Clean Technologies and Environmental Policy
https://doi.org/10.1007/s10098-023-02560-w

ORIGINAL PAPER

Revenue efficiency of bioenergy industry: the case of European Union (EU) member countries

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Received: 26 December 2022 / Accepted: 8 June 2023

Abstract
Bioenergy plays a crucial role in numerous sectors such as industry, electricity, heating, cooling, and transportation. Previous research on bioenergy focused on the production and strategies to improve bioenergy development and distribution in the EU. This study computes the revenue efficiency level and investigates the economic determinants of revenue efficiency of the bioenergy industry in EU28 countries between 1995 and 2018. The study employed the nonparametric data envelopment analysis method to compute the revenue efficiency level, and ordinary least squares, random effects, and fixed effects models were applied to investigate the determinants of revenue efficiency. The results show that most of the countries are efficient, given a high-efficiency score, with France, Malta, Sweden, and Slovakia as the most efficient, while Cyprus is the least efficient. Furthermore, empirical results indicate that capital and labor have a negative impact, while GDP and the size of biomass have positive and significant impact on revenue efficiency of the bioenergy industry in EU28 countries during the period studied. This study provides an insight for bioenergy policymakers and investors-to the understanding of the impact of revenue efficiency on the sustainability of the bioenergy industry.

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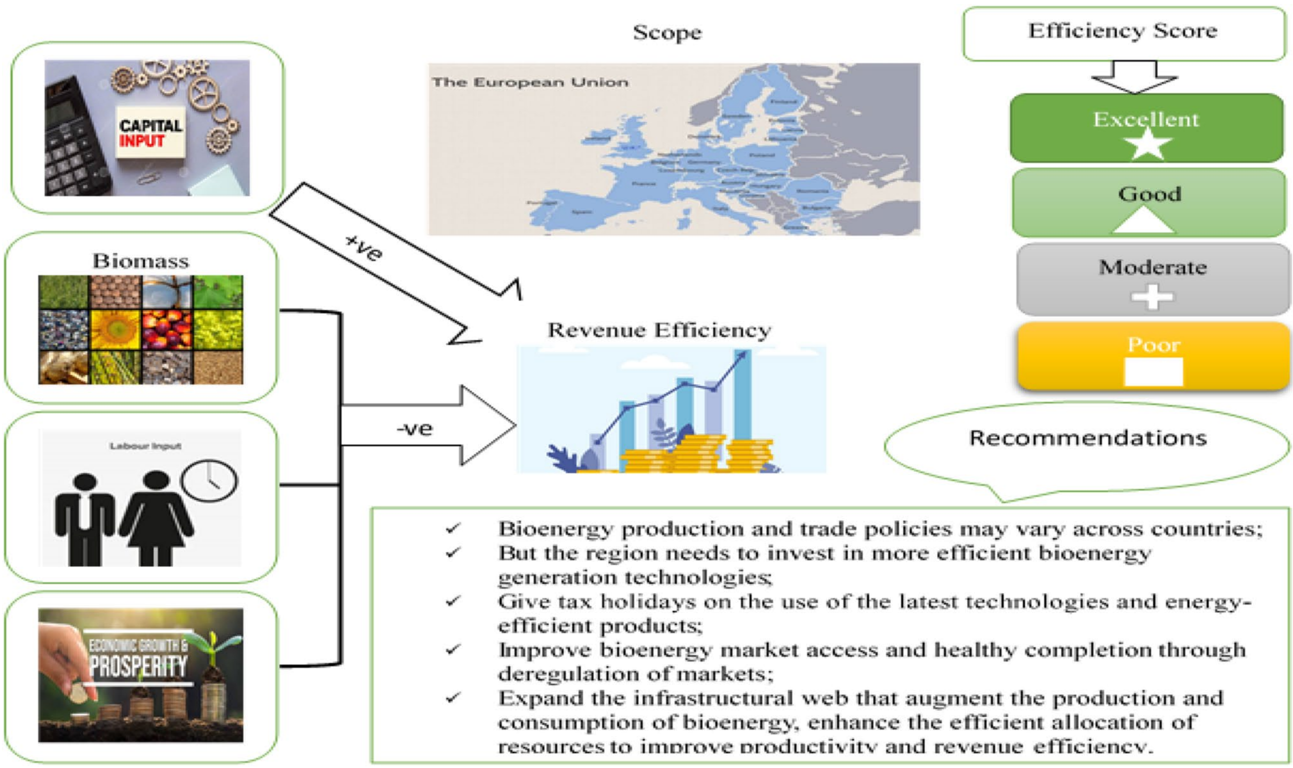
Published online: 22 June 2023

Graphical abstract



Keywords Revenue efficiency · Bioenergy · DEA · EU28 countries

Introduction

Bioenergy is viewed as among the important choices to minimize greenhouse gas emissions and alternative non-renewable fuels globally. There is a huge prospect from bioenergy to produce a surmountable share of energy supply in electricity, heating, and transport fuel, though there are certain challenges facing the bioenergy market of the EU region. Bioenergy is considered a possible solution to energy problems (volatility of price, energy insecurity, and environmental impact) and sustainable development. This is the rationale behind the EU's investment in bioenergy and it is projected to account for 50% of renewable energy output by 2020 following the National Renewable Energy Action Plans (NREAPs) (Caputo 2014). Biomass currently accounts for more than 10% of the world's energy supply and approximately 80% of renewable energy, while two-thirds of this energy is produced in developing countries, the rest of which is produced in developed countries (Popp et al. 2014). According to Welfle (2017), because of the versatility of bioenergy and its potential for integration with all stages of development strategies and the agenda, bioenergy is clearly an attractive energy choice, as it is widely agreed that bioenergy can produce energy with lower greenhouse gas emissions compared to other energy sources, such as fossil fuels.

Bioenergy is projected to play a key role in contributing over 50% to European countries' renewable energy goals, as more than 60 countries currently have national goals or policy measures promoting renewable energies (International Energy Agency 2011). While this is largely influenced by the prices of and the dependence on fossil fuels, it is also motivated by the need to mitigate greenhouse gas emissions and increasing policy initiatives supporting bioenergy pathways (Junginger et al. 2011; Welfle 2017). As a result of these recent energy policies, Europe is now the main trading market for bioenergy, with more than 30% of bioenergy products currently consumed in Europe been imported and an expected increase in demand of nearly 50% between 2010 and 2020. This dramatic increase in demand for biofuels depends not only on the prices of fossil fuels, but also on the ambitious mandates of bioenergy in Europe. Also, the demand for fuels such as wood pellets is expected to increase by more than double by 2020 as a result of government subsidies on renewable energy consumption (Böttcher et al. 2012). The European Union is seeking to identify possible options for bioenergy development due to increasing demand for clean energy to mitigate greenhouse gas emissions and curb energy insecurity. While the development of bioenergy policies by the European Union has been driven by security of energy supply and environmental concerns, it is also considered as an opportunity for accelerated rural and economic development, most especially among the EU's developing countries (English et al. 2006; Bah et al. 2020). The bioenergy industry is also considered to be a major contributor to rural economies, as it provides employment and improves the living standards of local farmers in the region (Jin & Sutherland 2016; Solomon 2010; Smeets et al. 2008).

