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Dynamic Technical and Environmental Efficiency Performance of Large Gold Mines in Developing Countries

Isaiah Hubert Magambo¹, Johane Dikgang², Dambala Gelo³ and Fiona Tregenna⁴

Abstract

This study used the by-production model specification to separate emission-generating technologies from ‘desirable outputs’ technology. It then employed the dynamic efficiency model, following the Dynamic Directional Input Distance Function specifications to compute the deterministic, dynamic environmental and technical efficiencies of large gold mines in developing countries. Using firm-level data from 2009 to 2018, the study found that on average, dynamic technical efficiency in these mines was 73%; the average dynamic technical efficiency was observed to have a decreasing trend, of 0.3% annually. The study also found that on average, dynamic environmental efficiency was 56%. However, the average dynamic environmental efficiency trend had a decrease of 0.6% annually. The poor performance and downward trends could be attributed partly to downward investment trends over time, and the increasing complexity of extracting gold deposits from low-grade ore, as well as to prices. They could also be the result either of poor institutional capacity, as far as environmental policies, regulations, and enforcement are concerned; or of supply-side structural rigidity – in particular, low-capacity, and unreliable energy supply, mostly from bad inputs such as coal and heavy fuels or both, which calls for the use of alternative energy sources.

Keywords: environmental efficiency, gold mines, technical efficiency, undesirable output

JEL Codes: D24, D25, Q55, Q58.

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1. Introduction

Increasing mining activity in general, and particularly gold-mining activity, has attracted environmental concern globally, as gold mining is known to be high-polluting and resource-intensive. The environmental costs are often externalised to a third party: the surrounding communities that host the mining operations. The environmental and social impact of gold mining is particularly acute in most countries with rich gold deposits (Conde, 2017; Oliveira, Camanho and Zanella, 2017; Shen, Muduli and Brave, 2015).

In recent years there has been increasing public concern over perceived and actual environmental impacts such as climate change and health outcomes. In reaction to the repercussions of climate change there have been several global efforts, such as the signing of the Kyoto Agreement in 1997, followed by conferences in Copenhagen and Cancun (2010), Durban and Doha (2011), Warsaw (2013) and Paris (2015) that have placed increasing attention and emphasis on reduction of emissions to mitigate climate-change effects. In the same spirit, many countries have dedicated a portion of their resources to designing and implementing solutions that mitigate the effects of greenhouse gases (GHGs) to achieve sustainable development. Similarly, the global mining industry is adopting several measures to move towards a more sustainable framework (Rashidi and Saen, 2015; Shen, Muduli and Brave, 2015); there has been a multidisciplinary call to reconsider different mining approaches to ensure sustainability is achieved.

The fundamental issues in sustainable mining involve assessing a finite and non-renewable resource, declining ore-grade complexities, and price trends; tailing storage facilities; and the type of mining operation being performed, especially open-cut mining. Similarly, resource-intensity debate informs core sustainability issues regarding water, energy, chemical consumption, and pollutant emissions (Mudd, 2007). These issues can be compounded into three groups: social, economic and environmental.

The environmental crisis has given rise to growing public demand for socially responsible and ecologically viable mining practices (Fonseca, McAllister and Fitzpatrick, 2014). Over the last two decades, mining and mineral exploration companies have adopted various environmental management practices in response to society's pressure for better environmental protection (Nikolaou and Evangelinos, 2010). In advancing the idea of a sustainable mining industry, large mining corporations are responding with concerted efforts to publish sustainability reports based on the Global Reporting Initiative (GRI) framework; though the effectiveness of the framework has been contested by some scholars, on the grounds that it could mislead decision-makers who are concerned with sustainability, or prompt mining companies to

camouflage unsustainable practices (Fonseca, McAllister and Fitzpatrick, 2014). But the initiative has demonstrated that efforts are being made towards achieving the objective of sustainable mining.

Measuring and monitoring sustainability performance and its determinants have been among proposed approaches to achieving sustainable mining. Thus, there have been several methodological advancements to empirically examine the performance of firms and industries. Several studies have attempted to empirically examine the technical, environmental, or eco-efficiency performance of the gold-mining industry in developed countries (Shao, Yu, X and Feng, 2019; Oliveira, Camanho and Zanella, 2017; Hosseinzadeh, Smyth, Valadkhani and Le, 2016; Koop and Tole, 2008; Kumah, 2006). While most have contributed substantially to static efficiency analysis, few studies have included environmental efficiency. Only a limited number of studies have employed dynamic efficiency analysis for either technical or environmental efficiency in gold mines. The static efficiency-based model ignores the difference between quasi-fixed and variable factors, as well as the explicit role of time, and how adjustment of the quasi-fixed factors to their observed long-run levels takes place.

Dynamic analysis estimates the real changes in production and environmental efficiencies by considering production occurs in both periods (t and $t+1$); investment occurs in the first period (t), which account for adjustment costs and provides greater physical capacity in the second period ($t+1$). Thus, dynamic analysis incorporates the adjustment costs of quasi-fixed inputs into a model of a firm's behaviour. The dynamic efficiency model integrates the static shadow cost approach and the dynamic duality model of intertemporal decision-making (Silva, Lansink and Stefanou, 2015).

