Impact of Unconducive Macro-Business Environment on Productive Efficiency and Capacity Utilization among SMEs in Liberia

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Abstract: An accommodating macro business environment is one that encourages firms to operate efficiently. Such conditions strengthen incentives for firms to be innovative and to increase productive efficiency. Unconducive macro business environment acts as a negative input to the production process. We use the 2008/09 Liberia's Small Business Enterprise Survey data to estimate firm level score of unconducive macro business environment using a two parameter Rasch Model. The estimated scores were incorporated in an output-semi-oriented radial Data Envelopment Analysis (DEA) model as undesirable inputs. The DEA model was used to estimate technical efficiency and capacity utilization of each enterprise. Estimated technical efficiency and revenue gap were regressed on all inputs using a Tobit model. The results indicate that increase in unconducive macro business environment decreased capacity utilization. To promote the role of small and medium enterprise in sustainable economic development, Liberia needs to improve enterprise's access to financial services, increase supply of electricity, and combat corruption by public officials.

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1. Introduction

Liberia is a small country situated in West Africa. According to the 2008 census, the population of the country is about 3.5 million people living. The country covers 111,369 square kilometers. Liberia was set up by citizens of the United States as a Colony for former American slaves, one of only two states so established. Liberia declared herself as an independent nation in 1847. The country is rich in natural resources such as rubber, timber, iron ore, diamond and tin. Years of mismanagement and corruption led to the country's fourteen years of civil war which started in the late 1989 and ended in 2003. The war resulted in the wide spread destruction of properties worth of billions of dollars, loss of more than 250,000 lives and massive displacement of people. The current unemployment rate is estimated to be over 85% and half of the population lives in abject poverty (IMF, 2008).

Liberia has a rich natural resource base, including fertile lands for agriculture and tree crops, extensive forestry resources, iron ore, gold, diamonds, and the ocean and coastal areas. Natural resource-based manufacturing industries have the potential to create significant numbers of jobs, provide substantial budget revenues, and initiate rapid economic growth and development. Moreover, the government of Liberia has identified SMEs in the manufacturing or the industry sector as an engine of economic growth (IMF, 2008). These kinds of SMEs have historically played an important role in contributing to rapid economic growth and development of many countries around the world. In particular, manufacturing SMEs play significant contribution in the transition of agriculture-led economies to industrial ones by providing opportunities for value adding activities that absorb productive resources at all levels of the economy. These enterprises also forms flexible economic systems in which small and large international firms are interlinked. Such linkages are very crucial for the attraction of foreign direct investment. In Liberia, in order to develop SMEs that are productive efficient (an important measure of competitiveness), the macro-business environment has to be conducive.

The objective of this study is threefold: advise the government of Liberia on the importance of improving macro-business environment to promote small and medium enterprise and entrepreneurial spirit; use Liberia data to demonstrate a method of developing the index of macro-business environment using Item Response Theory Model, specifically the Rasch Model (Rasch, 1960); and show how the estimated index is incorporated in the Data Envelopment Analysis model as an undesirable input. Therefore, the estimated productive efficiency and capacity utilization measures account for both micro and macro-business environment faced by each firm in Liberia.

In particular, productive efficiency occurs when an economic decision making unit is utilizing all of its resources efficiently, producing most output from least input. This means that no more output can be produced from the given inputs without reducing output. Equivalently, productive efficiency occurs when the highest possible output of one good is produced, given the optimal production level of the other goods. Productive efficiency requires that the decision making unit operate using best-practice technological and managerial processes. By improving these processes, the unit can outward-shift its production possibility frontier and increase efficiency further. Therefore, productive efficiency is concerned with producing goods and services using optimal combination of all inputs to produce maximum output at the lowest cost possible. For inefficient units, productive efficiency can be improved through resource reallocation.