Bioenergy feedstock such as methanol, biodiesel, and ethanol can be directly used to generate energy or transformed to more suitable energy carriers. The US recorded the share of biofuels used for road transport at 4% in 2008 and it was approximately 3% in the EU. This is expected to increase overtime by the use of blends or pure biofuels and also as a result of the EU's renewable energy ambition. The promotion of the use of bioenergy is driven by the increasing demand for clean energy, the need to increase energy efficiency, the price of fossil fuels, especially oil, the utilization of local energy sources so as to improve the region's competitiveness and also increase local security of energy supply, and finally, the implementation of policies and bioenergy targets (Junginger et al. 2011; Kalt and Kranzl 2011; Jin and Sutherland 2016; Strzalka et al. 2017). However, Kalt and Kranzl (2011) concluded that bioenergy feedstock prices are sometimes assumed or expected to decrease as a result of advancements in technologies and strategies of production and supply. Additionally, bioenergy products are more expensive than other energy sources such as fossil fuels. This would go a long way to affect the revenue efficiency of the industry as the cost of production and conversion would reflect on prices and consequently affect consumption of bioenergy products (English et al. 2006; Kalt and Kranzl 2011; Jin and Sutherland 2016). Bioenergy has played a crucial role in the increase in electricity from renewable sources over the last decade. It was recorded as the third major contributor after hydropower and wind, respectively. Also, biomass in general has played an important role in electricity, transportation, heating and cooling, and other domestic uses since 2005 till date, and its contribution to these various sectors has doubled over the years, and it is said to be above the NREAPs projections for the period. However, the industry's efficiency will be determined by future demand for biofuels and technological advancements in the Eurozone (Scarlat et al. 2015).

Revenue efficiency in the bioenergy industry is linked to infrastructure investment, investment in bioenergy technologies, improving market access, energy crop supply, and production capacity, among other things (Scarlat et al. 2013; Caputo 2014). Expansion and conversion of plantation areas for farming of energy-rich crops, expansion of infrastructure web that would efficiently link bioenergy production sites and consumers, and conversion of waste from biomass, animal waste, organic waste, agricultural waste, and production waste as alternatives for bioenergy production will improve biomass energy efficiency (Searchinger et al. 2008; Scarlat et al. 2013; Caputo 2014; Welfle et al. 2017; Alsaleh et al. 2021). This is necessary for the EU developing countries to be competitive in the bioenergy market, and also improve efficiency in the industry.

The use of bioenergy for transportation fuels, electricity, and heating is continuously viewed as an opportunity to enhance energy security, help to mitigate environmental degradation and resource depletion, and increase economic and sustainable development. However, there are various challenges to bioenergy development and the use of bioenergy in the EU region. The problem of the bioenergy industry of the EU region in the light of revenue efficiency is connected with the issues of self-sufficiency of the region in the production of energy-rich crops, cost of importation, shortage in supply of energy crops due to ever increasing demand for food, energy from the exporting countries, and the demand for such crops by other countries to meet their own food demands. Climate change, development of new bioenergy technologies, and development of competing non-bioenergy-based technologies which are capital intensive, determine the cost-effectiveness of bioenergy utilization. Competition for land usage for food crops, bioenergy feedstock, and other plantation crops has also led to strategies to increase crop yields which have environmental impacts (Alsaleh et al. 2021). These factors affect prices (bioenergy and food) and the competitiveness of bioenergy products in the energy market. For example, the World Bank ascribed 75% of the rise in food prices in the EU to bioenergy production in 2013. Therefore, this study is aimed at providing an insight into the revenue efficiency of the bioenergy industry of EU28 countries as a probable justification for the huge investment, substitution of plantation area for food crops with energy-rich crops, and also answering the questions: what is the revenue efficiency level of the bioenergy industry of EU28? Also, what are the economic determinants of the revenue efficiency of the bioenergy industry in EU28 countries?

The paper is organized as follows: in "Review of empirical literature" section, an empirical literature review of revenue efficiency and bioenergy industry is discussed. "Material and methodology" section discusses the methodology, which includes the variable description, empirical model, and estimation strategy. The empirical results are discussed in "Empirical results" section, while the conclusion and policy recommendations are discussed in "Conclusion and policy recommendations" section.

Review of empirical literature

There are a host of issues in the bioenergy industry. Most importantly is the revenue efficiency of bioenergy. Researchers have different opinions regarding the efficiency of bioenergy. While some concentrate on the fuel-food dilemma (Kyrylov et al. 2022; Vasile et al. 2016), others concentrate on the deforestation in order to increase yields of energy-rich crops, which leads to the loss of the forest's capacity to act as a carbon sink (Alsaleh and Abdul-Rahim 2022; Locoh et al. 2022; Kalt and Kranzl 2011), while some insist that bioenergy is not necessarily going to be sustainable (Xuân and Thu 2023). Bioenergy is considered a possible solution to energy problems and sustainable development. This is the rationale behind the EU's investment in bioenergy and it is projected to account for 50% of renewable energy output by 2020 (Caputo 2014). However, the efficiency of biomass energy depends on how it can be effectively converted into power, heat, fuel, etc. According to Alsaleh e al. (2016), EU member countries, both developing and developed, have not attained or achieved full efficiency in the bioenergy industry; however, developed countries have higher efficiency levels because they produce more, export more, consume less, and import less than developing EU countries. This is similar to the case in China where bioenergy, despite being the major source of renewable energy, the demand for consumption outweighs the production and supply of biomass (Zhang et al. 2014).