Moreover, previous studies have examined both technical and environmental efficiency in a single-equation-model setting. The single-equation model may be criticised when both undesirable and desirable outputs are outcomes of the production process, as the model treats the undesirable outcome as input; this act violates production theory. Therefore, this study used the two-equation model specification proposed by Fernandez, Koop and Steel (2002), which employs a separable distance function by means of which good output and bad output can be modelled separately. Specifically, the two-equation model follows the by-production model of Murty, Russell and Levkoff (2012) to model polluting technologies.

In the context of the debate around mining and sustainable development, this paper contributes to the literature by using a two-equation (by-production) model specification to model polluting technologies, which separates emission-generating technologies from desirable-output technology. The study extends the current static analysis of environmental efficiency in large

gold mines in developing countries into dynamic analysis of environmental and technical efficiency, following dynamic directional input distance function computations, which incorporate the role of time and adjustment costs of quasi-fixed inputs into a model.

The rest of the paper is structured as follows: Section 2 is a theoretical and empirical literature review of efficiency methodological dynamics. Section 3 presents the methodology used in the study as well as the data, which include descriptions of the variables used in the model and their measurements. Section 4 contains the estimations and empirical results, while Section 5 concludes the paper by discussing the main findings and recommendations of this study and outlining future research opportunities.

2. Literature review

Many empirical studies have measured technical and environmental efficiency or eco-efficiency (i.e., the combination of economic efficiency and environmental efficiency) in a static model; however, most of these studies have used the single-equation model specification, which in principle violates the fundamental assumptions of the production theory. In addition, the specification does not take into consideration the material balance assumption, which advocates that in a system or process, the material inputs must balance the material outputs. Such studies include Li, Chiu and Lu (2018); Song, Peng, Wang and Zhao (2018); Chen and Jia (2017); Oliveira et al., (2017); Godoy-Durán, Galdeano-Gómez, Pérez-Mesa and Piedra-Muñoz (2017); Zhang, Zhou and Choi (2013); Barros, Managi, and Matousek (2012); Bravo-Ureta, Solís, López, Maripani, Thiam and Rivas (2007); Färe et al., (2005); Lee et al., (2002); Hailu and Veeman (2001); Reinhard and Thijssen (2000); Reinhard et al., (1999); and Baumol and Oates (1988).

The recent development of the two-equation model – which addresses the weakness of the single-equation model, as far as undesirable and desirable outputs are concerned – now has a new orientation, to specify emission-generating technology. Out of various specifications, the by-production model specification of Murty et al., (2012) has proved to be the best. The few empirical studies that have adopted this approach include Serra, Chambers and Lansink (2014), in a DEA setting, and Kumbhakar and Tsionas (2016), using a Stochastic Frontier (SF) approach.

Many previous studies have been limited to static assessment, in which important differences in environmental performance have been identified among decision-making units (DMUs). The static approach prevents the identification of efficiency values linked to a specific trend of each DMU through time, or to random annual changes. This study thus extends static analysis

by including temporal variations in efficiency, using adjustment cost directional distance functions.

The selection of a directional distance function specification, among others, has always been supported in the literature, for two reasons: first, it provides flexibility when choosing the direction of the projection of the observed production bundle on the frontier. This flexibility allows construction for non-radial measures, which are essential in constructing dynamic efficiency (Serra, Chambers and Lansink, 2014), as the dynamic efficiency measurement of input technical efficiency requires that variable inputs and investment in the quasi-fixed factors (i.e., the dynamic factors of production) are treated (though not in the same proportion) asymmetrically⁵. Second, the directional distance function provides the flexibility to incorporate technological constraints imposed externally (Serra, Chambers and Lansink, 2014). These technological constraints could originate from government restrictions and regulations that might limit the use of certain inputs (e.g., the government may restrict the quantity of agricultural chemicals or pesticides to below a level that would be harmful to the environment). The adjustment cost directional distance functions have primarily been used to generate measures of productive inefficiency and total factor productivity growth. The adjustment-cost model of the firm has been widely used in empirical work (e.g., Letterie et al., 2010; Letterie and Pfann, 2007; Nielsen and Schiantarelli, 2003; Luh and Stefanou, 1996; 1993). In addition, a few empirical works employ the adjustment cost directional input distance function, including Setiawan and Lansink (2018); Ang and Oude Lansink (2018); Tovar and Wall (2017); Kapelko, Lansink and Stefanou (2017); Kapelko and Lansink (2017); Kapelko et al., (2015); Silva, Lansink and Stefanou (2007, 2015); and Serra et al., (2011). Though several empirical studies have analysed dynamic efficiency, no empirical study has extended the by-production model from static environmental efficiency into dynamic analysis.

