EFFECTIVE MANAGEMENT OF WASTE RECYCLING AND TREATMENT FIRMS TOWARDS SUSTAINABLE DEVELOPMENT GOALS AND A CIRCULAR ECONOMY

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Abstract: ***Firms in the waste recycling and treatment industry are a key sector in the development of a circular economy and contribute significantly to national environmental sustainability goals. This research aims to assess the productivity and efficiency of these firms and propose recommendations for their effective management. The study utilizes enterprise survey data from the waste recycling and treatment sector spanning 2015-2022. It employs Data Envelopment Analysis (DEA) to measure efficiency, the Generalized Method of Moments (GMM) to measure Total Factor Productivity (TFP), and subsequently evaluates the impact of various factors on business productivity and efficiency within the industry. The research findings indicate that the average efficiency of waste recycling and treatment firms is moderate, at 59.851%. Smaller firms tend to be more efficient, and efficiency tends to increase as firms grow to a certain size. Environmental impact variables, financial constraints, and capital structure are identified as the primary factors affecting the efficiency and productivity of firms in the waste recycling and treatment industry.***

• Keywords: *waste recycling and treatment firms, circular economy, efficiency, productivity, DEA, GMM.*

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1. Introduction

Orienting business towards sustainable development goals and the circular economy are relevant research topics in current business theory and practice. The increasingly developed global economy also entails a large amount of waste, causing significant negative impacts on the environment, threatening the sustainable development of the economy (Boons & Lüdeke-Freund, 2013). Therefore, governments of various countries are gradually transitioning to sustainable production models and a circular economy to minimize the negative and unwanted impacts of economic activities. The circular economy is a great opportunity for manufacturing enterprises to deploy environmentally friendly products, cleaner production, and the activities of waste recycling and treatment firms contribute significantly to the goals of this circular economy. Climate change and environmental issues are increasingly complex, requiring countries around the world to quickly implement many actions to prevent future environmental disasters, paving the way for many studies related to the circular economy (Ferasso et al., 2020; Geissdoerfer et al., 2020).

Waste recycling and treatment enterprises play a crucial role in the transition to a circular economy and sustainable production (based on the 3R principle: reduce, reuse, and recycle). Analyzing the operational efficiency of waste recycling and treatment firms based on efficiency and productivity indicators is therefore an important topic that directly impacts the circular economy. Research in the field of recycling and waste has analyzed issues related to environmental performance and eco-efficiency practices from a multidisciplinary perspective in various areas, including the efficiency of recycling firms (Marques et al., 2012), the efficiency of urban waste management (Díaz-Villavicencio et al., 2017; Molinos-Senante et al., 2023; Rios & Picazo-Tadeo, 2021), efficiency in industrial waste recycling and treatment (Li et al., 2020), and solid waste management and urban solid waste recycling (Amaral et al., 2022; Bui et al., 2022; Ferraro et al., 2023). Early efficiency studies focused on indicators at the national level; studies conducted at the enterprise level with waste recycling firms are still limited (Pedersen et al., 2021, Kurki & Lähdesmäki, 2023). In general, studies have shown that waste treatment and recycling firms often have low efficiency levels (Li et al., 2019; Marques et al., 2012; Parte-Esteban & Alberca-Oliver, 2015), with fluctuations at different stages (Li et al., 2020).

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The lack of incentive factors (Marques et al., 2012) as well as internal and external factors can explain poor business performance or inefficiency (Li et al., 2019; Parte-Esteban & Alberca-Oliver, 2015).

According to statistics from the Ministry of Natural Resources and Environment, Vietnam discharges 1.8 million tons of plastic waste into the environment each year. Vietnam's plastic consumption has increased by about 15% annually, leading to a steadily increasing amount of plastic waste. Efficiently operating waste recycling and treatment firms in Vietnam will make an important contribution to sustainable economic development and the circular economy. Research measuring the efficiency and productivity of this specific group of firms in Vietnam is still very limited.

Therefore, this study delves into measuring and analyzing business performance with micro-level data, using a balanced panel of waste recycling and treatment firms. The study first uses the Data Envelopment Analysis (DEA) model to measure efficiency, the Generalized Method of Moments (GMM) model to measure Total Factor Productivity (TFP) and then assesses the impact of factors such as capital structure, financial constraints, CO2 emissions, enterprise size, and other characteristic variables on the efficiency and productivity of firms in the waste recycling and treatment industry.