Several estimation methods have been extensively used to estimate the revenue efficiency of different organizations/firms, and industries. Approaches such as parametric, non-parametric, and productivity indices are mainly developed for the measurement of productive efficiency (Coelli et al.. 1998), as cited in Latruffe et al. (2004). However, methods such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are the most frequently used methods and have been applied to various datasets, ranging from time series to cross sectional and panel datasets. Recent studies such as Maudos and Pastor (2003), Ho and Zhu (2004), Sufian (2007), examine the efficiency of different sectors in Spain, Taiwan, and Singapore, respectively, using DEA. While findings by Latruffe et al. (2004) show that cost-efficient firms are as well profit-efficient, highlighting the role of the least-cost method of production in profit efficiency. Maudos and Pastor (2003) investigated the efficiency of forty-one (41) firms in Taiwan. The study suggested that the high efficiency score of the production frontier, which is expected to be the measure of performance, is not a sufficient justification of high performance as the results obtained suggest otherwise. However, Sufian (2007) found a high efficiency score in a study in Singaporeans. Krasuska and Rosenqvist (2012) examined the efficiency of the bioenergy industry in Poland. The study found that the major factor influencing profitability and competitiveness of energy crops is their prices, which is a clear reflection of the pressure on the demand for energy crops in Poland. However, from the perspective of revenue efficiency, they posit that a significant reduction in the cost of producing biomass is the key and it is expected in the near future.

More recently, studies such as Popp et al. (2014), Broekel et al. 2013; Carayannis et al. 2016; Ervural et al. 2016) have employed this method to examine the efficiency of different firms, countries, and regions. While Broekel et al. (2013) examine the efficiency of innovation, or rather the impact of innovation on efficiency in Germany from 2004 to 2008, using DEA, Their findings show that innovation affects efficiency positively as the efficiency score is well above average irrespective of the cities. Carayannis et al. (2016) employed the DEA technique to test for efficiency in 185 different regions of 23 European countries. Unlike the findings of Broekel et al. (2013), their results indicate innovation is a function of efficiency in the regions, and there exists an intermittent efficiency gap across the regions, suggesting that innovation is also influenced by country-specific efficiency levels.

Similarly, Alsaleh et al. (2016) also applied this method to investigate the efficiency of the EU28 bioenergy industry during the period from 1990 to 2013. The study found that the region is currently faced with a decreasing return to scale, suggesting further increases in input are increasing output at a decreasing rate even though some of the EU member countries are fully efficient in their industry. Ervural et al. (2016) applied the DEA method to examine the efficiency of different provinces of Turkey. Their study highlights the importance of proper investment decisions as investment influences efficiency.

Finally, in an attempt to investigate the factors influencing efficiency, previous studies such as Zubair et al. (2021), Abdulwakil et al. (2020), Alsaleh et al. (2017), Ariff and Luc (2008), Banker et al. (2010), Kolawole (2006), Rachmina et al. (2014), Vu and Nahm (2013), applied different panel data analyses to different firms and industries in different countries. The fixed-effect model was used to examine the determinants of revenue efficiency of small-scale paddy rice farmers in Nigeria, and the findings show that, aside from agricultural input prices such as seeds, fertilizers, and so on, the major factor affecting the profit efficiency of the farmers studied is infrastructure. Similarly, Alsaleh et al. (2017) applied the fixed-effect model was used to analyze the technical efficiency determinants of the bioenergy industry in the EU28 countries and found that variables such as capital input, labor input, GDP, inflation and real interest rates had a significant impact on the technical efficiency of the bioenergy industry. While Abdulwakil et al. (2020) applied the least square dummy variable with bias corrected to examine bioenergy efficiency determinants in the EU28 countries.

The findings reveal that factors such as investment, inflation, and economic growth affect the efficiency of the industry significantly.

Accordingly, Rachmina et al. (2014) examined the profit efficiency of 192 vegetable farmers in Indonesia using the MLE. The result also reveals that the efficiency determining factors under study are seed price, infrastructure, wage (stressing the importance of labor input), fertilizers, and capital formation. Kamarudin et al. (2016) examined the macroeconomic determinants of revenue efficiency of 31 firms in Bangladesh between the periods of 2004 and 2011, decomposing the firms into state-owned and privately owned firms. The study employed multivariate panel regression analysis. Their results reveal that variables such as economic growth and the size of the firm have a negative impact on the efficiency of state-owned firms but have a positive impact on private-owned firms. While Isik and Hassan (2002) finds that size is an important factor influencing the revenue efficiency of firms in Turkey.

In addition, Ariff and Luc (2008) studies the cost and profit efficiency, as well as the determinants of profit efficiency of 28 Chinese firms between the periods 1995 and 2004, using the Tobit regression. The results reveal that the size of the firms is a major factor influencing efficiency. It also suggests that medium-sized firms are more efficient than small and large ones. Similarly, Vu and Nahm (2013) examines the determinants of profit efficiency of firms in Vietnam from 2000 to 2006, using the Tobit regression model. They found that the profit efficiency of these firms was favorably influenced by GDP per capita and inflation rates. The growth in GDP per capita increases the profit efficiency significantly, while lower inflation rates also lead to an increase in the profit efficiency of the banks during the period considered.

Interest in the efficiency of the bioenergy industry has grown significantly over the years. This is because the efficiency level is an important measure of the profitability of the industry. However, the aspect of revenue efficiency of the industry has remained relatively untouched, with no previous studies focusing on the revenue efficiency of the bioenergy industry. This study is therefore significant as it examined the revenue efficiency level of the bioenergy industry in EU28 countries and identifies the economic factors influencing revenue efficiency in the region.

Material and methodology

Revenue efficiency

Approaches such as productivity indices, parametric and nonparametric analysis indices, are primarily designed for efficiency and performance measurement (Coelli et al. 1998) as cited in Latruffe et al. (2004). The DEA approach, however, is a nonparametric method that uses linear programming to create a piece-wise frontier that encompasses all observations of decision making units, such as businesses, industries as well as country level observations. The DEA approach was first used by Charnes et al. (1978), to compute the efficiency of each decision-making unit. This method has since gained interest in the study of efficiency due to its ability to recognize the possible progress of inefficient units by comparing the unit with a convex combination of units placed at the productivity frontier. It allows the analyst to specify the causes and levels of inefficacy for each input and output. The DEA is capable of quantifying inputs and outputs simultaneously while using different units of measurement (Latruffe et al. 2004). This is the major advantage of the DEA as a measure of efficiency over other approaches. Hence, the DEA equation is presented as follows (Coelli et al. 2005; Zhu 2014; Zubair et al. 2021):

$$\text{Max} \quad \sum_{r=1}^{s} qrq\, Y^*_{rq} \tag{1}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} Yrj \leftthreetimes_j \geq Y^*_{rq} \quad r = 1, 2, \ldots, s, \tag{2}$$

$$\sum_{j=1}^{n} Xij \leftthreetimes_j \leq X^*_{iq} \quad i = 1, 2, \ldots, m, \tag{3}$$

$$\begin{gathered} \leftthreetimes_j\, Y^*_{rq} \geq 0 \\ \sum_{j=1}^{n} \leftthreetimes_j = 1 \quad j = 1, 2, \ldots, n \end{gathered} \tag{4}$$

where y_{rq} is the quantity of rth output ($r = 1, 2, \ldots, s$) of DMUq, x_{iq} is the price of ith input ($i = 1, 2, \ldots, m$), x^*_{iq} is the cost minimizing quantity of input, when input and output prices are given. y_{rj} is quantities of rth output ($r = 1, 2, \ldots, s$) of DMU_j, ($j = 1, 2, \ldots, n$), x_{ij} is quantity of input i, where ($i = 1, 2, \ldots, m$) of DMU_j ($j = 1, 2, \ldots, n$), λ_j is the weight allocated to DMU_j ($j = 1, 2, \ldots, n$) (Coelli et al. 2005).

