manufacturing. For instance, in the European Union, the service sector requires approximately one-eighth of the energy required by the manufacturing industries to generate one unit of gross production [29,40,43,52,70].

There are several methods and techniques for energy modelling. Greening et al. [32] grouped energy modelling four analysis techniques decomposition of energy trends, econometric methods, 'Top-down' and 'Bottom-up' models and Industry-specific microeconomic analyses. The description of these techniques is the following:

1.1. Decomposition of energy trends

This technique is used to determine changes in energy consumption with respect to changes in industrial structure, output mix and energy and emissions trends. For example, Bhattacharyya and Matsumura [5] used this technique to analyse the reduction in greenhouse gas emissions in 15 European Union countries, identifying that the driving factors of emissions are energy and other industrial activities. The reduction in emissions intensity depended mainly on changes in the energy mix and a reduction in energy intensity. Unander [80] evaluated manufacturing energy use in 10 IEA countries using a decomposition analysis, demonstrating that

* Faculty of Administration, Universidad del Rosario, Bogotá, Colombia.
E-mail address: cipmusa@yahoo.com.

0038-0121/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.seps.2012.11.004

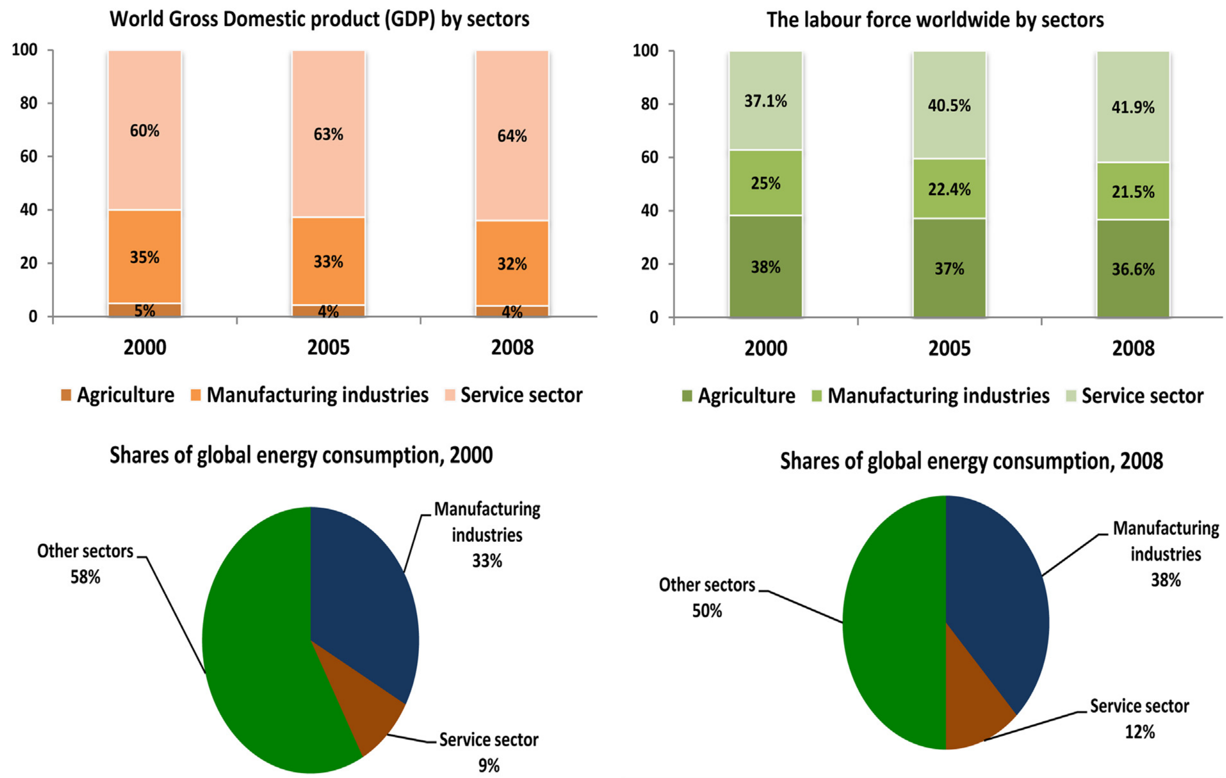

Fig. 1. Global trends in the service sectors in comparison of other economic activities. *Sources*: [42] *and* [11].

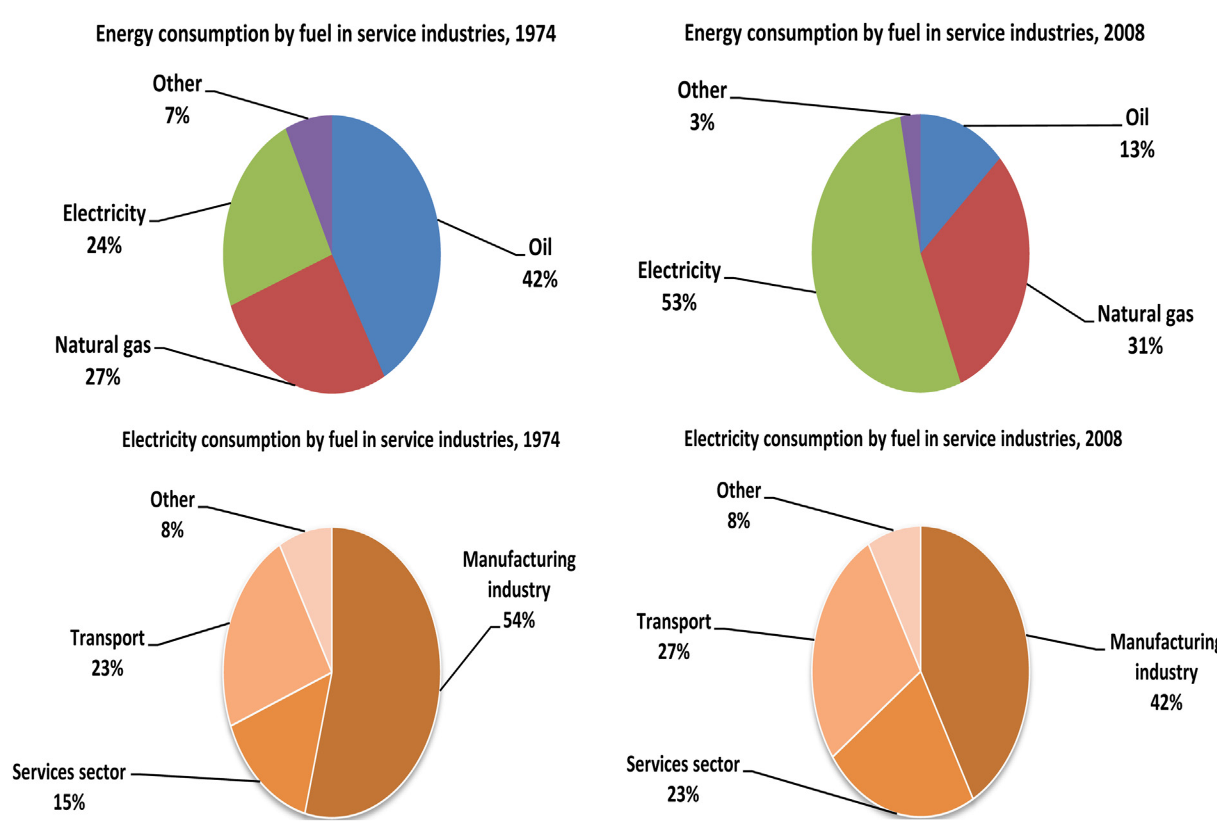

Fig. 2. Global trends in energy consumption in the services industries. *Sources:* [42].

the reduction in energy use was driven by structural changes and falling energy intensities in individual manufacturing branches. The main advantages of this technique are that generates an aggregate measurement with respect to changes in energy consumption and can be used as complement with other analysis techniques. In contrast, the main disadvantages of this method are that require high quality of data, difficulty of interpretation with some methods and no causal relationships might be inferred [1].