The literature review reveals that extensions of the efficiency measures have mostly been focused on the modelling of polluting technology, for which the analyses were static; however, in this rapidly changing world, the extension of the literature to account for the effect of the time element in economic decision-making is imperative. Studies that estimate dynamic efficiency in developing countries are very limited; most previous studies on efficiency are based on a static model. Even though static models do not incorporate a time dimension or the role of adjustment costs for quasi-fixed inputs over the long run, they do not separate quasi-

⁵ Most firms optimise their long-term plan by reducing variable-input quantities and expanding investment in quasi-fixed inputs, as investment provides more physical capacity.

fixed inputs from variable inputs, which may result in underestimating the actual path of efficiency. To the best of our knowledge, no study has been performed in a developing country that has extended an environmental and technical efficiency analysis from the static to the dynamic. This study combines the best-practice specification for environmental and technical efficiency of Murty et al., (2012,2018) and the dynamic direction computation of Silva, Lansink and Stefanou (2015) to extend the static technical and environmental efficiency analysis of large gold-mining firms in developing countries into a dynamic analysis.

3. Methodology

The study uses a mixed methodological approach: the two-equation model is specified, which accounts for technical and environmental efficiency, following Murty et al., (2012); while the estimation of the model follows dynamic directional input distance function specifications, which incorporate the adjustment costs of quasi-fixed inputs into a model, thus explaining the role of time and how adjustment of the quasi-fixed factors to their observed long-run level takes place.

Building on the two-equation (by-production) model of Murty et al., (2012) to separate two technologies, two overall efficiencies will be derived: production of good output, which provides technical efficiency; and production of bad output, which provides environmental efficiency. In its deterministic setting, the model was extended following the specification of Serra, Chamber and Lansink (2014), as follows:

The by-production model advocates separability of the joint production technology; the joint technology T is a combination of the sub-technologies T_1 and T_2 :

$$T = T_1 \cap T_2 \quad (1)$$

$$T_1 = \{(y_D, y_U, x_1, x_2) | f(y_D, x_1, x_2) \leq 0\}$$

$$T_2 = \{(y_D, y_U, x_1, x_2) | y_U \geq q(x_2)\}$$

Each firm uses conventional production inputs x_1 and bad/undesirable inputs x_2 to produce a desirable/marketed output y_D and a bad/undesirable output y_U , where:

x_1 = labour, capital

x_2 = fuel

y_D = amount of gold produced

y_U = amount of CO₂ produced

T1 represents the transformation process of the inputs into the desirable output; this provides the estimations for technical efficiency. T2 represents the generation process of the undesirable/bad output. This provides the estimates for environmental efficiency.

The separation of environmental and technical efficiency follows the static specification of Murty et al. (2012)⁶. To extend the models into a dynamic specification, this study used the Dynamic Directional Input Distance Function proposed by Silva, Lansink and Stefaneou (2015) to calculate technical and dynamic technical efficiency; the generic framework for Dynamic Directional Input Distance Function is as follows:

$$\vec{D}_t(y, x, I, k; g_x, g_I) = \sup\{\beta: (x - \beta g_x, I + \beta g_I) \in V(y; k)\} \quad (2)$$

where $V(y; k)$ represents a technology, which can use the input x to produce output y given level of capital k . y is the output vector, x is the variable input vector; k is capital (a quasi-fixed input vector), I represents net investment (a quasi-fixed input) and g_x, g_I are direction distance vectors for the variable inputs and quasi-fixed inputs respectively.

We can extend generic equation (2) **Error! Reference source not found.** to specify the dynamic technical efficiency (T_1) equation. Dynamic Directional Input Distance Function (period t)

$$\vec{D}_t(y_{Dt}, x_{1t}, I_t, k_t; -g_{x1}, g_I) = \max_{\theta, \lambda^j} \beta \quad (3)$$

s.t.

$$\begin{aligned} y_t &\leq \lambda Y_t \\ x_{1t} - \beta g_{x1} &\geq \lambda X_{1t} \\ I_t - \delta k_t + \beta g_I &\geq \lambda (I_t - \delta k_t) \\ N1\lambda &= 1 \end{aligned}$$

Dynamic Directional Input Distance Function (period t+1)

$$\vec{D}_{t+1}(y_{Dt+1}, x_{1t+1}, I_{t+1}, k_{t+1}; -g_{x1}, g_I) = \max_{\theta, \lambda^j} \beta \quad (4)$$

s.t.

$$\begin{aligned} y_{Dt+1} &\leq \lambda Y_{Dt+1} \\ x_{1t+1} - \beta g_{x1} &\geq \lambda X_{t+1} \\ I_{t+1} - \delta k_{t+1} + \beta g_I &\geq \lambda (I_{t+1} - \delta k_{t+1}) \\ N1\lambda &= 1 \end{aligned}$$

Dynamic Directional Input Distance Function (mixed period) period 2 given technology in period 1:

⁶ In the literature of efficiency analysis, two main approaches always refer, namely parametric (Stochastic Frontier Analysis, or SFA) and non-parametric (Data Envelopment Analysis, or DEA). However, the two techniques seldom tell consistent stories, even when applied to the same dataset. Moreover, Fried, Lovell, Schmidt and Schmidt (2008) showed that consistency from the two approaches is entirely empirical, and depends on the nature of the data used. This study used the non-parametric technique.