To select the appropriate combination of inputs and outputs, Cooper et al. (2000) suggested a required condition which provides guidance. This rule of thumb is as follows:

$$n \leq \max\, \{m * s,\ 3(m + s)\} \tag{5}$$

where DMUs are represented by n, inputs are denoted by m, while s represents the number of outputs.

Determinants of revenue efficiency

The second estimation focused on the macroeconomic factors that influenced the revenue efficiency level of the EU28 countries. To examine the relationship between revenue efficiency and independent variables, the study applied a regression analysis which is presented in the model below, following Coelli et al. (1998).

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \mathcal{E}_{it}, \quad i = 1, \ldots, N \tag{6}$$

where Y is revenue efficiency i with time t, x points to the determining factors of revenue efficiency, β denotes the vector of the coefficient of our independent variables, Ɛ is the white noise standard error, i and t are the number of countries and time, respectively, while N denotes the number of observations. Revenue efficiency is adopted as the dependent variable in this model. We further expand Eq. (6) to introduce the specific x variables in our model.

$$\mathrm{RE}_{it} = \beta_0 + \beta_1 \ln \mathrm{CI}_{it} + \beta_2 \ln \mathrm{LI}_{it} + \beta_3 \ln \mathrm{GDP}_{it} + \beta_4 \ln \mathrm{BM}_{it} + E_{it} \tag{7}$$

where *RE* is the revenue efficiency, *LnCI* denotes the natural log of capital input, *LnLI* represents the natural log of labor input, *LnGDP* represents the natural log of gross domestic product, while *LnBM* denotes the natural log of biomass. The error term, denoted by E, is the vector of coefficients, and the subscripts i and t represent individual countries and time, respectively.

Once the revenue efficiency scores have been defined, the macroeconomic determinants can be analyzed using standard linear regression techniques, including random or fixed effects. Therefore, following Alsaleh et al (2016) and Zubair et al. (2021), the second-stage estimation examined the revenue efficiency-macroeconomic determinants relationship. Thus, this study applied the ordinary least squares (OLS), random effects (RE), and the fixed effects (FE) estimators to data related to the EU28 region, EU developed countries, and EU developing countries over the period 1995–2018.

The estimation begins with testing for cross sectional dependence in the panel of EU15 developed and EU13 developing countries for the period 1995–2018. The CD test has substantial importance before starting empirical estimations. Without testing CD, the outcomes obtained from estimations will become inefficient and biased (see Nickell 1981; Pesaran and Smith 1995). Besides, the selected countries for the study are interlinked through trade and economic structure, so changes in any one country may affect others. Thus, we employed the Breusch–Pagan LM tests to check CD (Breusch and Pagan 1980). The test failed to reject the null hypothesis of no cross sectional dependence given an LM statistic of 44.87 and 73.96, and probabilities of 0.319 and 0.142 for RE and FE, respectively, which are significantly greater than 0.05 (see Table 2). Thus, they indicate the absence of a common factor affecting the cross sectional units. Hence, there is sufficient evidence suggesting the absence of cross sectional dependence in our models between 1995 and 2018.

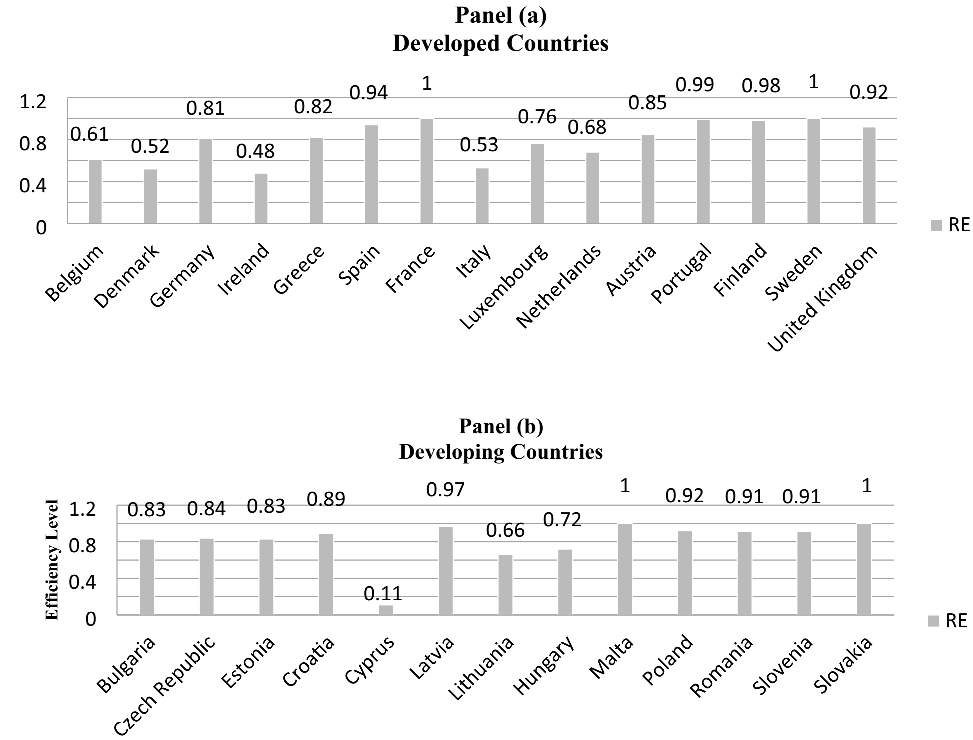
Empirical results

Revenue efficiency of bioenergy industry

This section presents the efficiency score of individual countries in the European Union and it is between 0 and 1. Panel (A) of Fig. 1 summarizes the average revenue efficiency level of the bioenergy industry in EU15 developed countries from 1995 to 2018. The average revenue efficiency of bioenergy industries in the EU 15 developed countries has shown a remarkable outcome for the period. However, there are variations in the results as regards to the levels of revenue efficiency in bioenergy industries across the EU15 developed countries. While some countries have exhibited a high level of revenue efficiency, others still have a low level of revenue efficiency. The results from Fig. 1 has shown that most of the EU15 developed countries are highly efficient, with only a few having efficiency scores below 0.79, which is the average score of the region for the period studied. France and Sweden show full efficiency levels, meaning they are 100% efficient with an average efficiency score of 1. Portugal, Finland, Austria, Greece, Germany, and Luxembourg also have excellent efficiency scores, but below the fully efficient score with scores of (0.99, 0.98, 0.85, 0.82 and 0.81) respectively, while the Netherlands and Belgium accounted for good revenue efficiency with scores of 0.68 and 0.61 respectively. Denmark and Italy recorded moderate efficiency levels with scores of 0.52 and 0.5 respectively, while Ireland appeared to be the least efficient among the EU15 developed countries with a poor revenue efficiency score of 0.48.