2. Research method

2.1. Effective measurement method

Analyzing the efficiency of firms in the recycling and waste treatment industry is developed using the non-parametric DEA boundary model, which allows determining the relative efficiency of N firms (DMUs or decision-making units) without imposing production function forms. Charnes et al. (1978) developed a non-parametric DEA boundary method that allows taking into account radial efficiency in DEA-oriented models. According to the original model established by Charnes et al. (1978), we calculate the Debreu-Farrell indices and constant returns to scale, the input-oriented index for DMUs or firms, including the objective function and constraints, can be calculated as follows:

$$\max \sum_{k=1}^{s} v_{kJ}\, y_{kJ}$$

$$\sum_{k=1}^{s} v_{kJ}\, y_{kj} - \sum_{i=1}^{m} u_{iJ}\, x_{ij} \leq 0 \qquad \sum_{i=1}^{m} u_{iJ}\, x_{ij} = 1$$

$$v_{kJ}; u_{iJ} \geq \varepsilon$$

$$j = 1, 2, \ldots, n;\ k = 1, 2, \ldots, s;\ i = 1, 2, \ldots, m$$

After that, the Charnes, Cooper & Rhodes (CCR) model developed by Charnes et al. (1978) with constant returns to scale, along with market deviations and the differences of firms by scale, was developed into the model proposed by Banker et al. (1984) with variable returns to scale, or also called the Banker, Charnes & Cooper (BCC) model. The efficiency scores under variable returns to scale represent the efficiency index without taking into account the operating scale. The BCC model with the dual representation is as follows:

$$\min \theta_J - \varepsilon\left[\sum_{k=1}^{s} h_k^{+} + \sum_{i=1}^{m} h_i^{-}\right]$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j = \theta_J x_{iJ} - h_i^{-} \qquad \sum_{j=1}^{n} y_{kj}\lambda_j = y_{kJ} + h_k^{+}$$

$$\lambda_j; h_i^{-}; h_k^{+} \geq 0 \qquad \sum_{j=1}^{n} \lambda_j = 1$$

The study applied Coelli's (1998) multi-stage DEA algorithm, using linear programming in six stages and allowing comparison of inefficient units with the nearest efficient reference to overcome this limitation. This nearest reference is located on the efficiency frontier and does not change according to the units of measurement (Coelli, 1998). This study used physical capital (K), labor (L), and energy (TOE) as input variables. The output variable is the added value of the firms.

2.2. Methods of measuring total factor productivity TFP

Production function model

Assume that the production function has the following Cobb-Douglas:

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} \qquad (1)$$

Y_{it} is the physical output of firm *i* in period *t*. K_{it}, L_{it} and M_{it} are the inputs of capital, labor, and intermediate inputs, respectively, and A_{it} is the Hicks-neutral efficiency level of firm *i* in period *t*. We assume that econometricians observe Y_{it}, K_{it}, L_{it}, M_{it}. and A_{it} is unobservable. Taking the natural logarithm of (1) leads to

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + u_{it},$$

trong đó $ln\,(A_{it}) = \beta_0 + u_{it}$ (2)

β_0 measures the average efficiency between firms and over time; u_{it} is the individual deviation over time - and the producer compared to that average, which can then be further decomposed into observable (at least predictable) and unobservable components. This leads to the following equation:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + v_{it} + e_{it} \qquad (3)$$

Taking wit = b0 + vit denotes firm-level productivity and ε_{it} is a component with independent, identical distribution, representing unpredictable deviations from the average due to measurement errors, unpredictable lags or other external circumstances. Typically, empirical researchers estimate