$$\overrightarrow{D}_{t+1}(y_{Dt}, x_{1t}, I_t, k_t; -g_{x1}, g_I) = \max_{\theta, \lambda^j} \beta \quad (5)$$

s.t.

$$\begin{aligned} y_{Dt} &\leq \lambda Y_{Dt+1} \\ x_{1t} - \beta g_{x1} &\geq \lambda X_{t+1} \\ I_t - \delta k_t + \beta g_I &\geq \lambda (I_{t+1} - \delta k_{t+1}) \\ N1\lambda &= 1 \end{aligned}$$

Dynamic Directional Input Distance Function (mixed period) period 1 given technology in period 2:

$$\overrightarrow{D}_t(y_{Dt+1}, x_{1t+1}, I_{t+1}, k_{t+1}; -g_{x1}, g_I) = \max_{\theta, \lambda^j} \beta \quad (6)$$

s.t

$$\begin{aligned} y_{Dt+1} &\leq \lambda Y_{Dt} \\ x_{1t+1} - \beta g_{x1} &\geq \lambda X_{1t} \\ I_{t+1} - \delta k_{t+1} + \beta g_I &\geq \lambda (I_t - \delta k_t) \\ N1\lambda &= 1 \end{aligned}$$

Equations 3 to 6 were employed to calculate dynamic technical efficiency (Dyn_Tech_eff); where y_{Dt} and y_{Dt+1} are the amount of gold (the desirable output) produced in period t and t+1 respectively; x_{1t} and x_{1t+1} represent the vector of the variable inputs (non-polluting inputs) which are labour and energy, used in period t and t+1 respectively; the quasi-fixed input factors include capital (k_{t+1}) and net investment (I_{t+1}); g_{x1} and g_I are direction distance vectors⁷ for the variable inputs and quasi-fixed inputs respectively; and δ is the depreciation rate, which was set at 20%.

For dynamic environmental efficiency (Dyn_Env_eff), equation (4) can be used to extend T₂ equation (3) as follows. Dynamic Directional Input Distance Function (period t)

$$\overrightarrow{D}_t(y_{Ut}, x_{2t}, I_t, k_t; -g_{x2}, g_I) = \max_{\theta, \lambda^j} \beta \quad (7)$$

s.t

$$\begin{aligned} y_{Ut} &\leq \lambda Y_{Ut} \\ x_{2t} - \beta g_{x2} &\geq \lambda X_t \\ I_t - \delta k_t + \beta g_I &\geq \lambda (I_t - \delta k_t) \\ N1\lambda &= 1 \end{aligned}$$

Dynamic Directional Input Distance Function (period t+1)

⁷ The direction vector adopted in the empirical application is $(g_{x1}, g_I) = (x_1, I)$, i.e., the actual quantities of variable inputs and investments.

$$\overrightarrow{D}_{t+1}(y_{Ut+1}, x_{2t+1}, I_{t+1}, k_{t+1}; -g_{x2}, g_I) = \max_{\theta, \lambda^j} \beta \quad (8)$$

s.t

$$y_{Ut+1} \leq \lambda Y_{Ut+1}$$

$$x_{2t+1} - \beta g_{x2} \geq \lambda X_{2t+1}$$

$$I_{t+1} - \delta k_{t+1} + \beta g_I \geq \lambda (I_{t+1} - \delta k_{t+1})$$

$$N1\lambda = 1$$

Dynamic Directional Input Distance Function (mixed period) period 2 given technology in period 1. In this equation, the first inequality constraint sign has been changed to accommodate the environmental definition, for which environmental efficiency requires that more investment should lead to fewer emissions of pollutants.

$$\overrightarrow{D}_{t+1}(y_{Ut}, x_{2t}, I_t, k_t; -g_{x2}, g_I) = \max_{\theta, \lambda^j} \beta \quad (9)$$

s.t

$$y_{Ut} \geq \lambda Y_{Ut+1}$$

$$x_{2t} - \beta g_{x2} \geq \lambda X_{2t+1}$$

$$I_t - \delta k_t + \beta g_I \geq \lambda (I_{t+1} - \delta k_{t+1})$$

$$N1\lambda = 1$$

Dynamic Directional Input Distance Function (mixed period) period 1 given technology in period 2:

$$\overrightarrow{D}_t(y_{Ut+1}, x_{2t+1}, I_{t+1}, k_{t+1}; -g_{x2}, g_I) = \max_{\theta, \lambda^j} \beta \quad (10)$$

s.t

$$y_{Ut+1} \geq \lambda Y_{Ut}$$

$$x_{2t+1} - \beta g_{x2} \geq \lambda X_t$$

$$I_{t+1} - \delta k_{t+1} + \beta g_I \geq \lambda (I_t - \delta k_t)$$

$$N1\lambda = 1$$

Equations 3 to 6 were employed to calculate dynamic technical efficiency(Dyn_Env_eff), where y_{Ut} and y_{Ut+1} are the amounts of CO₂ (an undesirable output) produced in period t and t+1 respectively; x_{2t} and x_{2t+1} represent the vector of the variable inputs, which are fuel and gold output(y_D), used in period t and t+1 respectively; the quasi-fixed input factors include capital (k_{t+1}) and net investment (I_{t+1}); g_{x2} and g_I are direction distance vectors for the variable inputs and quasi-fixed inputs respectively; δ is the depreciation rate. Moreover, since the dynamic formula can accommodate two periods, the longer period was estimated step by step, repeatedly picking the subsequent year and making the previous year a base year.