Based on panel (B) of Fig. 1, the revenue efficiency level from the illustration shows that most of the EU13 developing countries are highly efficient, with only a few having an efficiency score below 0.81, which is the average score of the region for the period studied. Malta and Slovakia appeared to be fully efficient with an efficiency score of 1, which means they are 100% efficient. Latvia, Poland, Romania, Slovenia, Croatia, Bulgaria, the Czech Republic, and Estonia also have excellent scores, but they are lower than the fully efficient score, with scores of (0.97, 0.92, 0.9, 0.91, 0.89, 0.84, 0.83 and 0.82, respectively), while Hungary and Lithuania have good revenue efficiency levels with scores of (0.72 and 0.66).Cyprus and Ireland recorded poor revenue efficiency levels and appeared to be the least efficient in the region with scores of 0.11 and 0.48, respectively (see Fig. 2). Generally, these results indicate that a significant number of countries in the European Union, both developed

Fig. 1 Revenue efficiency of bioenergy industry



and developing, have employed modern strategies and technologies that have helped improve their revenue efficiency in the bioenergy industry.

Table 1 shows the mean revenue efficiency of the bioenergy industry in the European Union from 1995 to 2018. The results show that the mean revenue efficiency score of the EU13 developing region is higher than that of the developed region, with efficiency scores of 0.81 and 0.79, respectively, and the overall revenue efficiency score for the EU28 region is 0.80. In addition, results from the annual average suggest that the developed region only had efficiency scores higher than the developing in 1998, 1999, 2000, and 2016 with efficiency scores of (0.72 vs. 0.68), (0.73 vs. 0.70), (0.74 vs. 0.73) and (0.83 vs. 0.81) respectively (see Fig. 2).

Determinants of revenue efficiency of bioenergy industry

In order to examine the determinants of Revenue Efficiency in the EU28 region, this study estimated three different and suitable models in order to see their performances. These three models reflect the determinants of revenue efficiency of the bioenergy industry in the developed and developing countries of the EU28 (categorized into EU15 and EU13), as well as the entire EU region. The effect of country-specific factors and macroeconomic factors on the level of revenue efficiency of the EU28 bioenergy industry for the period 1995–2018 is presented in Table 2. The results indicate that the bioenergy industry in the EU28 region depends more on highly efficient inputs of labor and raw materials in order to increase output. Interestingly, this explains why capital input is insignificant. Labor input showed a negative relationship with revenue efficiency and is statistically significant. The positive labor input sign also showed a negative correlation between the bioenergy industry's labor input in the EU28 area and the level of revenue efficiency of the bioenergy industry, i.e., a decreased labor input would lead to more revenue efficiency. This finding is pointed toward efficient labor productivity and identifies the importance of optimum labor input. Findings in Model 1 indicate that due to a large wage bill, high labor inputs may become detrimental to businesses. Also, the results suggest a positive relationship between GDP growth and the revenue efficiency level of the bioenergy industry in the EU28 region. This implies that the higher the level of economic growth, the higher the level of revenue efficiency of the industry. Interestingly, the coefficient of capital input is positive although it is statistically insignificant.

This model was subjected to the following statistical tests to ensure that the results obtained are accurate and reliable. First, the VIF test was carried out to ensure that there is no presence of a multi-collinearity problem in the model, and the mean VIF is 1.87, which is sufficiently VIF 5, indicating that there is no multi-collinearity among the independent variables included in the model.

Secondly, the Breusch and Pagan Lagrangian multiplier (BPLM) test was conducted in order to select the better model between the RE and OLS. Interestingly, the BPLM