On the other hand, capacity utilization is a concept which refers to the extent to which an economic decision making unit uses its installed productive capacity. It refers to the relationship between actual output that is produced with the installed equipment and the potential output which could be produced with it, if the capacity was fully used. Capacity utilization is defined as the ratio of actual output to some measure of potential output given a firm’s short-run stock of capital and other fixed inputs and fixed state of technology. It captures the output gap between actual output and capacity output. While productive efficiency analysis focuses on profit maximization or cost minimization; capacity utilization analysis is a short-run concept that focuses on efficient use of existing capital stock. Chronic under-capacity utilization is a disincentive for long-term investment decisions and limits enterprise growth.

It is imperative that major goals of all economic decision making units are to achieve productive efficiency and fully utilize existing capacity. In order to achieve these goals, economic decision making units faces two types of business environment: micro and macro business environment. Micro business environment consist of different types of stakeholders such as customers, employees and suppliers that are controlled by managers. Macro business environment include all exogenous factors that influence decision making on resource use and performance of any business. While changes in the micro environment will directly affect the firm's activities, changes in the macro environment will indirectly affect the firm’s operating costs and therefore its aggregate performance. Berger and Udell (1995) argue that unconducive macro business environment increase the cost of technology adoption and hence reduce long-term economic growth at the country level. Macro business environment also influence availability of credit (Aghion et. al., 2006), contract enforceability (Acemoglu et. al. 2007), investor protection (Bink et al., 1992; Rui et al., 2004), and business entry costs (Aghion et. al., 2006). Therefore, productive efficiency of small and medium enterprises (SMEs) depends on the macro business environment existing within the country and the capability of management to adapt to these variables (Chikan, 2006).

However, in the literature, productive efficiency and capacity utilization analyses address the issue of micro-business environment. The assumption is that all economic decision making units in any economy face the same level of macro-business environment. This assumption is weak, especially in developing countries where macro-business environment is not dictated by the rule of the game.

Liberia business enterprises identified four domains of macro business environment as the most limiting. They include access to finance, crime and theft, inefficient infrastructures and corruption. While availability of microfinance derivatives have been viewed as a critical element for the development of SMEs, access to, and costs of finance are reported to be a severe problem in most African countries. Levy (1993) highlighted the consequences of limited access to financial resources by SMEs. Typically, SMEs face higher transactions costs than larger enterprises in obtaining credit (Saito et al., 1981) and funds to finance working capital (Peel and Wilson, 1996; Thorsten and Demirque-Kunt, 2006). In addition, information asymmetries associated with lending to small scale borrowers have continued to restrict the flow of finance to SMEs.

Generally, an accommodating financial macro business environment encourages enterprises to operate efficiently by promoting innovativeness that increases productive efficiency. More productive SMEs, in turn, create jobs and contribute more to tax revenue needed to finance public health, education, and other services; key factors for sustainable development. In contrast, a poor macro business environment increases the obstacles to conducting business activities and decreases a country's prospects for reaching its potential in terms of employment, production, and welfare.

An essential requirement for economic growth and sustainable development is the provision of efficient, reliable and affordable infrastructure and business services, such as water and sanitation, power, transport and telecommunications. The availability of efficient infrastructure and business services are important determinant of the pace of market development and output growth. Good infrastructures efficiently connect firms to their customers and suppliers, and enable the use of modern production technologies. Conversely, deficiencies in infrastructure create barriers to production opportunities and increase costs for all enterprises, from micro enterprises to large multinational firms (Canning, 1999).

On the other hand, crime disrupts firms' entry into domestic and export markets, and this has particular effects on resource allocation and productive efficiency. Under these conditions, business operators are led by market mechanisms to prevent theft, which clearly affects resource allocation as well as adjusting inventory and reordering strategies to ensure continuous supply of goods and services. Insecurity leads to increased production costs and loss of productive efficiency. Corruption by public officials also presents major administrative and financial burden on enterprise. Corruption creates an unfavorable macro business environment by undermining the operational efficiency of enterprises and raising the costs and risks associated with doing business in any country.