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \qquad (4)$$

Estimated productivity can be determined by the following equation once ω_{it} is also solved

$$\hat{\omega}_{it} = \hat{v}_{it} + \hat{\beta}_0 = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} \qquad (5)$$

and the TFP yield can be obtained as an exponential function of $\hat{\omega}_{it}$ meaning

$$\hat{\Omega}_{it} = \exp(\hat{\omega}_{it})$$

Choosing a TFP measurement method

Although the foundation of total factor productivity analyses from production functions originated from Solow's (1957) research, recent years have seen studies on TFP measurement still attracting the interest of many economists. Such as the semi-parametric method initiated by Olley & Pakes (1996) and later Levinsohn & Petrin (2003), which is a combination of parametric and semi-parametric techniques, called the robust production function estimation method. Ackerberg et al. (2006) then extended OP's semi-parametric estimation to address multicollinearity and identification issues with the labor variable. Subsequently, Wooldridge (2009) pointed out that the semi-parametric estimates of OP, LP, and ACF can be performed using a one-step GMM method, while standard semi-parametric estimates use a two-step estimation procedure to obtain robust estimates of input elasticities. Wooldridge (2009) argues that the moment conditions implied by the semi-parametric estimates can be easily implemented in the GMM approach. Therefore, the approach proposed by Wooldridge (2009) has some advantages over standard semi-parametric estimation. This study uses Wooldridge's (2009) approach to measure TFP.

2.3. Model for assessing the impact of factors on the efficiency and productivity of waste recycling and treatment firms

$$E\_DEA_{it} = \beta_0 + \beta_1 \times lnKL_{it} + \beta_2 \times lnLC_{it} + \beta_3 \times VNG_{it} + \beta_4 \times DNNN_{it} + \beta_5 \times FDI_{it} + \beta_6 \times Fsize_{it} + \beta_7 \times Fsize2_{it} + \beta_8 \times LnCO2_{it} + \beta_7 \times WWD_{it} + c_i + u_{it} \qquad (6)$$

$$TFP\_GMM_{it} = \beta_0 + \beta_1 \times lnKL_{it} + \beta_2 \times lnLC_{it} + \beta_3 \times VNG_{it} + \beta_4 \times DNNN_{it} + \beta_5 \times FDI_{it} + \beta_6 \times Fsize_{it} + \beta_7 \times Fsize2_{it} + \beta_8 \times LnCO2_{it} + \beta_7 \times WWD_{it} + c_i + u_{it} \qquad (7)$$

In which,

E_DEA_{it} is the business efficiency of the waste recycling and treatment industry estimated by the multi-stage DEA method.

$lnKL_{it}$ is the business efficiency of the waste recycling and treatment industry estimated by Wooldridge's GMM method (2009).

$lnKL_{it}$ is the logarithm of KL (KL - capital intensity calculated as capital per labor); $lnLC_{it}$ is the logarithm of LC (LC calculated as income per labor); *VNG* is the external capital ratio calculated as total liabilities/total assets.

$DNNN_{it}$ and FDI_{it} are dummy variables that take the value 1 if the firm is a state-owned enterprise (SOE) or a foreign direct investment (FDI) enterprise, respectively, or 0 otherwise.

$Fsize_{it}$ is the logarithm of total assets and $Fsize2_{it}$=*Fsize***Fsize.*

$LnCO_{2it}$ is the logarithm of the firm's CO2 emissions, representing the firm's environmental impact (Laura & Pilar, 2024). Due to data limitations, the study only uses CO2 emissions as the sole proxy.

WWD_{it} is a financial constraint index, based on the research by Whited & Wu (2006).

$$WW_{it} = -0.091 \times CFA_{it} - 0.062 \times DIV_{it} + 0.021 \times TLTD_{it} - 0.044 \times Fsize_{it} + 0.102 \times IRG_{kt} - 0.035 \times RG_{it}$$

Where CFA is cash flow/total assets. *DIV* is a dummy variable that takes the value of 1 if firm *i* in year *t* has a profit and 0 otherwise. *TLTD* is the debt burden measured by total debt over total assets, *Fsize* is the logarithm of total assets, *IRG* and *RG* are respectively the revenue growth of industry *k* and the firm.