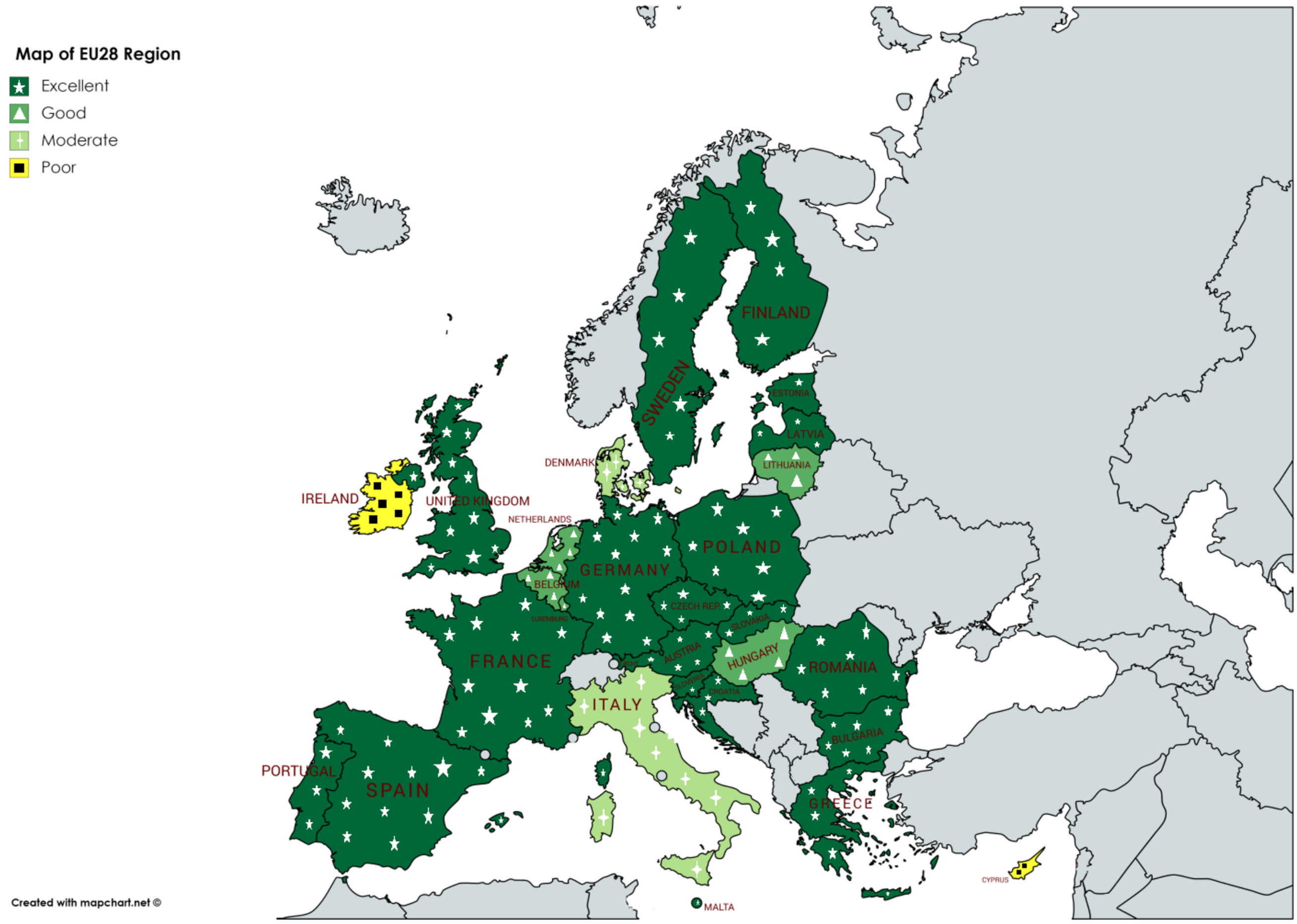


Fig. 2 The level revenue efficiency level of bioenergy industry

test is statistically significant given a *p*-value of 0.000. Thus, it can be concluded that the RE model is more appropriate than the OLS pooled model due to heterogeneity in the used data. On the other hand, the Hausman test was conducted to choose the appropriate model between the FE and the RE models. A significant *Haus* statistic with a *p*-value = 0.000, led to the rejection of the null hypothesis. It is therefore concluded that the FE model is more appropriate for this estimation. In addition, the Tobit model was adopted for robustness checking for the FE model.

Estimates of the determinants of revenue efficiency in EU15 developed countries for the period 1995–2018 are presented in Table 3. As with model 1, this model was subjected to the VIF test for multi-collinearity, the BPLM test and the Hausman test. The VIF test was carried out to ensure that there is no presence of multi-collinearity in the model, and the mean VIF is 2.36, which is sufficiently VIF 5, indicating that there is no multi-collinearity among the independent variables included in the model. The BPLM test was conducted in order to select the more appropriate model between the RE and OLS. A BPLM test is significant given a *p*-value of 0.000. We reject the null hypothesis and thus, concluded that the RE model is more appropriate than the OLS pooled model due to heterogeneity in the used data. The Hausman test was further conducted to select the appropriate model between the FE and the RE models. A significant *Haus* statistic with a *p*-value = 0.163, led to the conclusion that the RE model is more appropriate for this estimation. In addition, the Tobit model was adopted for robustness checking for the FE model.

The results in Table 3 suggest that capital input, GDP, and size of biomass variables had positive coefficients, suggesting they influenced revenue efficiency of the bioenergy industry positive during the period studied, while labor input has a negative impact on revenue efficiency of the industry over the same period. The Tobit regression estimator confirms the reliability and robustness of the RE model in terms of signs, significance and the magnitude of impact of the explanatory variables on revenue efficiency. Additionally, this shows that labor input and GDP have a negative and significant relationship with revenue efficiency level, and the size of biomass showed a significant and positive

Table 1 Average of revenue efficiency of the bioenergy industry in EU28 from 1995 to 2018

Year	Developed countries	Developing countries	EU28 countries
1995	0.66	0.74	0.70
1996	0.64	0.74	0.69
1997	0.69	0.73	0.71
1998	0.72	0.68	0.70
1999	0.73	0.70	0.72
2000	0.74	0.73	0.73
2001	0.76	0.77	0.76
2002	0.81	0.85	0.83
2003	0.80	0.86	0.83
2004	0.80	0.83	0.82
2005	0.80	0.88	0.84
2006	0.83	0.86	0.85
2007	0.82	0.87	0.85
2008	0.81	0.85	0.83
2009	0.84	0.84	0.84
2010	0.84	0.85	0.85
2011	0.83	0.86	0.84
2012	0.83	0.86	0.84
2013	0.84	0.85	0.84
2014	0.84	0.84	0.84
2015	0.83	0.85	0.84
2016	0.83	0.81	0.82
2017	0.85	0.83	0.84
2018	0.86	0.87	0.86
Average	0.79	0.81	0.80

relationship with revenue efficiency rate. Meanwhile, capital input shows a positive but insignificant relationship with the revenue efficiency rate. The coefficients for labor input are significant at 1%, GDP is significant at 10%, and biomass is significant at 5%. The coefficient for capital input appeared to be statistically insignificant.

The findings reveal that a 1% increase in GDP would lead to a rise in the revenue efficiency rate by 0.9%. Similarly, a 1% percentage increase in the size of biomass can increase revenue efficiency by 0.10%. Furthermore, a percentage decrease in labor input would increase the revenue efficiency level by 0.5%. However, results show that a 10% increase in capital input would result in a 0.3% increase in revenue efficiency, although this effect appeared to be statistically insignificant both in the RE model and the Tobit model for the EU15 developing countries.

Estimates of the determinants of revenue efficiency for EU13 developing countries for the period 1995–2018 are presented in Table 4. We first conducted the VIF test for multi-collinearity to ensure that there was no multi-collinearity problem in our dataset. Then we conducted the BPLM test, which was conducted in order to select the more appropriate model between the RE and OLS, and the Hausman test, which was conducted to select the appropriate model between the FE and the RE models. The mean VIF test is 3.03, which is sufficiently lower than the established VIF = 5, indicating that there is no multi-collinearity problem in our dataset. The BPLM test is significant given a p-value of 0.000. We reject the null hypothesis and thus, concluded that the RE model is more appropriate than the OLS pooled model due to heterogeneity in the used data. However, the Hausman test statistic is insignificant given a *p*-value of 0.142. We therefore conclude that the RE model is more appropriate for this estimation, while the Tobit model was adopted for robustness check for the FE model.

Results in Table 4 suggest that labor, capital, and the quantity of biomass inputs have negative coefficients. This implies that these factors can reduce the revenue efficiency of the bioenergy industry. On the other hand, GDP has a positive coefficient, indicating increasing economic growth can lead to an increase in revenue efficiency. While capital is significant at a 10% level, labor and GDP are significant at 1% levels of significance. However, the size or quantity of biomass is statistically insignificant both in the RE model as well as the Tobit model.