It is therefore obvious that unconducive macro business environment is a latent negative input in the production process. In the data, the four most limiting macro business environment domains (i.e., access to finance, crime and theft, infrastructure, and corruption) are represented by seventeen indicators. A two parameter Rasch was used to estimate scores of unconducive macro business environment at the enterprise level. These estimates were incorporated as a negative input in the Data Envelopment Analysis model to estimate firm level productive efficiency. The assumption is that since macro business environment affects the manager's decision making process on resource allocation, it also affects productive efficiency and capacity utilization. In the following section we describe the Rasch model used to estimate the score of unconducive macro business environment at the firm level. The DEA model with negative inputs is presented in section 2, followed by data description in the same section. Results and discussion and conclusion from the study are, respectively, presented in sections 3 and 4.

2. Literature Review

2.1 A two Parameter Rasch Model

A latent variable such as macro business environment is a characteristic that is not directly observable. It can therefore be measured indirectly through its effects on observable response on measurable indicators or items of macro business environment. Item Response Theory (IRT) models provide statistical models for establishing the relationship between observable responses on indicators or items and the expected latent variable, in this case the index of unconducive macro business environment.

The Rasch model (Rasch 1960, 1961) as developed further by Wright (1977) and Fischer (1995) is the basis of all IRT model; specifically for IRT models with dichotomous responses. In the standard Rasch model, the probability of a correct or positive response for an indicator or item $\boldsymbol{i}$ by firm $\boldsymbol{n}$ is modeled as a function of an item parameter, $\boldsymbol{\delta_i}$, representing item difficulty, and a firm parameter, $\boldsymbol{\theta_n}$, representing the magnitude of the unobservable latent trait. Given an indicator or an item, $\boldsymbol{x_{in}}$, this relationship can be presented using the following expression:

$$\Pr(x_{in}=1\,|\,\theta_n)=\left[\frac{\exp(\theta_n-\delta_i)}{1+\exp(\theta_n-\delta_i)}\right]. \qquad (1)$$

In Equation (1), for each item, there is one parameter that indicates difficulty of the item in terms of contributing towards the latent variable. For this study, the latent variable measures the level of macro business environment at the firm level. In Equation (1), notice that firms level macro business environment score are placed on a common scale with indicators or items contribution. In Equation (1) it is assumed that the error term of the latent responses have a logistic distribution. Other formulation arises when it's assumed that the latent responses have a standard normal distribution or extreme value distribution. Normally, the effects of indicators or items are assumed to be constant across firms. This means that, when present, each indicator contributes equally towards the measure of macro business environment. If this is not considered to be true, the two parameters of Rasch model can be estimated as follows:

$$\Pr(x_{in}=1\,|\,\theta_n)=\left[\frac{\exp\{\lambda_i(\theta_n-\delta_i)\}}{1+\exp\{\lambda_i(\theta_n-\delta_i)\}}\right], \qquad (2)$$

where, $\boldsymbol{\lambda_i}$ is a discrimination parameter, which determines how well an indicator discriminate among different indicators of unconducive macro business environment. Generally, in Equation (1) and (2) it is assumed that $\boldsymbol{\theta \sim N(0,\tau)}$. In Equation 2, either the variance or λ_1 is set to one for model identification purposes (Zheng and Rabe-Hesketh, 2007).

To estimate equation (1) or (2) and following Zheng and Rabe-Hesketh (2007), we require a response model, two levels of nesting, and a latent variable that measure macro business environment. The linear predictors for enterprise $\boldsymbol{n}$ can be presented as:

$$\upsilon_{in}=X_{in}\delta_i+\theta_n Z_n \lambda_i. \qquad (3)$$

In Equation (3), $\boldsymbol{X_{in}}$ and $\boldsymbol{Z_n}$ are design matrices, and $\boldsymbol{\delta_i}$ and $\boldsymbol{\lambda_i}$ parameters as explained in Equation (1) an (2). The parameter $\boldsymbol{\theta_n}$ is the estimated each enterprise's latent score on macro business environment. The linear dependent variable, $\boldsymbol{v_n}$, represents the vector of the logarithms for indicator i=$\boldsymbol{1,\ldots, I}$ and enterprise $\boldsymbol{n}$ or the log odd of correct response for indicator $\boldsymbol{x_{in}}$. Based on Equations (1) through (3) the corresponding design matrices for a dichotomous Rasch model are:

For Equation (1): $$\begin{bmatrix}\upsilon_{1n}\\ \upsilon_{2n}\end{bmatrix}=\begin{bmatrix}-1 & 0\\ 0 & -1\end{bmatrix}\begin{bmatrix}\delta_1\\ \delta_2\end{bmatrix}+\theta_n\begin{bmatrix}1\\ 1\end{bmatrix}, \qquad (4.1)$$

For Equation (2): $\begin{bmatrix} v_{1n} \\ v_{2n} \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} + \theta_n I_{2x2} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ \lambda_2 \end{bmatrix}$. (4.2)

In Equation (4.1), all λ_i are equal to one and in the second expression only λ_1 is set to one for model identification purposes. The column of these design matrixes correspond directly to the variables that are needed to fit both models. The data has to be transformed into a long format to create the required design matrices.

2.2 Data Envelopment Analysis (DEA) Model with Undesirable Inputs

Data Envelopment Analysis (DEA) is a nonparametric mathematical programming technique for measuring the efficiency of a set of economic decision making units, first introduced by Charnes, Cooper, and Rhodes (1978). The original DEA models were applicable only to technologies characterized by positive inputs and outputs. In subsequent literature there have been various approaches to enable DEA to deal with negative data or undesirable inputs or outputs as summarized in Emrouznejad et al. (2008). In order to handle undesirable inputs or outputs some researchers have suggested data transformation so that all negative data are turned positive by substituting a very small positive value for negative output (Seiford and Zhu, 2002). However, by default in a DEA model, an output variable with a small positive value will not be expected to contribute to the efficiency rating of any decision making unit.

Other approaches include treating absolute value of undesirable outputs as inputs and undesirable inputs as outputs (Scheel, 2001). Sharp et al. (2006) proposes a modified slack-based DEA model in which both undesirable inputs and outputs could be handled. However, the results from both approaches tend to depend on the adopted data transformation method. Charnes et al. (1985) proposed an additive DEA model that can be applied directly to undesirable inputs and outputs. The additive DEA model correctly identifies Pareto efficient and inefficient decision making units. As shown by Pastor (1996), with additive DEA model, an absolute constant can be added to the undesirable input or output without changing the results. There are two limitations however of additive DEA model (Emrouznejad et al., 2010): the model is designed to estimate efficient input-output levels for inefficient units and not to provide measures of efficiency for all decision making units; and except for output or input oriented models under variable returns to scale, the results depend on the unit of measurement of the inputs and outputs.

The range directional measure models of Portela et al. (2004) are also used to construct DEA models with undesirable inputs and outputs. They proposed two approaches. The first approach is for cases where efficient input-output levels are sought to improve those variables where the decision making unit is furthest from the best attainable level. The second approach is for those cases where improvement is prioritized for variables where the decision making unit is closest to the best efficient input-output levels. Compared to the additive models, the range directional measure models yields efficiency measures that are very similar to those obtained from the radial DEA models (Emrouznejad et al., 2010).

Semi-oriented radial measure DEA models can be used to estimate measures of efficiency and can also handle both undesirable inputs and outputs. These models are based on the premise that some variables may take positive values (desirable) for some decision making units and negative values (undesirable) for other decision making units. This means that in order to improve performance the absolute value of the variable should raise or fall depending on whether the decision making unit has a positive or negative value on that variable.

The output oriented variable returns to scale semi-oriented radial measure DEA model with negative input can be operationalized as follows. Let input variables $\boldsymbol{X_i}$, $\boldsymbol{i} \in \boldsymbol{I}$ such that some inputs are positive for some decision making units and negative for others. Also let that the output variable

$\boldsymbol{Y_r}$ $\boldsymbol{r \in R}$ are positive for all decision making units. Following Emrouznejad et al. (2010) we can define the input variable with positive and negative observations as $X_{lj} = X^1_{lj} - X^2_{lj}$ such that:

$$X^1_{lj} = \begin{cases} X_{lj} & if \quad X_{lj} \geq 0, \\ 0 & if \quad X_{lj} < 0, \end{cases} \quad \& \quad X^2_{lj} = \begin{cases} 0 & if \quad X_{lj} \geq 0, \\ -X_{lj} & if \quad X_{lj} < 0. \end{cases} \tag{5}$$