4. Results

4.1 Descriptive statistics

The study used firm-level data on energy consumption, labour, capital, fuel and water consumption as input variables. The volume of gold produced is considered a desirable output, while CO₂ is an undesirable or unintended output. The data were collected from two different mining reports: annual financial statements, and sustainability reports. (This information is in the public domain and is published voluntarily by companies on an annual basis.)

From the annual financial statements, the following variables and their measurements were extracted: volume of gold produced in a year, which is measured in ounces (oz); capital spent in a year and net investment, measured in millions of US dollars (M\$); and labour, which is measured as total number of employees in a particular mine. The variables captured from the sustainability reports include energy (meaning total energy used by a mine) measured in gigajoules (GJ); total carbon dioxide (CO₂) emissions, measured as total kilotons (kt) of carbon dioxide emitted in a year; amount of water used in the production process, measured in cubic metres (m³); and fuel, measured as total fuels used by the mine in kilolitres (kl). In the few cases where coal was used, this study converted amounts of coal into fuel equivalents.

The dataset comprises a sample of 34 large gold-mining companies (see Appendix Table 1, description of the mining firms used in the analysis), observed for 10 years (2009-2018). The choice of these firms was based on the availability of core information and firm-specific data on the variables required for the analysis.

Table 1 below presents the descriptive analysis of the variables used in assessing the dynamic environmental and technical efficiency of the mining firms. It shows that the variables are normally distributed, as the standard deviation is relatively close to the mean for each, despite the large range between the minimum and maximum values of all the variables. The variation in range is because the operations of the mines are not homogenous, even though they all deal with gold mining.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
gold	340	185000	136000	3000	719000
capital	340	199.273	354.616	21	2387.384
investment	340	53.5	58.029	0.26	348.4
labour	340	2763.344	1809.99	117	9020
energy	340	1425.852	1432.674	128.908	9250
CO2	340	333.082	420.554	12	2178.667
fuel	340	7253.68	15081.33	66.095	88454

Column 1 in Table 1 above shows the names of the variables; column 2 shows the number of observations; column 3 shows the mean value of the respective variables; column 4 presents the standard deviation; columns 5 and 6 show the range of each variable by presenting its minimum and maximum values.

4.2 Estimation of Dynamic Technical Efficiency

Equations 3 and 4 are used for static analysis, estimating technical efficiency in period 1 and 2 respectively. The dynamic analysis was carried out in two stages. First, the computation of technical efficiency in period 1 relative to period 2 technology (Dyn_Tech_eff12), following the equation 5 specification. Second, the computation of technical inefficiency in period 2 relative to period 1 technology (Dyn_Tech_eff21), as specified in equation 6⁸. The results are presented in

Table 2 below:

Table 2: Average dynamic technical efficiency

Year	Dyn_Tech_eff12	Dyn_Env_eff21
2010	0.742	0.702
2011	0.714	0.763
2012	0.717	0.742
2013	0.761	0.713
2014	0.807	0.696
2015	0.766	0.745
2016	0.744	0.737
2017	0.676	0.746
2018	0.711	0.682
Total	0.738	0.725

⁸ Equations 5 and 6 give the technical inefficiency score; to get the efficiency score, we use the $e^{(-ineff)}$ algorithm (Battese & Coelli, 1988).

Table 2 show that on average, dynamic technical efficiency in period 1 relative to period 2 technology (Dyn_Tech_eff12) was 74%, while the average dynamic technical efficiency in period 2 relative to period 1 technology (Dyn_Tech_eff21) was 73%. Of the two dynamic efficiencies (Dyn_Tech_eff12 and Dyn_Tech_eff21), Dyn_Tech_eff21 is of interest, since in dynamic efficiency it is logical to compare the current performance to the previous status quo. The figures show that dynamic technical performance is not high, or even satisfactory. The trend for average performance across firms over time is estimated using a random-effect panel regression, and the results are presented in Table 3 below:

Table 3: Average trends of dynamic technical efficiency

VARIABLES	(1) Dyn_tech_eff12	(2) Dyn_tech_eff12
Year	-0.00296***(0.000781)	-0.00296***(0.000781)
Constant	6.696***(1.573)	6.696***(1.573)
Observations	306	306
Number of DMU	34	34

Standard errors in parentheses

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

Table 3 above presents the findings of the panel regression of efficiency scores on the time variable. The regression results reveal that on average, both Dyn_tech_eff12 and Dyn_tech_eff21 were decreasing at 0.3% per annum, and both trends are significant at 95% level of confidence. The average trend of the Dyn_tech_eff12 and Dyn_tech_eff21 figures is depicted in Figure 1 below:

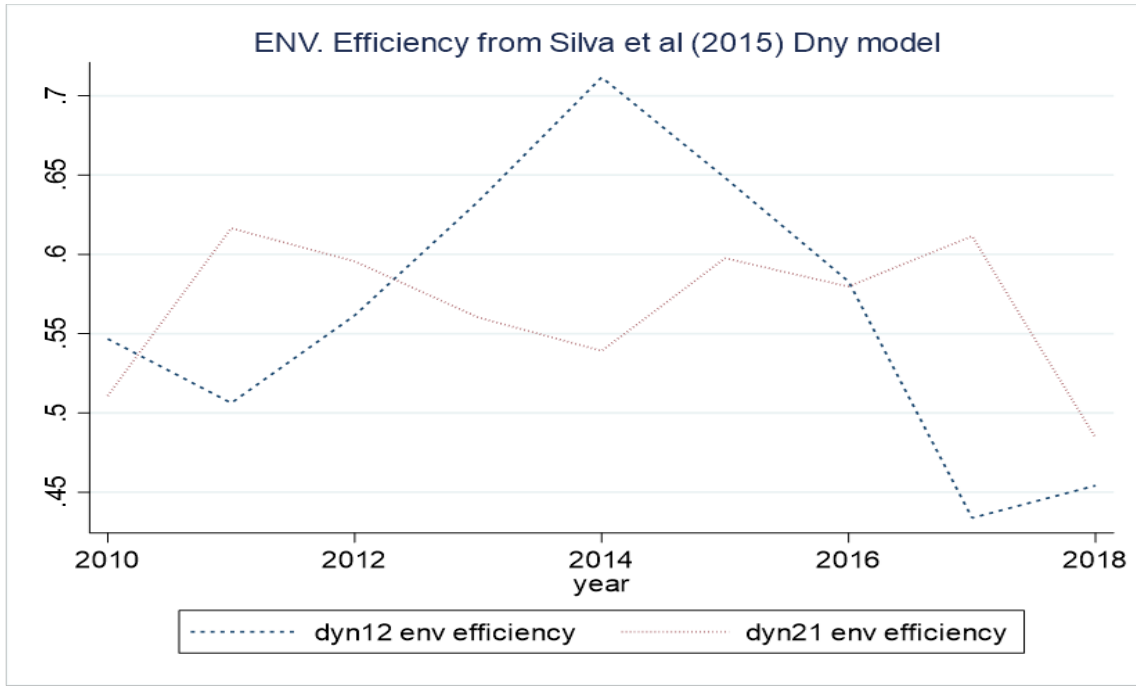


Figure 1: Average Dynamic Technical Efficiency Over Time

Although the average trend for both Dyn_tech_eff12 and Dyn_tech_eff21 shows a similar decrease, the patterns are different; Dyn_tech_eff12 had its peak in 2013, while Dyn_tech_eff21 reached its peak in 2014. These patterns could be partly attributed to the trend in net investment (among other reasons), presented in Figure 2 below:

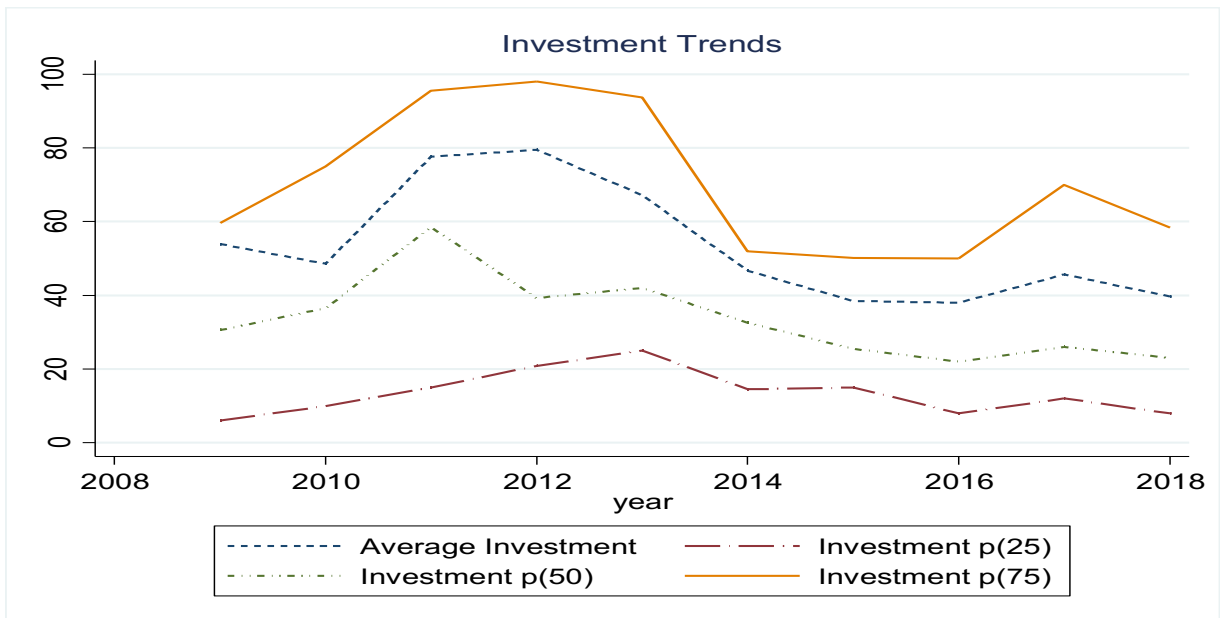


Figure 2: Trends in Net Investment

The above figure shows the average net investment (Average Investment) trend, and the net investment trends for the 25th, 50th and 75th percentiles: investment p(25), investment p(50) and investment p(75) respectively. Generally, the net investment (adjustment costs) increases

between 2011 and 2013 could be attributed to the increase in the physical capacity in 2014 (when Dyn_tech_eff21 reached its peak). Thereafter, the decreasing net investment from 2014 can easily be associated with the decrease in Dyn_tech_eff21.