A firm is financially constrained if the WW_{it} index is high. The dummy variable $WWD_{it/}$ represents financial constraints and takes the value of 1 if firm *i* in year *t* belongs to the >= 1/3 quantile of the distribution and 0 otherwise

3. Results of experimental research

3.1. Data source

The study uses annual survey data from the General Statistics Office of Vietnam (GSO) for the waste recycling and treatment industry from 2015 to 2022 (Firms with VSIIC 2007 industry codes 37, 38, and 39). The data, after collection and removal of invalid observations, is in the form of panel data with a total of 3,192 observations over 8 years from 2015-2022**.**

Descriptive statistics of the variables included in the model are given in table 3.1 below

Table 3.1: Descriptive analysis of model variables

Variable	Unit	Number of observations	mean	min	max
KL	million/capita	3192	205.74	2.08E-08	2.01E+04
LC	million/capita	3192	8.53	3.42E-07	731.477
VNG	%	3192	0.47	0.000775	40.167
CO2	tons/enterprise	3192	3,215.59	5.61E-06	175407
DNNN	0/1	3192	0.06	0	1
FDI	0/1	3192	0.01	0	1
Fsize	log	3192	12.15	0.693	28.922
WWD	0/1	3192	0.67	0	1
E_DEA	%	3192	59.851	0	100
TFP_GMM	Gtri	3192	67.761	0.0000226	1023.98

Source: Author's Calculations Based on GSO Data

The research results show that most firms in the waste recycling and treatment industry are private firms, with only about 1% being FDI firms and 6% being state-owned firms, with an average enterprise size of approximately 109 employees per enterprise. The efficiency estimation results using the multi-stage DEA method show that the efficiency of firms in this industry is still low at 59.851% compared to the optimal level of 100% (or in other words, 0.59851 compared to 1). In particular, the highest DEA efficiency values were in 2016, 2017, and 2018 (reaching 62%, 63%, and 67% respectively), decreasing slightly in 2019 and quite sharply in the following years. By 2022, DEA efficiency reached only 53.74%, partly due to the impact of Covid-19. TFP_GMM also shows a relatively similar trend to the DEA efficiency trend in the early stages. Although affected by Covid-19, leading to a significant decrease in TFP_GMM in 2020, TFP_GMM in 2021 and 2022 subsequently showed a stronger recovery trend, confirming that capital quality, labor quality, as well as technological progress have improved significantly during this period.

3.2. Results of the impact assessment model

The study uses the fixed effects (FE) and random effects (RE) methods for estimation. The Hausman test results indicate that the FE model is more appropriate. The diagnostic test results show that the model does not have multicollinearity, has autocorrelation, and has heteroskedasticity, so the study implemented corrections using the feasible generalized least squares (FGLS) method.

The research results in all four models (1), (2), (3), and (4) are highly consistent. Most variables are statistically significant except for the FDI variable in all four models, some other variables are not statistically significant including the *lnKL*, *lnLC*, *Fsize2*, $LnCO_2$ (model 4), and DNNN (model 2) variables.

Table 3.2. Regression results of models assessing the impact on the efficiency and productivity of waste recycling and treatment firms

	(1)	(2)	(4)	(3)
Variable	E_DEA_FE	TFP_GMM_FE	E_DEA_FGLS	TFP_GMM_FGLS
lnKL	-0.136**	-0.128***	-0.332	-0.189***
	(0.0586)	(0.00261)	(0.543)	(0.0337)
lnLC	0.317***	0.0127***	0.0355	0.127***
	(0.0769)	(0.00343)	(0.453)	(0.0394)
VNG	-0.0055	-0.000945**	-0.00255*	-0.00337*
	(0.00882)	(0.000394)	(0.00113)	(0.000214)
DNNN	1.409***	0.0114	2.563***	0.0419*
	(0.710)	(0.0763)	(0.420)	(0.0163)
FDI	0.216	0.240	0.345	0.348
	(4.924)	(0.220)	(2.145)	(0.351)
Fsize	-0.0565	-0.0163***	-1.322*	-0.542***
	(0.0725)	(0.00324)	(0.584)	(0.168)
Fsize2	0.000923	0.000191***	0.0108	0.0164***
	(0.000758)	(3.38e-05)	(0.00898)	(0.00538)
LnCO2	2.938***	1.870***	-1.256	1.721***
	(0.141)	(0.00631)	(0.444)	(0.0468)
WWD	-0,137***	-0,0612*	-0,1589***	-0,1112*
	(0,0189)	(0,0315)	(0,0217)	(0,0425)
Intercept	47.90***	-0.846***	76.88***	2.885***
	(0.984)	(0.0439)	(8.530)	(1.010)
Number of observations	3,192	3,192	3,192	3,192
R-squared	0.797	0.906		
Number of firms	399	399	399	399
Hausman test	70.11***	228.71***		
Wooldridge test	28.252***	45.205***		
Modified Wald test	2159.75***	4445.6***		
VIF	3.43	4.22		