1.2. Econometric methods

These methods have several applications, including the evaluation of the effects of prices, taxes, and technologies on, among other things, energy consumption or conservation or to determine the decoupling between energy and production. For example, Werf [83] applied production functions to determine the substitution elasticities between capital, labour and energy, suggesting that the role of endogenous technological change in reducing the costs of climate policy may be larger than has been found by some climate policy models. Saunders [66] compared eight production/cost functions for exploring how gains in energy efficiency affect energy consumption. The results indicated that the value share of fuel is also a critical driver. In both the short and long term, fuel's value share is the primary determinant of the output/income component of rebound. The advantages of this method are that can be applied to analysis a large number of topics at varying levels of detail, and the causal relationship can be recognised and quantified. The disadvantages of econometric methods are that results depend of quality and availability of historical data, are sensitive to the procedures of estimation applied and can be difficult to transfer [79].

1.3. 'Top-down' and 'Bottom-up' models

The first type of model is used to study industrial technology policies or the impacts of technological change; e.g., Bretschger et al. [7] simulated the effects of carbon policies on consumption, welfare, and sectoral development in the long run, demonstrating the possibilities for decreasing energy consumption and carbon policy and how they are applied, especially in energy intensive sectors. The second model is applied to analyse the effects of specific technologies at different levels of aggregation; Murphy et al. [57] analysed greenhouse gas reduction policies regarding the Canadian manufacturing industry, such as a tax or emissions cap and tradable permits system using a hybrid energy-economy model, and they found that the trends in energy consumption and greenhouse gas emissions are set to increase, revealing the potential for technological transformation with the aim of changing this trend. The advantages of these models are that multiples factors can be modelled such as energy, emissions reductions, investments, prices, technologies, process, etc., and the disadvantage of these models are that it require higher levels of disaggregation, quantity of detailed data and specific frameworks and assumptions [6].

1.4. Industry-specific micro-economic analyses

Industry-specific micro-economic analyses include several models, including simulation, statistical or optimization techniques. In this vein, Henning and Trygg [36] analysed electricity use in non-energy-intensive sectors in Sweden, applying an energy system optimisation model indicating that electricity, which is used for heat production, can be replaced by fuel or district heating. The principal advantages of this analysis are that allow a detailed evaluation for a given or a share of a sector and include factors that would be complex to include in other techniques. In contrast, the principal disadvantages are the lack of interactions with other industrial sectors or the broader economy, and the scope of results might be restricted a specific analytical topic and not transferable to other areas [32].

In the service industries, these techniques have been applied to study energy use, CO_2 emissions, electricity consumption and barriers to adopting energy saving practices. Mairet and Decellas [52] analysed energy consumption trends in the French service sector using decomposition analysis, and concluded that the increase in energy consumption was mainly due to growth in the sector. Butnar and Llop evaluated changes in CO_2 emissions from the Spanish service sectors by applying an input–output subsystem approach and structural decomposition analysis. They showed that this sector increased CO_2 emissions mainly because of a rise in the emissions generated by non-services to cover the final demands of services. Collard et al. [15] analysed the effect of the use of information and communication technologies on electricity intensity in the French service sector using a factor demand model. They found that electricity intensity increased because of the use of computers and software. Schleich [67] and Schleich and Gruber [68] analysed the German context and concluded that limited information about energy use patterns and potential energy efficiency measures are the most important barriers to improving energy efficiency in the service industries.

Given this background and accounting for the fact that energy consumption grew the most quickly in the service sector due to a rapid expansion of this type of activity in the economy, further research on the energy use and CO_2 emissions in this sector is needed, particularly on the trends in energy consumption and greenhouse gas emissions and the application of new technologies and standards and features in production factors. This research should aim to determine opportunities and design adequate and effective energy policies to strengthen and motivate higher energy efficiency and lower CO_2 emissions in this sector.

The goal of this analysis is to increase the knowledge about energy use and CO_2 emission trends in the service industries. To do so, we apply different econometric approaches to the Swedish service sector in the period 1993–2008. To this end, energy efficiency and CO_2 emissions are analysed with traditional indicators such as energy intensity and CO_2 emission intensity. We use the Malmquist data envelopment analysis (DEA) model to assess eco-efficiency in terms of energy use and reduce CO_2 emissions within a production theory framework in which energy is one of the many inputs used to produce desirable or undesirable outputs [55,87]. This methodology has been applied in several energy studies. For instance, Pardo [62] studied energy efficiency in German and Colombian non-energy-intensive sectors. Ramanathan [64] and Oggioni et al. [59] have applied DEA to analyse energy as an input generating both desirable outputs (goods) and undesirable outputs (CO_2 emissions).

In Sweden, DEA has been used to model and compute productivity in public schools [27], describe economic efficiency in dairy farms [45], assess technical efficiency in urban bus systems [65], determine productivity development in hospitals [26] and evaluate productivity growth in retail electricity distribution [33].

The main contribution of this study is the application of DEA to analyse eco-efficiency in terms of energy efficiency and CO_2 emission performance in the service industries, which have been rarely studied in this field. The results and trends in eco-efficiency with respect to energy use and CO_2 emissions are then explained through second-stage regressions in terms of several key characteristics, using panel data analysis to determine the factors that determine eco-efficiency in the context of energy efficiency and decreasing CO_2 emissions in the service industries. The hypotheses that guide this research are the following: i. *the service industries have driven the increase in total energy consumption for the whole Swedish industrial sector.* ii. *Swedish service sector has a great potential to improve energy efficiency and decrease CO_2 emissions.* iii. *In Swedish service industries, higher energy taxes, investments and fuel substitutions drive to higher eco-efficiency in terms of energy efficiency and reduce CO_2 emissions.*

The following section describes the data and methodology used in this study. Section 3 reviews the economic and energy features and CO_2 emissions of the Swedish service industries. Section 4 presents and analyses the results. The conclusions are presented in Section 5.

2. Data and methodology

2.1. Data

The service industries (excluding electricity, gas and water supply and transportation services),[1] involve activities that take place in buildings used outside of manufacturing, agriculture and households, which comprise offices, banking, education activities, hospitals, retail trade, hotels, restaurants, computer and data processing services, and numerous others [48,74].

A dataset for Swedish service industries at 2-digit level of aggregation was collected from Swedish statistics [72] offices and International Standard Industrial Classification (ISIC Rev. 3.1) for the period 1993–2008. The service industry in this study excludes E: (40) electricity, gas, steam and hot water supply, (41) the collection, purification and distribution of water and I: (60–63) transport activities. The main data sources are the Swedish statistics [72] offices and the Organisation for Economic Co-operation and Development (OECD) database from the industry and services module. To apply the techniques used in this study, the following variables were obtained: capital input is measured as a stock by taking the value of gross fixed value; labour is measured by the total number of persons employed in service activities; energy is the final energy consumption by service activity measured in Terajoules (TJ); materials are measured by expenditure on materials, output is measured as value added and CO_2 emissions are measured in metric tons.[2] All monetary variables are standardised to euro values from 2005.

2.2. Methodology

This analysis is conducted in three steps: (i) traditional indicators of energy efficiency and CO_2 emissions are assessed; (ii) data envelopment analysis is applied to determine relative efficiencies in energy use and decreased CO_2 emissions, suggesting three models using the Malmquist productivity index; and (iii) panel data techniques are used to establish factors that may influence trends in the energy efficiency and CO_2 emissions of Swedish service industries.

2.2.1. Energy efficiency and CO_2 emissions

The first stage assesses traditional indicators of energy efficiency and CO_2 emissions by computing the energy intensity (EI) and CO_2 emission intensities (COI) (see Equations (1) and (2)). Changes in the intensities of energy and CO_2 emissions can be indicators of change in energy efficiency or the level of CO_2 emissions [39,49,63].

$$EI = E_{\mathrm{it}}/Y_{\mathrm{it}} \tag{1}$$

$$COI = CO_{it}/Y_{it} \tag{2}$$

E_{it} = Subsector's energy consumption in the year t.
CO_{it} = Subsector's CO_2 emissions in the year t.
Y_{it} = Subsector's production in year t.