4.3 Computation of dynamic environmental efficiency

In computing dynamic environmental efficiency, equations 9 and 10 were employed. Equation 9 was used to generate dynamic environmental inefficiency (the computation of environmental inefficiency in period 1 relative to period 2 technology), which was converted to dynamic environmental efficiency (Dyn_Env_eff12). Similarly, equation 10 was used to compute dynamic environmental inefficiency (the computation of technical efficiency in period 2 relative to period 1 technology), and the inefficiency scores were converted to dynamic environmental efficiencies (Dyn_Env_eff21). The results for both cases are presented in Table 4 below:

Table 4: Average Dynamic Environmental Efficiency

Year	Dyn_Env_eff12	Dyn_Env_eff21
2010	0.547	0.511
2011	0.506	0.616
2012	0.562	0.596
2013	0.633	0.560
2014	0.712	0.539
2015	0.648	0.598
2016	0.583	0.580
2017	0.434	0.611
2018	0.454	0.484
Total	0.564	0.566

Table 4 above shows that on average, the dynamic environmental efficiency in period 1 relative to technology in period 2 (Dyn_Env_eff12), and in period 2 relative to the technology in period 1 (Dyn_Env_eff21), was around 56%. The average dynamic environmental performance for large gold mines in developing countries was low over the study period. The overall trend was estimated by running panel regression of efficiency scores on the time variable; the results are presented in Table 5 below:

Table 5: Average Trend Dynamic Environmental Efficiency

VARIABLES	(1) Dyn_env_eff12	(2) Dyn_env_eff12
Year	-0.00634***(0.00143)	-0.00883***(0.00184)
Constant	13.42***(2.874)	18.34***(3.714)
Observations	306	306
Number of DMU	34	34

Standard errors in parentheses

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

Table 5 above reveals that even though dynamic environmental performance was low to start with, it shows a decreasing trend over time; on average, performance decreased by 0.6% for Dyn_env_eff12 and by 0.9% for Dyn_env_eff21. Both trends were significant, at the 5% level of significance. However, the pattern for dynamic environmental performance changed over time. The patterns are presented in Figure 3 below:

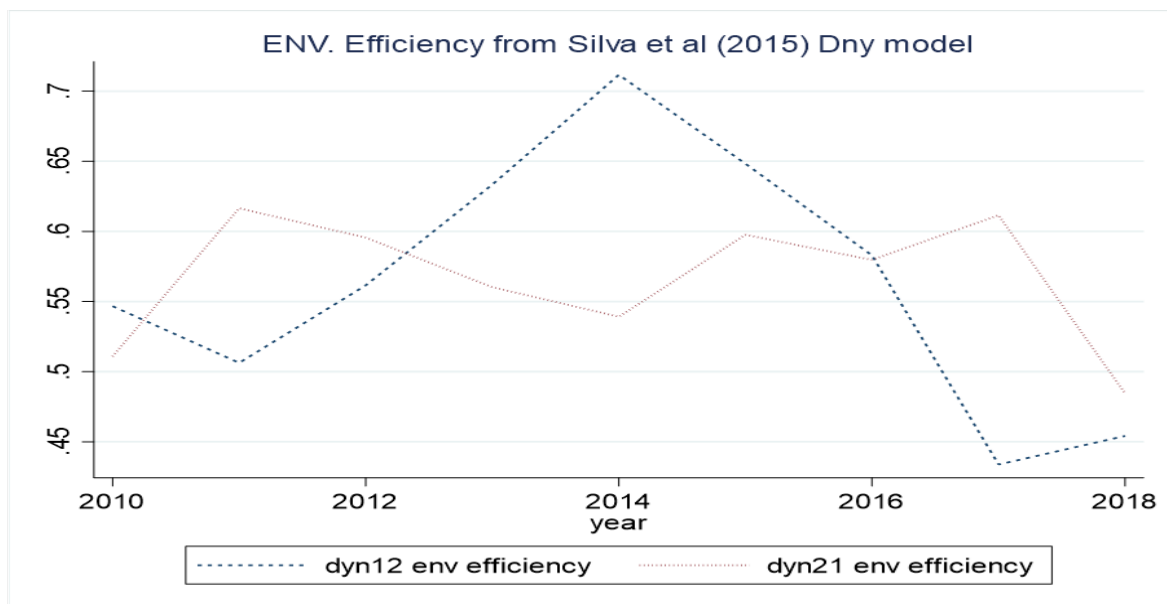


Figure 3: Average Dynamic Environmental Efficiency Over Time

Figure 3 above shows that in the large mining companies, dynamic environmental efficiency had a similar pattern to dynamic technical efficiency, but at a lower average. This suggests that there is a strong possibility that net investment is directed at high-tech solutions, which record high performance in terms of both converting low inputs to high output, and low consumption of bad inputs, which translates to low quantities of bad output; in other words, high environmental performance. Thus, dynamic analysis draws the attention of the operators and regulators towards how they should manage and enforce compliance on dynamic input factors

such as net investment, as these factors have great impact on both technical and environmental performance.