Source: Author's Calculations Based on GSO Data

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The capital structure as well as the capital utilization of firms in this industry are showing irrationality. This is reflected in the coefficients of the lnKL and VNG variables, which both have negative signs and are almost all statistically significant in the models; specifically, when lnKL and VNG increase by 1%, they reduce the TFP productivity of firms in the industry by 0.189% and 0.00337% respectively. Both internal capital and external debt are being used in a less effective manner and create a negative impact on enterprise productivity and efficiency.

Average income per capita is showing a positive impact on enterprise productivity and efficiency. Increased income will motivate and reassure employees to contribute, thereby improving work efficiency, which helps increase enterprise productivity and efficiency. Specifically, when average income per capita increases by 1%, TFP productivity increases by 0.127%.

State-owned firms operate more efficiently than other enterprise groups in this industry. In particular, the results show no impact of the presence of FDI firms on enterprise productivity and efficiency in the industry. This may be due to the limited number of FDI firms operating in the industry and may not have created a spillover effect to other firms in the industry. Smaller enterprise size brings more positive impacts to firms. In particular, the positive sign of the Fsize2 variable shows that a gradual increase in size will help increase enterprise efficiency. Smaller firms are helping to increase efficiency, but when a certain size is reached, efficiency tends to increase**.**

The $lnCO_2$ variable has a positive value and is statistically significant. This reflects the environmental impact of the enterprise. This shows that environmental impact is still bringing higher productivity to firms with an impact level of a 1% increase in environmental impact leading to a 1.721% increase in productivity, a relatively strong impact. A smaller amount of emissions and higher productivity can show that the role and technological level of firms in the industry are quite high, which is also reflected in the very high *TFP_GMM* value of the enterprise compared to the average.

The variable representing financial constraints *WWD* has a negative sign and is statistically significant in the models, showing that when financial constraints are greater, the more negative the impact on the efficiency and TFP productivity of the enterprise. When the *WWD* financial constraint index increases by 1%, it causes the efficiency and TFP productivity to decrease by 0.1589% and 0.1112% respectively.

4. Conclusion and recommendations

This study uses enterprise survey data from the waste recycling and treatment industry from 2015 to 2022, applying the multi-stage Data Envelopment Analysis (DEA) method to measure efficiency and the Generalized Method of Moments (GMM) to assess total factor productivity (TFP). From this, the study evaluates the impact of various factors on the productivity and efficiency of firms in the industry. The results show that the average efficiency of waste recycling and treatment firms is only 59.851%. Smaller firms achieve higher efficiency compared to larger ones. The main factors affecting enterprise efficiency and productivity in the industry include environmental impact, financial constraints and capital structure. Specifically, a 1% increase in lnKL and VNG leads to a decrease of 0.189% and 0.00337% in TFP productivity of firms in the industry, respectively, while a 1% increase in environmental impact increases productivity by 0.721%. Furthermore, the greater the financial constraints, the stronger the negative impact on enterprise efficiency and TFP productivity. Specifically, when the WWD financial constraint index increases by 1%, enterprise efficiency and TFP productivity decrease by 0.1589% and 0.1112%, respectively. Notably, a 1% increase in CO2 emissions increases the productivity of firms in the industry by a relatively high level of 1.721%. The presence of FDI firms has not yet shown a clear impact on the productivity of firms in the industry.

Some recommendations that can be drawn from the research results include that firms need to restructure their capital structure, control and use capital more effectively to improve capital management efficiency and help firms operate efficiently. Continuing support policies that encourage and reward employees will have a positive impact on the work efficiency of employees and firms. Firms in the industry need to increase the application of modern technologies and better manage environmental impact to minimize emissions and bring greater productivity to the industry. To enhance the role and spillover effects of FDI firms in this industry, the government needs to have policies to encourage FDI firms to invest in the industry in order to access more modern technologies and better management methods, thereby helping to improve the efficiency of the industry.

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