2.2.2. Measuring eco-efficiency performance using the Malmquist DEA model

In this study, the DEA model applied is the Malmquist productivity index [53]. The Malmquist productivity index assesses the total productivity index of the DMUs (service industries) analysed, allowing for changes in productivity to be broken down into changes in technical efficiency and changes in technological efficiency. In the energy analysis, this technique has been applied e.g. Zhou et al. [88] that presented a Malmquist CO_2 emission performance index for measuring changes in total factor carbon emission performance over time and Lv et al. [51] analysed total factor energy efficiency for 30 Chinese provinces. The method was originally proposed by Caves et al. [10]; and was further established by Fare et al. [26] to measure for technological and efficiency changes. To describe this methodology, we consider two periods, 't' and 't+1', where period t is the base period, and period t+1 is used as the reference technology. In period t, a particular firm uses $x^t \in R^M_+$ inputs to produce $y^t \in R^M_+$ outputs, while in period t the input and output quantities used are x^{t+1} and y^{t+1} respectively. Applying the definition of distance functions, we can represent the output distance function for a firm at the period s as

$$D^t(x^t, y^t) = \inf\left\{\theta \in R : \left(\frac{x^t, y^t}{\theta}\right) \in P^t\right\}, \tag{3}$$

where P^t is the output set, defined as $P^t = \{(x^{t+1}, y^{t+1}) : y^{t+1}$ can be produced by $x^{t+1}\}$; and $D^t(x^t,y^t) \leq 1$ if and only if $(x^t,y^t) \in P^t$. The same applies to the distance function in period $t+1$ (for more details see [12]. The definition of the Malmquist index is based on the application of distance functions. Fare et al. [25] defined the Malmquist index as the geometric means of the original index proposed by [10]:

$$M_0^{t,t+1} = \left[\frac{D_0^t(y^{t+1}, x^{t+1})}{D_0^t(y^t, x^t)} \frac{D_0^{t+1}(y^{t+1}, x^{t+1})}{D_0^{t+1}(y^t, x^t)}\right]^{1/2}, \tag{4}$$

where $D_0^t(y^{t+1}, x^{t+1})$ signifies the output distance from the observation in period $t+1$ to the period t technology; $D_0^{t+1}(y^t, x^t)$ signifies the output distance from the observation in period t to the period t technology. The Malmquist index in Equation (4) can also be further decomposed (as shown in Ref. [25] into two components: one capturing efficiency change and another one capturing technological change (shift in the production frontier):

$$M_0^{t,t+1} = \underbrace{\frac{D_0^{t+1}(y^{t+1}, x^{t+1})}{D_0^t(y^t, x^t)}}_{\text{Efficiency change}} \underbrace{\left[\frac{D_0^t(y^{t+1}, x^{t+1})}{D_0^{t+1}(y^{t+1}, x^{t+1})} \frac{D_0^t(y^t, x^t)}{D_0^{t+1}(y^t, x^t)}\right]^{1/2}}_{\text{Technological change}} \tag{5}$$

The Malmquist index in Equation (3) are also possible by decomposition into scale and pure efficiency change components as suggested Fare et al. [25] measured through variable returns to

[1] Service sector in the International Standard Industrial Classification of all Economic Activities (ISIC Rev.3.1) is classified in the following sections used in this study: F: Construction, G: Wholesale and retail trade, H: Hotels and restaurants, J: Financial intermediation, K: Real estate, renting and business activities, L: Public administration and defense; compulsory social security, M: Education, N: Health and social work, and O: Other community, social and personal service activities.

[2] Total CO_2 emissions exclude bioenergy emissions.

scale (VRS) assumption, which can define mathematically it as follows:

$$\text{Pure efficiency change} = \frac{D_{\text{VRS}}^{t+1}\left(y^{t+1}, x^{t+1}\right)}{D_{\text{VRS}}^{t}\left(y^{t}, x^{t}\right)} \tag{6}$$

$$\text{Scale efficiency change} = \left[\frac{D_{\text{VRS}}^{t+1}\left(y^{t+1}, x^{t+1}\right)/D_{\text{CRS}}^{t+1}\left(y^{t+1}, x^{t+1}\right)}{D_{\text{VRS}}^{t+1}\left(y^{t}, x^{t}\right)/D_{\text{CRS}}^{t+1}\left(y^{t}, x^{t}\right)} \times \frac{D_{\text{VRS}}^{t}\left(y^{t+1}, x^{t+1}\right)/D_{\text{CRS}}^{t}\left(y^{t+1}, x^{t+1}\right)}{D_{\text{VRS}}^{t}\left(y^{t}, x^{t}\right)/D_{\text{CRS}}^{t}\left(y^{t}, x^{t}\right)}\right] \tag{7}$$

$$\text{Technological change} = \left[\frac{D_{\text{CRS}}^{t}\left(y^{t+1}, x^{t+1}\right)}{D_{\text{CRS}}^{t+1}\left(y^{t+1}, x^{t+1}\right)} \frac{D_{\text{CRS}}^{t}\left(y^{t}, x^{t}\right)}{D_{\text{CRS}}^{t+1}\left(y^{t}, x^{t}\right)}\right]^{1/2} \tag{8}$$

Therefore, the Malmquist index in Equation (3) is a product of three terms:

$$M_0^{t,t+1} = PEC_0^{t,t+1} \times SEC_0^{t,t+1} \times TC_0^{t,t+1} \tag{9}$$

Where $PEC_0^{t,t+1}$ denotes the pure efficiency change, $SEC_0^{t,t+1}$ denotes the scale efficiency change and $TC_0^{t,t+1}$ denotes the technological change (see Equations (6)–(9)). Note that $M_0^{t,t+1} > 1$ denotes productivity growth, while $M_0^{t,t+1} < 1$ means productivity decline. The same applies for all the other components: $PEC_0^{t,t+1} > 1$ means an increase in pure local efficiency (i.e. a firm has improved its catch per input in comparison to similar firms in the sample, and has also moved closer to the optimal scale of production), $SEC_0^{t,t+1}$ means an increase in scale efficiency (i.e. a firm has taken advantage of returns to scale by adjusting its size towards optimal scale) and $TC_0^{t,t+1} > 1$ means an increase in technology.

To calculate the Malmquist index in Equation (5) and the resulting decompositions in Equations (6) and (7), it is necessary to assess four sets of DEA linear programming problems. The first two are just the reciprocal of [28] output-oriented efficiency measure and they vary between 0 and 1. The other two linear programmes occur where the reference technology is constructed from data in one period, whereas the observation to be analysed is from another period. Moreover, in order to extend the Malmquist index decomposition to account for the scale efficiency measure and pure technical efficiency measures in Equations (6) and (7), two additional linear programming problems with VRS assumptions must be solved (for more details see Refs. [13,14].

In this study, we used panel data for years 1993–2008, on 19 Swedish service industries as DMUs and two DEA models are suggested to measure eco-efficiency, where a service industry producing a vector of n outputs y from a vector of n inputs $x = (x_1, x_2, \ldots, x_n)$, indicating that the vector y_i represents the output package and the vector x_i represents the input package of the i_{th} DMU, $i = 1 \ldots m$. In the first model, the input vector x_0 is divided explicitly into every input component – Capital (C), Labour (L) and energy (E) – and value added of each service industry was used as a measure of output (Y).

In the second model, it evaluates eco-efficiency performance within a joint production framework in which both desirable and undesirable outputs are considered simultaneously. The input and output vector x_0 is divided explicitly into every input component such as – Capital (C), Labour (L) and energy (E) – and value added of each service industry was used as a measure of desirable output and CO_2 emissions are an undesirable output. In the case of DEA models for undesirable output, the literature suggests several possibilities (for more details see Refs. [50,69]. In this study, the reciprocal value of the undesirable output is used to incorporate the feature that more desirable outputs are preferred, as in Ref. [64]; who studied the linkages among CO_2 emissions, Gross Domestic Product (GDP) growth and energy consumption using DEA, and Zhou and Ang [87]; who applied DEA for measuring economy-wide energy efficiency performance considering undesirable outputs as CO_2 emissions. In these models, when the score is equal to one the service sector is efficient, whereas scores below one represent lower efficiencies.