In Equation (5), the left hand expression represents positive (desirable) inputs and the second hand expression represents negative (undesirable) inputs. If there is no decision making unit with negative inputs, then all the values of X^1_{lj} are positive numbers; otherwise they are mix of positive values and zeroes. Similarly, if there is no decision making unit with positive inputs, then all values of X^2_{lj} are negative numbers; otherwise they are mix of negative values and zeroes. To assess the efficiency of a reference decision making unit which has positive output and negative value in some inputs, the following output-oriented variable returns to scale semi-oriented radial measure DEA model can be estimated:

$$\begin{aligned} &\text{Max } h \\ &s.t. \sum_j \lambda_j X_{ij} \leq X_{ij0}; && \forall i \in I \\ &\quad \sum_j \lambda_j X^1_{lj} \leq X^1_{lj0}; && \forall l \in L \\ &\quad \sum_j \lambda_j X^2_{lj} \geq X^2_{ij0}; && \forall l \in L \\ &\quad \sum_j \lambda_j Y_{rj} \geq h Y_{rj0}; && \forall r \in R \\ &\quad \sum_j \lambda_j = 1; \quad \lambda_j \geq 0; && \forall j. \end{aligned} \tag{6}$$

In Equation (6), the undesirable inputs are presented as negative values. The aim is to estimate the efficient input-outputs level for the reference decision making unit. Equation (6) estimates technical efficiency rating (*$1/h^*$*) for the reference decision making unit. The variable h^* is the optimal solution of h in Equation (6), which measure the radial contraction of output to maximize efficiency. The measure of technical efficiency ($1/h^*$) ranges from one to infinity; meaning that (($1/h^*$) - 1.0) is the proportion by which outputs may be expanded if the firm is to produce on the best-practice frontier. In Equation (6), the negative value inputs are treated as output and the model seeks improved solutions, which raises the absolute value of the negative inputs or seek solutions that decrease the level of undesirable inputs. The last constraint imposes variable returns to scale.

Capacity utilization (CU) refers to the extent to which an enterprise actually uses its installed productive capacity. It refers to the relationship between actual output that is being produced with the installed equipment and stock, and maximum (optimal, or potential) output that could be produced with the same installed equipment at full capacity utilization. Capacity utilization is therefore a ratio of observed output (AO) to, optimal or potential output (PO). The reciprocal of the capacity utilization ratio (PO/AO) indicates the amount of output that could be increase if the existing capacity were to be optimally utilized. The output gap percentage (OG) can be measured as (OG= (AO-PO)/PO)*100); where (AO) is actual output and (PO) is maximum, optimal or potential output at the decision making unit full production capacity.

Based on Equation (6) the capacity utilization models proposed by Färe et al. (1989) and Färe et al. (1994) a DEA model that directly estimate capacity measure can be presented as:

$$
\begin{aligned}
&\text{Max } \varphi \\
&s.t. \sum_j \lambda_j X_{ij} \le X_{ij0}; && \forall i \in F \\
&\sum_j \lambda_j X_{ij} = \beta_{ij} X_{ij0;} && \forall i \in V \\
&\sum_j \lambda_j X_{lj}^1 \le X_{lj0}^1; && \forall l \in L \\
&\sum_j \lambda_j X_{lj}^2 \ge X_{ij0}^2; && \forall l \in L \\
&\sum_j \lambda_j Y_{rj} \ge \varphi Y_{rj0}; && \forall r \in R \\
&\sum_j \lambda_j = 1; \quad \lambda_j \ge 0; && \forall j.
\end{aligned} \tag{7}
$$