The findings reveal that a 1% increase in GDP would lead to a rise in revenue efficiency rate of about 4%. Furthermore, a percentage decrease in labor input would lead to an increase in revenue efficiency level by 0.27%. Similarly, results show that a 1% increase in capital input would result in a 0.03% decrease in revenue efficiency. However, the quantity of biomass appeared to be statistically insignificant both in the RE model and the Tobit model.

Discussion

This section provides the analysis of the revenue efficiency level as well as economic variables (internal and external) influencing the revenue efficiency of the bioenergy industry in the EU28 region. DEA was employed to measure the profit efficiency score of individual countries. This efficiency score is between 0 and 1. Figure 1 summarizes the average revenue efficiency level of the bioenergy industry in EU13 developing and EU15 developed countries respectively from 1995 to 2018. Table 1 summarizes the average revenue efficiency level of the EU region and also decomposes the region into developing and developed countries. Hence, we also have the average revenue efficiency level of EU15 developed countries and the EU 13 developing countries respectively. Secondly, we employed three panel regression models to examine the determinants of revenue efficiency of the bioenergy industry in the EU28 region, EU15 developed countries, and EU13 developing countries. These models contain three internal determining factors such as capital

Table 2 Summary of estimation for EU28 countries, 1995–2018

Model 1. Revenue efficiency estimation for EU28 countries 1995–2018

	Pooled OLS model	Random effect model	Fixed effect model	Tobit model
Capital input	0.082***	0.021	0.006	0.019
	(0.004)	(0.365)	(0.788)	(0.402)
Labor input	−0.062**	−0.341***	−0.304***	−0.340***
	(0.025)	(0.000)	(0.000)	(0.000)
GDP	−0.179	1.768***	3.171***	1.896***
	(0.397)	(0.000)	(0.000)	(0.000)
Biomass	−0.069***	0.041	0.038	0.041
	(0.006)	(0.199)	(0.258)	(0.198)
Constant	1.735***	−4.670***	−9.226***	−5.084***
	(0.004)	(0.002)	(0.000)	(0.003)
R^2	0.05	0.17	0.18	–
F-statistic	7.90	–	34.2	–
	(0.000)		(0.000)	
Breusch–Pagan LM test		3725.36***		
		(0.000)		
Hausman test			18.66***	
			(0.009)	
CD		44.87	73.96	
		(0.142)	(0.319)	

***, ** and * indicate significance at the 1%, 5%, and 10%, respectively, values in parentheses are *p*-values, CD indicates cross sectional dependence test (Breusch-Pagan LM test)

Table 3 Summary of analysis for EU15 developed countries, 1995–2018

Model 2. Revenue efficiency estimation for EU developed countries 1995–2018

	Pooled OLS model	Random effect model	Fixed effect model	Tobit model
Capital input	0.080**	0.031	0.026	0.031
	(0.019)	(0.258)	(0.336)	(0.251)
Labor input	−0.152**	−0.538***	−0.364**	−0.539***
	(0.020)	(0.000)	(0.029)	(0.000)
GDP	−0.746***	0.964*	2.572**	0.909*
	(0.004)	(0.061)	(0.012)	(0.096)
Biomass	0.055*	0.106**	0.114**	0.106**
	(0.094)	(0.014)	(0.012)	(0.013)
Constant	2.982***	−2.136	−7.680**	−1.956
	(0.000)	(0.254)	(0.026)	(0.305)
R^2	0.09	0.15	0.16	–
F-statistic	9.27	–	15.65	–
	(0.000)		(0.000)	
Breusch–Pagan LM test		1845.25***		
		(0.000)		
Hausman test			6.53	
			(0.142)	

***, ** and * indicate significance at the 1%, 5%, and 10% levels respectively, values in parentheses are *p*-values

input, labor input and the size of biomass, and GDP as the external determining factor. Model 1 explores the effect of macroeconomic and internal-specific determinants of revenue efficiency for the period 1995–2018 in the EU28 region (see Table 2). Model 2 estimates the impact of macroeconomic and internal-specific determinants of revenue

Table 4 Summary of analysis for EU13 developing countries, 1995–2018

Model 3. Revenue efficiency estimation for EU developing countries 1995–2018

	Pooled OLS model	Random effect model	Fixed effect model	Tobit model
Capital input	−0.074	−0.079*	−0.098**	−0.079*
	(0.279)	(0.091)	(0.043)	(0.089)
Labor input	−0.003	−0.276***	−0.242***	−0.276***
	(0.947)	(0.000)	(0.000)	(0.000)
GDP	1.027**	3.899***	5.340***	3.904***
	(0.041)	(0.000)	(0.000)	(0.000)
Biomass	−0.196***	−0.064	−0.085	−0.065
	(0.000)	(0.191)	(0.102)	(0.189)
Constant	−1.215	−10.868***	−15.429***	−10.882***
	(0.436)	(0.000)	(0.000)	(0.000)
R^2	0.09	0.15	0.16	–
F-statistic	9.27 (0.000)	–	15.65 (0.000)	–
Breusch–Pagan LM test		1701.12*** (0.000)		
Hausman test			6.89 (0.142)	

***, ** and * indicate significance at the 1%, 5%, and 10% levels respectively, values in parentheses are *p*-values

efficiency for the period 1995–2018 in the EU15 developed countries (see Table 3), while Model 3 examines the impact of internal-specific determinants of revenue efficiency for the period 1995–2018 (see Table 4). The findings of this study provide insight into the factors that could impact the revenue performance of the EU region's bioenergy industry. The findings show a positive relationship between GDP and efficiency (Models 1, 2 and 3). This result is in line with Abdulwakil et al. (2020), Vu and Nahm (2013), Kosmidou (2008). This indicates that, during the study period, favorable economic conditions paved the way for higher demand for regional production, reducing the likelihood of default inputs. High economic growth will inspire countries to save more input by improving input efficiency and producing more. This enables the region to change its bioenergy consumption accordingly, resulting in faster increases in the output of bioenergy production and thus having a positive effect on the region's revenue efficiency levels. This rise is also in line with previous research, for example (Alsaleh et al. 2017).