Additionally, the Wilcoxon rank-sum test is applied to evaluate whether the results from the Malmquist DEA model (technical efficiency) are an adequate approach for assessing eco-efficiency. According to Banker and Natarajan [4]; this test is a nonparametric alternative to evaluate whether the differences between the two groups are significant. This test is assessed to establish whether empirical distributions of DEA scores $\widehat{F}(\widehat{\varepsilon}_j^{\text{DEA}})$ and traditional indicators of energy efficiency and CO_2 emissions $\widehat{F}(\widehat{\varepsilon}_j^{\text{EE}})$ are different. The hypothesis of this test is that the distribution of X-measurement in sample A (energy intensity and CO_2 emission intensity) is the same as in sample B (DEA scores of technical efficiency) containing η_A and η_B observations, respectively. The null hypothesis is as follows: $H_0 \rightarrow$ *the efficiencies of the two groups have the same distribution.* The statistical index *(S)* is obtained by summing the scores of group *A*. An approximately normal distribution with mean $m(m+n+1)/2$ and variance $mn(m+n+1)/12$ is followed by (S), which when normalised, yields the following equation:

$$T = \frac{S - \dfrac{m(m+n+1)}{2}}{\sqrt{\dfrac{mn(m+n+1)}{12}}} \tag{10}$$

where S is the sum of the score for one group, m is the number of DMUs in that group, and n is the number of DMUs in the other group. T has an approximately standard normal distribution [16].

2.2.3. Explaining results of eco-efficiency models through panel data techniques

Panel data techniques are used to determine the factors that might explain differences in eco-efficiency levels across Swedish service industries during the sample period. The literature has suggested that Ordinary Least Square (OLS) may be sufficient, and this method does provide consistent estimates for second-stage regressions from results obtained with DEA models [4,38,54].

The results of the DEA models (technical efficiency) and energy intensity (EI) are defined as dependent variables in several panel data models that included multiple determinants of energy efficiency and CO_2 emissions. The DEA scores are log-transformed due to the skewness of the DEA scores and to improve normality. The models used in this study are as follows:

Technical efficiency or energy efficiency:

$$RE_{i,t} = \alpha_0 + \alpha_1 ET_{i,t} + \alpha_2 FFC_{i,t} + \alpha_3 INV_{i,t} + \alpha_4 LPR_{i,t} + \alpha_5 CL_{i,t} + \varepsilon_{i,t} \tag{11}$$

where $RE_{i,t}$ is the technical efficiency or energy intensity; $ET_{i,t}$ represents the expenditures in energy taxes applied to the Swedish service industry in period t for service industry i; $FFC_{i,t}$ represents fossil fuel consumption; $INV_{i,t}$ are investments; $LPR_{i,t}$ is labour productivity, measured as output per worker; and $CL_{i,t}$ is the capital input measured as the capital–labour ratio in period t for service industry i. The stages used to apply the panel data techniques are the following.

2.2.3.1. Selection of panel data model. To determine the suitable panel model, we first apply an F test for the pooled OLS model against the fixed effects model (see Equation (11)). We then reject the null hypothesis and select the fixed effects model. Next, we apply the Breusch–Pagan test for pooled OLS against the random effects model (see Equation (12)). Finally, we employ the Hausman test for fixed effects against random effects (see Equation (12)–(15)).

The *F-statistical test* is as follows:

$$F_{\text{group effects}}(n-1, nT-n-k) = \frac{\left(R^2_{\text{FEM}} - R^2_{\text{Pooled}}\right)/(n-1)}{\left(1-R^2_{\text{FEM}}\right)\Big/(nT-n-k)} \tag{12}$$

where T is the total number of temporal observations; n is the number of groups, k is the number of explanatory variables and FEM is the fixed effects model (for more details see Ref. [31]).

The Breusch and Pagan [8] *Lagrange multiplier test for random effects* was developed by Breusch and Pagan [8] and modified by Baltagi and Li [2] and Baltagi and Wu [3]. The model is as follows:

$$LM = \frac{nT}{2(T-1)}\left(\frac{T^2\bar{e}'\bar{e}}{e'e} - 1\right)^2 \sim \chi^2(1) \tag{13}$$

where $\bar{e}'\bar{e}$ is the sum total of the squared residuals from the REM, and $e'e$ is the sum total of squared residuals from the pooled OLS.

The *Hausman test* [35] selects between the fixed effects model (FEM) and random effects model (REM), the error term is specified as

$$u_{it} = \gamma_i + \alpha_t + \varepsilon_{it} \tag{14}$$

where γ_i accounts for unobserved heterogeneity across service industries (or service industry specific effects) and α_t accounts for factors that uniformly affect all services industries over time (or time specific effects). The general assumption of the REM model is that unobserved service industry effects are uncorrelated with the exogenous variables. Therefore, the Hausman test can be used to test the assumption. Failure to reject the null hypothesis indicates that the REM is the better model. The Hausman statistic is distributed as χ^2 and is defined as,

$$H = (\beta_{\text{FEM}} - \beta_{\text{REM}})'(V_1 - V_2)^{-1}(\beta_{\text{FEM}} - \beta_{\text{REM}}) \sim \chi^2(k) \tag{15}$$

where β_{FEM} are estimators from FEM model; β_{REM} are estimators from REM model. V_1 and V_2 stand for consistent estimates of the asymptotic covariance matrices of β_{FEM} and β_{REM}, respectively; k denotes the dimension of slope vector β.

2.2.3.2. Determine the consistency and robustness of estimations. To determine whether the estimation is consistent and robust, we test for heteroscedasticity in each regression model using the likelihood ratio (LR) test (see Equation (16)) and for serial autocorrelation using the Wooldridge test.

Testing for heteroscedasticity estimates the model by iterated GLS assuming the presence of heteroscedasticity and then by feasible GLS assuming homoscedasticity. The log likelihood of both the regressions is then compared to verify whether they are significantly different. This is done by calculating the likelihood ratio, which is distributed chi-square [58]. The LR test is as follows:

$$LR = -2(L_1 - L_0) \tag{16}$$

L_0 and L_1 are the log-likelihood values associated with the full and constrained models, respectively. If the constrained model is true, LR is approximately χ^2 distributed with d_0–d_1 degrees of freedom, where d_0 and d_1 are the model degrees of freedom associated with the full and constrained models, respectively [31].

2.2.3.3. Correction of problems in the estimations. Maximum likelihood estimation (MLE) for random effects can be used to correct autocorrelation and heteroscedasticity in a random effects model [9,46]. The MLE is as follows:

$$l_i = -\frac{1}{2}\left(\frac{1}{\sigma_e^2}\left[\sum_{t=1}^{T_i}\left(y_{it} - x_{it\beta}\right)^2 - \frac{\sigma_u^2}{T_i\sigma_u^2 + \sigma_e^2}\left\{\sum_{t=1}^{T_i}\left(y_{it} - x_{it\beta}\right)^2\right\}\right] + \ln\left(T_i\frac{\sigma_u^2}{\sigma_e^2} + 1\right) + T_i \ln\left(2\pi\sigma_e^2\right)\right) \tag{17}$$

A fixed effects regression with [17] standard errors can control for both heteroscedasticity and cross-sectional dependence in fixed effects models. This estimator is applied in two stages. In the first stage, all model variables $z_{it} \in \{y_{it}, x_{it}\}$ are within-transformed as follows [37]:

$$\tilde{z}_{it} = z_{it} - \bar{z}_i + \bar{\bar{z}} \text{ where } \bar{z}_i = T_i^{-1}\sum_{t=t_{i1}}^{T_i} z_{it} \text{ and } \bar{\bar{z}} = \left(\sum T_i\right)^{-1}\sum_i\sum_t z_{it} \tag{18}$$

The second stage then estimates the transformed model:

$$\tilde{y}_{it} = x'_{it}\theta + \tilde{\varepsilon}_{it} \tag{19}$$

3. Economic and energy features and CO_2 emissions in the Swedish service industries

In Sweden, the service sector has increasingly become a sector where new industrial composition is characterised by products and services with a greater knowledge content, greater productivity and higher value added [77]. This sector[3] accounted for approximately 12% of industrial energy consumption and 13% of total CO_2 emissions in 2008. In the same year, service industries accounted for approximately 66% of employment, 52% of industrial gross production and 64% of industrial value added and consisted of 500,000 companies. In terms of costs, energy accounts for approximately 1.19% of the total production costs; additionally, the service sector pays an average of 75% of the total electricity tax and 44% of the total fuel taxes paid by the Swedish industrial sector.