5. Conclusion

Dynamic technical and environmental efficiencies were measured in this study, in terms of the two-equation model specification for the polluting technology, which separates desirable and undesirable outputs. The computations were based on dynamic (adjustment cost) directional input distance functions for the technologies used. The key findings of the study are as follows: The dynamic technical efficiency results show that on average, dynamic technical efficiency in period 2 relative to period 1 technology was 73%. Although this performance is satisfactorily high, the industry has experienced a significant (at 5% level of significance) decreasing trend in overall average dynamic technical efficiency of 0.3% per annum. This decreasing trend could be attributed to net investment trends: net investments increased between 2011 and 2013, which led to high physical capacity in subsequent years (2012-2014); thereafter, net investment showed a decreasing trend, which also affected performance. The decrease in performance could also be attributed to the reported (World Gold Council, 2018) increasing complexity of accessing low-grade gold deposits. Prices were also low, which implies low output with high inputs and low economic margins, which leaves little room for high net investment.

The dynamic environmental efficiency results revealed that on average, dynamic environmental efficiency in period 2 relative to period 1 technology was 56%. Over the study period, dynamic environmental performance was indeed low. Correspondingly, it showed a decreasing overall trend of 0.6% annually. The reasons for this low performance and decreasing trend could be attributed partly to low investment trends. They could also be as a result either of poor institutional capacity as far as environmental policies, regulations and enforcement are concerned, or of supply-side structural rigidity – in particular, low and unreliable energy supply, which calls for the use of alternative energy sources, mostly from bad inputs such as coal or heavy fuels or both.

Given the findings above, this study recommends that mining firms devote their attention to their dynamic inputs, such as net investment. Firms should constantly adjust their investment – especially in technology, which will lead to high technical performance (even when mining low-grade deposits) and high environmental efficiency. Moreover, the regulators should give the mines incentives to invest more in advanced technology (especially those with low bad inputs), and in sustainable and reliable energy sources, over time. Mines should also strengthen

their institutional capacity to constantly review the rules and regulations and to monitor their environmental compliance.

This study was bound by the availability of data. We acknowledge the fact that in developing countries, there are many large gold mines; nevertheless, most mines either do not report all the relevant data, or the annual reports are structured as combined (aggregate) data for all the mines in the company. Such reports were not considered, as this analysis was performed at the firm (mine) level; consequently, fewer mines were analysed. We also acknowledge that mining operations produce several pollutants, including the nitrogen oxides; due to data availability, this study was limited to analysing the production of carbon dioxide (CO₂) only.

To extend the study, we suggest investigating two areas: firstly, quantifying the determinants of dynamic technical and environmental efficiency; and secondly, extending the dynamic (adjustment cost input directional distance function) environmental efficiency approach into a stochastic frontier analysis (SFA) framework.

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Appendix

Appendix Table 1: Description of the mining firms used in the analysis

S/No.	Name of mine	Country	Region
1	Buzwagi	Tanzania	East Africa
2	Bulyanhulu	Tanzania	East Africa
3	North Mara	Tanzania	East Africa
4	Geita gold mine	Tanzania	East Africa
5	Tshepong operations	South Africa	South Africa
6	Phakisa	South Africa	South Africa
7	Bambanani	South Africa	South Africa
8	Target 1	South Africa	South Africa
9	Doornkop	South Africa	South Africa
10	Joel	South Africa	South Africa
11	Kusasaletu	South Africa	South Africa
12	Masimong	South Africa	South Africa
13	Unisel	South Africa	South Africa
14	Kalgold	South Africa	South Africa
15	Phoenix	South Africa	South Africa
16	Hidden Valley	South Africa	South Africa
17	Surface dumps	South Africa	South Africa
18	South Deep	South Africa	South Africa
19	Mine Waste Solutions	South Africa	South Africa
20	Mponeng	South Africa	South Africa
21	TauTona	South Africa	South Africa
22	Kopanang	South Africa	South Africa
23	Moab Khotsong	South Africa	South Africa
24	Sadiola	Mali	West Africa
25	Morila	Mali	West Africa
26	Siguiri	Guinea	West Africa
27	Damang	Ghana	West Africa
28	Tarkwa	Ghana	West Africa
29	Iduapriem	Ghana	West Africa
30	Obuasi	Ghana	West Africa
31	Serra Grande	Brazil	Latin America
32	AGA Mineração	Brazil	Latin America
33	Cerro Corona	Argentina	Latin America
34	Cerro Vanguardia	Argentina	Latin America