Interestingly, in all three models (1, 2 and 3), we find a negative relationship between labor input and revenue efficiency and they are all statistically significant. This result is consistent with previous research, such as (Alsaleh et al. 2017; Rachmina et al. 2014; Molyneux & Thornton 1992; Staub et al. 2010). This posits that the rate of cost reduction in biomass production and transformation is low as a result of the high cost of labor, suggesting that higher profits made by the organization with more efficient labor are not sufficient to offset the high wage bill, hence resulting in the negative effect of labor input on revenue efficiency of the industry. Similarly, Model (3) suggests that capital inputs affect revenue efficiency negatively and is statistically significant at a 10% level. This could be as a result of the time needed for capital inputs to translate into profitability through increased bioenergy production output or it could be the effect of excess capital. This is consistent with previous studies such as Alsaleh et al. (2017) and Kosmidou (2008) in an attempt to study the determinants of technical efficiency in EU28 developed countries. The consensus is that the bioenergy industry's profitability is directly related to the quality of fixed assets it controls as part of the input to produce a given level of output over a period of time. This case shows that fixed asset capital does not normally yield a profit for a certain period of time in which the effect can negate profitability. As seen in our result, capital formation is expected to reduce profit until the underdeveloped bioenergy industry in EU13 developing countries becomes well developed, and this usually takes a long time as there is continued investment in new bioenergy technologies. However, Alsaleh et al. (2016) finds that the region is currently faced with a decreasing return to scale, suggesting further increases in input are increasing output at a decreasing rate even though some of the EU member countries are fully efficient in the industry. The entire region needs to do more in the aspect of technicality to enable them to get more output from the current level of input due to improvements in technology to enhance the revenue efficiency level in the region.

In addition, competition among capitals can lead to a negative impact on revenue and profitability, as posited in the theory of falling rate of profit. However, this unhealthy competition among capitals could be corrected through improved labor productivity, which will result in increased output per capital stock and consequently improve revenue efficiency.

Our empirical findings indicate that the quantity of biomass can increase the revenue efficiency of the bioenergy industry, especially in the EU developed countries, as shown in Table 3 (Model 2). This finding is consistent with Abdulwakil et al. (2020), Ariff and Luc (2008), Kamarudin et al. (2016). Biomass is considered the major source of renewable energy for both power and cooking, cooling, and heating, and it currently contributes over 80% of the renewable energy supply (Scarlat et al. 2013). Hence, it plays a significant role in revenue efficiency as well as contributing to employment in the region. Biomass is also considered as an attractive energy option due to its flexibility characteristics and its potential for integration with all stages of the sustainable development agenda, which is reflected in the prices of biomass feedstock and revenue efficiency.

Conclusion and policy recommendations

The importance of revenue efficiency to a firm has been established. There is still a call for further studies in the area of revenue efficiency of bioenergy in industry, especially on the determinant of revenue efficiency, so as to explain the rationale behind the efficiency of some countries' bioenergy industries are efficient while others are not.

Most existing work is focused on the investigation of the efficiency of the bioenergy industry. With little or no studies examining the revenue efficiency of the bioenergy industry and its determinants. This study examined two issues. First, it examined the revenue efficiency of the bioenergy industry in EU28 countries, and second, it examined the economic determinants of revenue efficiency. Based on the empirical findings, the study concludes that the region is quite efficient with an average revenue efficiency score of 0.80. When segregated into developed and developing countries, the EU13 developing countries account for a higher efficiency of 0.81 as compared to that of the developed region, which stands at 0.79. However, individual country examinations show that countries such as Cyprus, Lithuania, and Hungary in the developing region are below the average efficiency score of 0.11, 0.66 and 0.72 respectively. Similarly, countries such as Ireland, Denmark, Italy, Belgium, the Netherlands, and Luxembourg in the developed category are below the average efficiency score of 0.48, 0.52, 0.53, 0.61, 0.68 and 0.76 respectively. The reason behind the poor performance of Cyprus, which is the least efficient in the region, could be a lack of commitment to achieving the EU28 NREAPs of 20% renewable energy by 2020 and weak or ineffective renewable energy policies.

Also, the study reveals that among the internal factors included in the study, quantity of biomass input emerged as the only factor with a positive impact on revenue efficiency. This impact is, however, only noticeable in the developed region. Labor and capital inputs have negative impacts. GDP is the only macroeconomics determinant in the study and has a positive impact on revenue efficiency and this outcome is consistent across all estimated models. In addition, the study provides crucial information on future development and possible improvement of an underdeveloped bioenergy industry based on the empirical outcome.

The result of this study has implications for policymakers and investors alike. Based on our results, we find convincing evidence of the negative impact of labor input on revenue efficiency. This result holds regardless of the countries' level of development as all regressed models yield consistent negative results. Therefore, we recommend that policy makers concentrate on strategies to improve labor productivity, such as ensuring access to requisite education and training to improve the effectiveness and productivity of labor, and providing healthcare facilities to reduce the risk of illness and absence from work. Following our results, we find evidence of the negative impact of capital input on revenue efficiency. This shows that the bioenergy industry of the region is highly capital intensive. The probable explanation for the negative effect of capital input on revenue efficiency could be attributed to the underdeveloped bioenergy industry. Therefore, it is recommended that policy makers lower corporate taxes and/or reduce the rate of interest in order to reduce the cost of capital. More so, skilled labor should be engaged to increase the productivity of capital and, in turn, improve revenue efficiency.

Generally, bioenergy production and trade policies may vary across countries, but the region needs to invest in more efficient bioenergy generation technologies and give tax holidays on the use of the latest technologies and energy-efficient products, improve effective bioenergy market access and healthy completion through deregulation of markets, expand the infrastructural web that would efficiently link bioenergy production sites and consumers, enhance the efficient allocation of resources (inputs) required to improve the level of productivity and, subsequently, generate more revenue. Finally, the less efficient/inefficient countries need to utilize the experience, strategies and technologies gained from more efficient countries.

Our sample was restricted to EU member countries. Therefore, the results may be peculiar to the nature and characteristics of these countries and may not be applicable to other European countries or the world at large. This study only analyzed a selected group of variables that may influence the revenue efficiency of the bioenergy industry. Hence, it might be fruitful for future research to identify and examine other factors that may influence the revenue efficiency of the industry. In addition, future research could explore how revenue efficiency may help hasten the energy transition. Also, alternative empirical methodologies for panel regression, such as dynamic heterogeneous panels, could be considered to examine the determinants of revenue efficiency. Lastly, future studies should consider a different time frame to confirm the consistency of the findings.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by MMA, ASA-R, MA and CS. The first draft of the manuscript was written by MMA and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding The authors have no relevant financial or non-financial interests to disclose.

Data availability The authors have the relevant data and would make it available upon reasonable request.

Declarations

Ethical approval Ethical approval is not required for this study.

Consent to participate Consent to participate is not applicable to this study.

Consent to publication Consent to publish is not required for this study.

Competing interests The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

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