The trends in activity and energy indicators in the service industries between 1993 and 2008 show that production value, value added and employment increased by 68%, 67% and 37%, respectively; while energy, electricity consumption and CO_2 emissions increased by 27%, 15% and 17%, respectively. In absolute terms, the service industries have driven the increase in total energy consumption for the whole Swedish industrial sector. In manufacturing industries, especially the energy-intensive sectors, strong reductions in energy intensity and CO_2 emission intensity have offset the effect of growth that might otherwise have generated increased energy demand. As a result, energy consumption in the manufacturing industries decreased by 1.5% between 1993 and

[3] These statistics do not include transport activities and electricity, gas and water supply.

2008, whereas the service industry increased its energy consumption by 27% in the same period.

4. Results and discussion

We now show and discuss the results on energy use and CO_2 emissions derived from the methods explained above to determine the different factors that affect energy consumption and CO_2 emissions in this sector.

4.1. Energy intensity and CO_2 emission intensity

The average energy intensity and CO_2 emission intensity for the service industries over the total sample period were 1.84 TJ/Million€ and 78.21 Ton/Million€, respectively. All of the service sectors exhibited decreased energy intensity and CO_2 emission intensity per euro value added during the sample period.

4.2. Results of the Malmquist DEA model

Table 1 shows the results of technical efficiency from the Malmquist DEA-models proposed in this study. The average results of the two models for the Swedish service industries are 0.517 for model (1) and 0.582 for model (2). These results indicate that the Swedish services industries have excellent potential to increase energy efficiency and reduce CO_2 emissions. The results of the models suggest that the service sector could reduce energy input by nearly 48% and 42% on average respectively, maintain the same levels of output and reduce CO_2 emissions without consuming any additional inputs. These results are consistent with the energy baseline in the 2030 scenario developed by European Commission [22]; which estimated that final energy demand of the service industries is projected to decrease between 30% and 60% in 2030.

The Malmquist productivity index and other indices for the period 1993–2008 in Swedish service industries are shown in Table 2. For both models, the results are similar. We can see that the total productivity change score (the Malmquist index presented in column 1) is on average higher than one (for first model 1.02 and second model 1.01) indicating that several Swedish service industries experienced gains in productivity in the period considered. The change in the total efficiency score (column 2) is defined as the diffusion of best-practice technology in the management of the activity and corresponds to investment planning, technical experience and management and administration in the service industries. For the period of study, we can see that it is higher than one in both models signifying a growth in efficiency during this period for the majority of Swedish service industries.

Results in both models, for the pure efficiency change (column 3) and scale efficiency change (column 5) show diverse results, where various service industries obtaining simultaneous gains in both areas and others obtain gains in one, but losses in the other. The improvement in pure efficiency indicates a better balance between inputs and outputs. The scale efficiency is the consequence of size and in several service industries increases during the period. Technological change (column 4) is the result of innovation through new technologies. In both models, this index is higher than one in Swedish service sector indicating that innovation improved in the period.

The findings of the DEA models indicate that several service industries have increased energy efficiencies while decreasing CO_2 emissions. The Expert Group on Energy Efficiency [24] suggested that industrial energy efficiency has improved at a rate of 1% annually in recent decades. However, several studies and experience demonstrate that improvements could achieve double this rate over the medium or long run [19,23,82]. Moreover, results regarding efficiency in energy use and reduce in CO_2 emissions and total factor productivity have varied across years and services industries, but they show similar trends with respect to energy intensity and CO_2 emission intensity. To determine whether the results from the DEA models are adequate to measure eco-efficiency, the Wilcoxon test is applied. The test suggests that the results of the DEA models for energy and CO_2 emission intensity have the same distribution. This result is in accordance with the null hypothesis, H_0. The null hypothesis in each case is that the median of the coefficients of correlation for one treatment is equal

Table 1
Results of technical efficiency from the Malmquist DEA model for the Swedish service industries.

	DEA model 1	DEA model 2
1993	0.507	0.568
1994	0.535	0.578
1995	0.547	0.592
1996	0.550	0.599
1997	0.582	0.597
1998	0.589	0.610
1999	0.565	0.620
2000	0.482	0.583
2001	0.484	0.577
2002	0.514	0.573
2003	0.530	0.595
2004	0.477	0.566
2005	0.468	0.560
2006	0.472	0.557
2007	0.474	0.549
2008	0.501	0.591
Annual average	0.517	0.582

Table 2
Average of total factor productivity (TFP), total efficiency (EC), pure efficiency (PE), technological change (TC) and scale efficiency changes (SEC) in Swedish service industries (1993–2008).

	DEA model 1					DEA model 2				
	TFP	EC	PE	TC	SEC	TFP	EC	PE	TC	SEC
93–94	0.99	0.90	1.07	1.10	0.84	0.94	0.87	1.02	1.08	0.85
94–95	1.13	1.31	1.07	0.86	1.22	1.12	1.25	1.02	0.89	1.22
95–96	1.01	1.27	1.01	0.79	1.26	1.01	1.19	1.00	0.85	1.18
96–97	1.11	0.92	1.05	1.21	0.87	1.12	0.91	0.98	1.23	0.93
97–98	0.96	0.82	1.02	1.16	0.81	0.94	0.88	1.03	1.06	0.86
98–99	1.02	1.01	0.99	1.01	1.02	1.01	1.00	1.03	1.00	0.97
99–00	0.91	0.57	0.76	1.60	0.74	1.05	0.75	0.92	1.41	0.81
00–01	0.95	1.05	1.01	0.91	1.04	0.90	0.98	0.98	0.91	1.00
01–02	1.08	0.88	1.10	1.23	0.80	1.09	0.93	1.00	1.17	0.94
02–03	1.03	1.73	1.07	0.60	1.61	1.00	1.48	1.07	0.68	1.38
03–04	1.05	0.55	0.84	1.91	0.65	1.06	0.63	0.91	1.69	0.69
04–05	1.04	0.97	0.97	1.07	1.01	0.98	0.93	0.97	1.05	0.96
05–06	0.97	1.37	0.98	0.71	1.41	0.91	1.24	1.01	0.73	1.23
06–07	0.97	0.98	1.00	0.99	0.98	0.94	0.96	1.02	0.98	0.94
07–08	1.08	1.48	1.13	0.73	1.31	1.16	1.52	1.12	0.77	1.35
Annual average	1.02	1.05	1.00	1.06	1.04	1.01	1.03	1.01	1.03	1.02

Table 3
The compared efficiency scores from the Wilcoxon signed ranks test.

Pairs	Wilcoxon signed ranks test	
	Z	*P*-value
DEA Model 1 vs. EI (Energy consumption/value added)	−8.467	0.000
DEA Model 1 vs. CO_2I (CO_2 emissions/value added)	−15.112	0.000
DEA Model 2 vs. EI (Energy consumption/value added)	−7.865	0.000
DEA Model 2 vs. CO_2I (CO_2 emissions/value added)	−15.112	0.000

Notes: EI: energy intensity, CO_2I: CO_2 emission intensity.

Table 4
Results of the regression analysis for eco-efficiency (technical efficiency) and energy intensity (EI).

Parameters	Technical efficiency				EI (Energy/value added)	
	DEA model 1		DEA model 2			
	Fixed effects	Driscoll-Kraay standard errors	Fixed effects	Driscoll-Kraay standard errors	Random effects	MLE
Constant	4.979*** (0.517)	4.979*** (0.805)	2.629*** (0.255)	−0.217*** (0.730)	−6.141*** (0.372)	−6.276*** (0.407)
Energy taxes	0.129** (0.039)	0.129* (0.053)	0.002 (0.014)	0.002 (0.013)	−0.028 (0.025)	−0.022 (0.026)
Fossil fuel Consumption	−0.679*** (0.063)	−0.679*** (0.098)	−0.465*** (0.032)	−0.465*** (0.083)	0.676*** (0.037)	0.688*** (0.039)
Investments	0.023* (0.013)	0.023** (0.009)	0.008 (0.007)	0.008** (0.002)	−0.117*** (0.024)	−0.114*** (0.024)
Labour productivity	0.911*** (0.045)	0.911*** (0.094)	0.065** (0.023)	0.065*** (0.036)	−0.958*** (0.031)	−0.961*** (0.031)
Capital–labour ratio	−0.264*** (0.045)	−0.264*** (0.063)	−0.016 (0.023)	−0.016 (0.019)	0.161*** (0.027)	0.160*** (0.027)
F-test statistic	$F(18, 280) = 124.95$ 0.000 *Reject OLS*		$F(18, 280) = 465.02$ 0.000 *Reject OLS*		$F(18, 280) = 185.58$ 0.000 *Reject OLS*	
LM test	$chibar^2(01) = 1641.43$		$chibar^2(01) = 1804.52$		$chibar^2(01) = 1556.21$	
Prob > $chibar^2$	0.000 *Reject OLS*		0.000 *Reject OLS*		0.000 *Reject OLS*	
Hausman test	$chi^2(5) = 15.94$		$chi^2(5) = 14.84$		$chi^2(5) = 14.60$	
Prob > chi^2	0.007 *Reject RE*		0.011 *Reject RE*		0.012 *Reject FE*	
Test for heteroscedasticity [a] Prob > chi^2	LR $chi^2(18) = 388.90$ 0.000		LR $chi^2(18) = 483.77$ 0.000		LR $chi^2(18) = 297.53$ 0.000	
Wooldridge test for autocorrelation[b]	$F(1, 18) = 9.489$		$F(1, 18) = 16.744$		$F(1, 18) = 48.885$	
Prob > F	0.006		0.000		0.000	
Pesaran's test	0.347		0.003		–	
No. obs	304	304	304	304	304	304

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 heterocedasticity.
[b] If Prob > F > 0.05, indicate no serial correlation.

to the median of the coefficients of correlation for another treatment and confirms similar trends between the intensity indicators and the DEA model. Table 3 presents the results of the Wilcoxon tests, which demonstrate that the DEA models used in this study are an adequate approach to measure eco-efficiency in terms of energy use and CO_2 emissions.

4.3. Determinants of eco-efficiency in the Swedish service industries

In this section, panel data techniques are applied according to the methods explained in Section 2.2.3 to explain the observed variation and main factors that determine eco-efficiency across the service industries. The dependent variables are the results of the technical efficiency and energy intensity in the various regression models.

Table 4 shows the results of the regression analysis for eco-efficiency from the DEA models and energy intensity based on value added. The three estimations show similar results. The specifications of the test to determine the proper panel data model indicate that, in the case of DEA models, the fixed effects estimation is adequate, and for energy intensity, a random effects model[4] is the most appropriate. The estimations of residuals for fixed effects and random effects suggest the presence of heteroscedasticity and serial correlation that must be corrected with Driscoll and Kraay standard errors for fixed effects and MLE for random effects.

The results show that higher energy taxes, investments and productivity lead to higher eco-efficiency in terms of energy efficiency and reduce CO_2 emissions, while higher fossil fuel consumption reduces eco-efficiency. In addition, the capital–labour ratio demonstrates a complementary relationship between energy and production factors. Note that the signs of the coefficients for the DEA score are the inverse of those for efficiency and energy intensity because the two results are inverses of one another [81].

Energy taxes have a positive effect on eco-efficiency in terms of energy use and decreasing CO_2 emissions. In the Swedish service sector, these taxes include the fuel and electricity taxes and the CO_2 tax. This taxation system is considered one of the most innovative and effective of those applied around the world because the taxes were indexed and linked to the consumer price index in Sweden. This structure guarantees a constant real value of the tax rates [71]. However, the impact and effects of these taxes on Swedish industry have been mitigated for three main reasons: *i.* the exemptions of the taxes on industry have resulted in an actual taxation level of only 20% of the total energy and CO_2 taxes. For example, in the industrial sectors, the total energy and CO_2 taxes have increased almost 43% (from 25.2 €/1,000 L in 1993 to 60.5 €/1,000 L in 2008), whereas in other sectors as households the total energy and CO2 taxes have increased more than doubled (from 160.1 €/1,000 L in 1993 to 369 €/1,000 L in 2008). ii. Only a relatively small fraction (30%) of the energy supplied to industry was fossil fuel-based when the taxes were implemented in the 90s. iii. For several industrial companies, especially service industries and non-energy intensive sectors, energy costs are a relatively small fraction of total costs (<3%) and therefore are a low impact. Thus energy issues have low priority in these sectors [34,44,60,71]. These facts align with the result that energy taxes only have a significant coefficient in one of the models applied in this study, DEA.

Fossil fuels are included in the analysis to determine the role of this fuel in eco-efficiency. The results in the three models indicate that a decrease in fossil fuel consumption generates higher eco-efficiency in the form of higher energy efficiency and lower CO_2 emissions in the Swedish service industries. In other words, improved energy efficiency and decreased CO_2 emissions from Swedish industries has been generated by a shift from fossil fuels to low carbon or cleaner fuels, such as electricity, which in Sweden is not carbon-intensive and is based largely on nuclear and hydropower

[4] MLE is specified as the most efficient estimation in estimators that use information on the distribution of the endogenous variables given the exogenous variables [86]. Taking into account the results of Hausman Test indicated that random effect is the best model in the case of our empirical analysis.

and on industrial and cogeneration plants [75,76]. This confirms that improvements in energy efficiency and the reduction of CO_2 emissions depend of the use of high-quality, low carbon and clean fuels.

Investments likely have a positive effect on eco-efficiency but are not significant in several models probably because investments in the service sector have not primarily attempted to improve energy use or decrease CO_2 emissions. However, they can contribute to eco-efficiency by the application of new standards to improve energy use. This includes, for example, energy-saving practices and processes, energy efficiency policies for new buildings, use of district heating in buildings and more energy-efficient appliances and equipment [40,41,43].

Labour productivity has a positive and significant effect on eco-efficiency, indicating that service industries with higher labour quality of have higher energy efficiency and lower CO_2 emissions. These results concur with the trends in productivity in Sweden, which has the highest labour productivity growth rates among developed countries [20,21]. Notably, Mulder and Groot [56] and Pardo [61] suggested that improvements in labour productivity simultaneously generate higher energy efficiency in the industrial sector.

The relationship between the capital–labour ratio and energy in the service industries suggest complementary, which concurs with Fuss [30] and Thompson [78]; who demonstrated that capital and energy are complementary in the short run and substitutable in the long run. Technological changes embodied in industries' capital stocks contribute to improving energy efficiency and decreasing CO_2 emissions when the energy-saving technical changes are related to innovations that increase production, reduce labour, energy and capital costs, or make use of alternative materials that generate complementarities among production factors [84].

All of the findings in this study are important for designing suitable energy policies to increase energy efficiency and decrease CO_2 emissions in the service industries. The design and application of various strategies and policy instruments are important because energy consumption have grown the quickest in this sector and have driven the increase in total energy consumption and CO_2 emissions for the whole Swedish industrial sector. The strategies for significant improvements in the service industry's eco-efficiency must include access to information, energy management systems, improved decision-making processes, energy training for employees and the ability to measure and verify the achieved energy savings.

5. Conclusions

This paper analysed eco-efficiency in terms of energy use and CO_2 emissions in the Swedish service industries during the period of 1993–2008 using intensity indicators, the Malmquist DEA model and panel data models. The tests used in the different techniques applied in this study demonstrate that the methods are adequate to generate consistent, robust and reliable estimates in the analysis of energy efficiency and CO_2 emissions from both the traditional indicators and DEA.

The results of the DEA analysis indicate that energy efficiency and CO_2 emission intensity varied across years and service industries. Several service industries have increased eco-efficiency by increasing energy efficiency and decreasing CO_2 emissions and total factor productivity, especially in recent years. However, this sector has the potential to further improve energy efficiency and decrease CO_2 emissions. The results of the panel data techniques suggest that increased energy taxes, investments and productivity generate higher eco-efficiency, while higher fossil fuel consumption generates lower eco-efficiency. The capital-labour ratio shows a complementary relationship with energy.

The findings of this study are important for developing effective energy policies that improve energy use and energy management in the service industries. Further research is necessary in this industrial sector, focusing on identifying and understanding the barriers to adoption of energy efficient technologies, good practices and energy management systems and possibilities to improve eco-efficiency.

Acknowledgements

The author would like to thank Professor Dr Semida Silveira for the helpful suggestions and comments. The author is grateful for the financial support provided by the Swedish Energy Agency and KTH for the development of this research. We also thank the support of the University of La Salle and Universidad del Rosario.

References

[1] Ang BW, Zhang FQ. Survey of index decomposition analysis in energy and environmental studies. Energy 2000;25:1149–76.
[2] Baltagi B, Li Q. A Lagrange multiplier test for the error components model with incomplete panels. Econometric Reviews 1990;9:103–7.
[3] Baltagi H, Wu P. Unequally spaced panel data regressions with AR(1) disturbances. Econometric Theory 1999;15:814–23.
[4] Banker R, Natarajan R. Statistical tests based on dea efficiency scores. In: Cooper W, Seiford L, Zhu J, editors. Handbook on data envelopment analysis. New York: Kluwer Academic Publishers, Inc.; 2004. p. 265–98 [Chapter 11].
[5] Bhattacharyya S, Matsumura W. Changes in the GHG emission intensity in EU-15: lessons from a decomposition analysis. Energy 2010;35:3315–22.
[6] Böhringer C, Rutherford T. Combining bottom-up and top-down. Energy Economics 2008;30:574–96.
[7] Bretschger L, Ramer R, Schwark F. Growth effects of carbon policies: applying a fully dynamic CGE model with heterogeneous capital. Resource and Energy Economics 2011;33:963–80.
[8] Breusch T, Pagan R. The Lagrange multiplier test and its applications to model specification in econometrics. Review of Economic Studies 1980;47:239–53.
[9] Calzolari G, Magazzini L. Autocorrelation and masked heterogeneity in panel data models estimated by maximum likelihood. Empirical Economics 2011. http://dx.doi.org/10.1007/s00181-011-0487-7.
[10] Caves DW, Christensen LR, Diewert WE. The econometric theory of index numbers and the measurement of input, output, productivity. Econometrica 1982;50:1393–414.
[11] Central Intelligence Agency (CIA). The world factbook, https://www.cia.gov/library/publications/the-world-factbook/index.html; 2011.
[12] Coelli T, Prasada D, O'Donnell C, Battese G. An introduction to efficiency and productivity analysis. 2nd ed. New York: Springer; 2005.
[13] Coelli T. A guide to DEAP version 2.1: a data envelopment analysis (computer) program, CEPA working paper 96/8. NSW Australia: Department of Econometrics, University of New England, www.uq.edu.au/economics/cepa/deap; 1996.
[14] Coelli T, Prasada Rao DS, Battese GE. An introduction to efficiency and productivity analysis. Boston: Kluwer; 1998.
[15] Collard F, Feve P, Portier F. Electricity consumption and ICT in the French service sector. Energy Economics 2005;27:541–50.
[16] Cooper W, Seiford L, Tone K. Data envelopment analysis. A comprehensive text with models, applications, references and DEA-Solver software. 2nd ed. Springer; 2007.
[17] Driscoll J, Kraay A. Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics 1998;80:549–60.
[18] Drucker P. Managing in the next society. New York: St. Martin Press; 2002.
[19] Ecofys. Economic evaluation of sectoral emission reduction objectives for climate change. Top-down analysis of greenhouse gas emission reduction possibilities in the EU. Ecofys Energy and Environment, AEA Technology Environment and National Technical University of Athens, http://ec.europa.eu/environment/enveco/climate_change/pdf/top_down_analysis.pdf; 2001.
[20] Edquist H. Intangible investment and the Swedish manufacturing and service sector paradox – what can Europe learn?. IFN Working Paper No. 863 Research Institute of Industrial Economics, http://snee.org/filer/papers/627.pdf; 2011.
[21] Edquist H. Can investment in intangibles explain the Swedish productivity boom in the 1990s? Review of income and wealth; 2011. http://dx.doi.org/10.1111/j.1475-4991.2010.00436.x.
[22] European Commission (EC). 2030 European energy and transport. Trends to 2030-update 2007. Directorate-General for Energy and Transport, http://ec.europa.eu/dgs/energy_transport/figures/trends_2030_update_2007/energy_transport_trends_2030_update_2007_en.pdf; 2008.
[23] European Commission (EC). Action plan for energy efficiency: realising the potential. Brussels, Belgium, http://ec.europa.eu/energy/action_plan_energy_efficiency/doc/com_2006_0545_en.pdf; 2006.

[24] Expert Group on Energy Efficiency. Realizing the Potential of energy efficiency: targets, policies, and measures for G8 countries. Washington, DC: United Nations Foundation; 2007. 72 pp.
[25] Fare R, Grosskopf S, Lovell CAK. Production frontier. UK: Cambridge University Press; 1994.
[26] Färe R, Grosskopf S, Lindgren B, Roos P. Productivity developments in Swedish hospitals: a Malmquist output index approach. In: Charnes A, et al., editors. Data envelopment analysis: theory, methodology and application. Boston, MA: Kluwer; 1995. p. 253–72.
[27] Färe R, Grosskopf S, Forsund F, Hayes K, Heshmati A. Measurement of productivity and quality in non-marketable services. With application to schools. Quality Assurance in Education 2006;14:21–36.
[28] Farrel M. The measurement of productive efficiency. Journal of the Royal Statistical Society, A 1957;CXX(Part 3):253–90.
[29] French Environment and Energy Management Agency (ADEME). Energy-efficiency monitoring in the EU-15, www.2.ademe.fr/servlet/getDoc?sort=-1&cid=96&m=3&id=2830 6&ref=14152&nocache=yes&p1=111; 2005.
[30] Fuss M. The structure of technology over time: a model for testing the 'Putty-Clay' hypothesis. Econometrica 1977;45:1797–821.
[31] Greene W. Econometric analysis. Global ed. of 7th revised ed. Pearson Education; 2011.
[32] Greening L, Boyd G, Roop J. Modeling of industrial energy consumption: an introduction and context. Energy Economics 2007;29:599–608.
[33] Hjalmarsson L, Veiderpass A. Productivity in Swedish electricity retail distribution. The Scandinavian Journal of Economics 1992;94:193–205.
[34] Harrison G, Kriström B. Carbon taxes in Sweden. Final report, http://www-sekon.slu.se/~bkr/Carbon.pdf; 1997.
[35] Hausman J. Specification tests in econometrics. Econometrica 1978;46:1251–71.
[36] Henning D, Trygg L. Reduction of electricity use in Swedish industry and its impact on national power supply and European CO_2 emissions. Energy Policy 2008;36:2330–50.
[37] Hoechle D. Robust standard errors for panel regressions with cross-sectional dependence. The Stata Journal 2007;7:281–312.
[38] Hoff A. Second stage DEA: comparison of approaches for modelling the DEA score. European Journal of Operational Research 2007;181:425–35.
[39] International Energy Agency (IEA). Tracking industrial energy efficiency and CO_2 emissions, http://www.iea.org/textbase/nppdf/free/2007/tracking_emissions.pdf; 2007.
[40] International Energy Agency (IEA). Worldwide trends in energy use and efficiency. Key insights from IEA indicator analysis. In support of the G8 plan of action, http://www.iea.org/papers/2008/indicators_2008.pdf; 2008.
[41] International Energy Agency (IEA). Technology roadmap energy-efficient buildings: heating and cooling equipment, www.iea.org/papers/2011/buildings_roadmap.pdf; 2011.
[42] International Energy Agency (IEA). IEA scoreboard 2009: 35 key energy trends over 35 years, http://www.iea.org/publications/free_new_Desc.asp?PUBS_ID=2141; 2009.
[43] International Energy Agency (IEA). Energy efficiency requirements in building codes, energy efficiency policies for new buildings, www.iea.org/g8/2008/Building_Codes.pdf; 2008.
[44] Johansson B. Economic instruments in practice 1: carbon tax in Sweden. Report Swedish Environmental Protection Agency, http://www.oecd.org/dataoecd/25/0/2108273.pdf; 2001.
[45] Johansson H. Technical, allocative, and economic efficiency in Swedish dairy farms: the data envelopment analysis versus the stochastic frontier approach. Copenhagen, Denmark: European Association of Agricultural Economists, International Congress, http://ageconsearch.umn.edu/handle/24478; 2005.
[46] Karlsson S, Skoglund J. Maximum-likelihood based inference in the two-way random effects model with serially correlated time effects. Empirical Economics 2004;29:79–88.
[47] Karmarkar U. Will you survive the services revolution? Harvard Business Review 2004;82:101–7.
[48] Krackeler T, Schipper L, Sezgen O. Carbon dioxide emissions in OECD service sectors: the critical role of electricity use. Energy Policy 1998;26:1137–52.
[49] Lapillonne B, Sebi C, Pollier K. Energy efficiency trends in EU services, www.odyssee-indicators.org/reports/services/services_eu27.pdf; 2011.
[50] Lowell J, Pastor T. Units invariant and translation invariant DEA models. Operations Research Letters 1995;18:147–51.
[51] Lv W, Hong X, Fang K. Chinese regional energy efficiency change and its determinants analysis: Malmquist index and Tobit model. Annals of Operation Research, in press.
[52] Mairet N, Decellas F. Determinants of energy demand in the French service sector: a decomposition analysis. Energy Policy 2009;37:2734–44.
[53] Malmquist S. Malmquist, index numbers and indifference surfaces. Trabajos de Estadistica 1953;4:209–42.
[54] McDonald J. Using least squares and Tobit in second stage DEA efficiency analyses. European Journal of Operational Research 2008;197:792–8.
[55] Mukherjee K. Energy use efficiency in the Indian manufacturing sector: an interstate analysis. Energy Policy 2008;36:662–72.
[56] Mulder P, Groot H. International comparisons of sectoral energy- and labour-productivity performance; 2004. Tinbergen Institute Discussion Paper. TI 2004-007/3.
[57] Murphy R, Rivers N, Jaccard M. Hybrid modeling of industrial energy consumption and greenhouse gas emissions with an application to Canada. Energy Economics 2007;29:826–46.
[58] Nair A, Sarkar A, Ramanathan A, Subramanyam A. Anomalies in CAPM: a panel data analysis under Indian conditions. International Research Journal of Finance and Economics 2009;33:192–206.
[59] Oggioni G, Riccardi R, Toninelli R. Eco-efficiency of the world cement industry: a data envelopment analysis. Energy Policy 2011;39:2842–54.
[60] Organisation for Economic Co-operation and Development (OECD). Environmentally related taxes in OECD countries. Issues and strategies, http://www.peblds.org/files/Publications/OECD/OECD_Environmentally_Related_Taxes.pdf; 2001.
[61] Pardo MCI. Energy efficiency development in the German and Colombian energy intensive sectors: a non-parametric analysis. WIT Transactions on Ecology and the Environment 2009;121:499–511.
[62] Pardo MCI. Energy efficiency development in German and Colombian non-energy-intensive sectors: a non-parametric analysis. Energy Efficiency 2011;4:115–31.
[63] Phylipsen G, Blok K, Worrell E. Handbook on international comparisons of energy efficiency in the manufacturing industry. Department of Science, Technology and Society, Utrecht University; 1998.
[64] Ramanathan R. A multi-factor efficiency perspective to the relationships among world GDP, energy consumption and carbon dioxide emissions. Technological Forecasting & Social Change 2006;73:483–94.
[65] Salas O. Technical efficiency during deregulation of the urban bus system in Sweden. Working papers in economics No 4. School of Economics and Commercial Law Göteborg University; 1998.
[66] Saunders H. Fuel conserving (and using) production functions. Energy Economics 2008;30:2184–235.
[67] Schleich J. Barriers to energy efficiency: a comparison across the German commercial and services sector. Ecological Economics 2009;68:2150–9.
[68] Schleich J, Gruber E. Beyond case studies: barriers to energy efficiency in commerce and the services sector. Energy Economics 2008;30:449–64.
[69] Schuschny A. The DEA method and its application to energy sector and CO_2 emissions in Latin American and the Caribbean. CEPAL, statistic and prospective studies; 2007 [In Spanish].
[70] Scrase I. White collar CO_2: energy consumption in the service sector. London: The Association for the Conservation of Energy, http://www.ukace.org/; 2000.
[71] Speck S. The design of carbon and broad-based energy taxes in European countries. In the reality of carbon taxes. In the 21st Century. A Joint Project of the Environmental Tax Policy Institute and the Vermont Journal of Environmental Law Vermont Law School; 2008.
[72] Statistics Sweden. National accounts, detailed yearly estimates, 1950–2008, www.scb.se; 2010.
[73] Stern R. The place of services in the world economy. Research Seminar in International Economics. Discussion Paper No. 530, http://www.spp.umich.edu/rsie/workingpapers/wp.html; 2005.
[74] Suh S. Are services better for climate change? Environmental Science & Technology 2006;40:6555–60.
[75] Sweden Energy. The electricity year 2010, http://www.svenskenergi.se/upload/Statistik/Elåret/ENG_Sv%20Energi_elåret2010.pdf; 2011.
[76] Swedish Institute. Energy: generating power for a sustainable future, http://www.sweden.se/upload/Sweden_se/english/factsheets/SI/SI_FS3_Energy/FS3-Energy-low-resolution.pdf; 2011.
[77] The Swedish Ministry of Industry, Employment and Communications. Innovative Sweden. A strategy for growth through renewal. Ds 2004:36, www.sweden.gov.se/content/1/c6/03/25/51/29e722a9.pdf; 2004.
[78] Thompson Henry. Complementarity in a simple general equilibrium production model. Canadian Journal of Economics 1985;17:616–21.
[79] UK Energy Research Centre (UKERC). UKERC review of evidence for the rebound effect technical report 3: elasticity of substitution studies. Working Paper REF: UKERC/WP/TPA/2007/011; 2007.
[80] Unander F. Decomposition of manufacturing energy-use in IEA countries. How do recent developments compare with historical long-term trends? Applied Energy 2007;84:771–80.
[81] U.S. Department of Energy. Energy efficiency and renewable energy. Planning, budget, and analysis – energy intensity indicators. Efficiency vs. intensity, http://www1.eere.energy.gov/ba/pba/intensityindicators/printable_versions/efficiency_intensity.html; 2008.
[82] WEC. Energy efficiency: a worldwide review. London: World Energy Council; 2004.
[83] Werf E. Production functions for climate policy modelling: an empirical analysis. Energy Economics 2008;30:2964–79.
[84] Wing I, Eckaus R. Explaining long-run changes in the energy intensity of the U.S. economy. Report No. 116. The MIT Joint Program on the Science and Policy of Global Change; 2004.
[86] Wooldridge J. Econometric analysis of cross section and panel data. Cambridge, MA: MIT Press; 2010.
[87] Zhou P, Ang W. Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy 2008;36:2911–6.
[88] Zhou P, Ang W, Han J. Total factor carbon emission performance: a Malmquist index analysis. Energy Economics 2010;32:194–201.

Clara Inés Pardo Martínez has a Bachelor in Food, Environmental and Sanitary Engineering, M.A. in Administration, PhD in Economics, University of Wuppertal, Germany and a Postdoctorate in energy, Royal Institute of Technology (KTH), Sweden. She has 10 years professional experience working as professor in several Colombian Universities, as consultant different private and public sectors in topics related to HSEQ management systems with the International standards ISO 9001, ISO 14001 and OHSAS 18001, energy management systems and clean production (this includes the design, development, implementation and audit of the management system, development of training in management systems) and as researcher in the Wuppertal Institute (with research focus on energy efficiency in the manufacturing industries using econometric analysis with the following software Eviews, Stata, SPSS and EMS). She has several publications in the field of energy efficiency and has been referee for different journals and projects.