In Equation (7), the optimal solution ϕ^* is the capacity utilization measure. Technical efficiency capacity utilization measure is estimated as ($1/\phi^*$). This measure ranges from zero to one, with one being full capacity utilization (i.e. 100 percent of capacity) given a set of fixed inputs. Values less than 1 indicate that the firm is operating at less than full capacity. The first constraint implies that inputs belonging to the set of fixed factors (*F)* and the second constraint imply that inputs belonging to the set of variable factors (*V*). In order to calculate the measure of capacity output, the bounds on the sub-vector of variable inputs are relaxed by allowing these inputs to be unconstrained by introducing a measure of input utilization rate (β_{ij}). The measure is estimated in the model for each decision making unit and variable input. The value of β_{ij} is the ratio of the optimal use of each variable input to its actual usage. For example, a value of 1.3 means that the variable input should be increased by 30% for a firm to be on the best-practice frontier. As shown by Coelli et al. (1998), sometimes even if all current inputs (both variable and fixed) are used efficiently, observed output may be less than potential or optimal output. That is, output could increase through efficiency gains, without changing the levels of the inputs. They suggest estimating lower but unbiased capacity utilization as (h^*/ϕ^*) obtained from Equations (6) and (7), respectively.

2.3 Source of Data and Analysis

The source of data is the Enterprise Surveys database maintained by World Bank and freely available at www.enterprisesurveys.org. The data was collected from 15 September 2008 to February 2009 through face-to-face interviews with firm managers and owners regarding the macro business environment they face. The survey also collected input-output and price data. Enterprises are categorized according to the number of employees as follows: small (5-19 employees), medium (20-99 employees) and large (more than 100 employee). Out of 150 firms that were surveyed; 73 are manufacturing firms and 67 service firms. This study focuses on the manufacturing sector that has less missing values. Also, the manufacturing sector is emphasized in the Liberia's Poverty Reduction Strategy Papers (IMF, 2008). Although, the share of the manufacturing sector to Liberia's gross domestic product is about 6% compared to 18% of the service sector, the service sector stem from the demand of services created by the manufacturing and public sectors. Development of the manufacturing sector entails growth of the service sector that is currently dependent on the public sector.

For the entire data set, the macro-business environment indicators are grouped into several domains and include: the obstacles to doing business; infrastructure; finance; labor; corruption, regulation, law and order, innovation and technology, and trade. However, business operators in Liberia identified four domains as the most limiting: access to finance; crime and theft; infrastructure; and corruption (Kaliba et al, 2011). The indicators in each of the four domains are summarized in Appendix 1. During data analysis, each indicator was structured as a dummy variable such that one represented present and zero otherwise (not present). This construct implies that higher value of $\boldsymbol{\theta_n}$ in Equation 2 shows unconducive macro business environment and vice versa. Equation (2) was estimated using Generalized Linear Latent and Mixed Models (gllamm) program in Stata. The program estimates this kind of models by maximum likelihood (Rabe-Hesketh et al. 2004a, 2004b). The index of macro-business environment ($\boldsymbol{\theta_n}$) was recovered using post estimation procedures available in Stata.

The survey also collects input-output data. The input-output data include five measures: labor cost (wages, salaries, and bonuses); cost of raw materials and intermediate goods; cost of electricity and other energy use; net book value of machinery, vehicle and equipments; net book value of land and buildings; and total annual sales. Assuming the law of one price, annual revenue was treated as output. The revenue gap percentage (RG) was calculated as (RG= (AR-PR)/PR)*100); where (AR) is actual reported revenue and (PR) is optimal or potential revenue under full production capacity. Variable inputs were: labor cost and cost of raw materials and intermediate goods. The fixed inputs were: net book value of machinery, vehicle and equipment, and net book value of land and buildings. While the revenue variable has no missing value, some observations in the cost variables were missing. Multiple imputations analytical techniques were to estimate the missing observations in the cost variables (Rubin, 1996).

The variable with undesirable inputs was the index of macro-business environment estimated using Equation 2. Theoretically, the index varies from negative infinity to positive infinity. However, reasonable values tend to be between -4 and 4 and are centered at zero (Kamata and Cheong, 2007). Therefore, in the DEA model, to increase the discriminating power of the index, it was multiplied by -100. Therefore, positive value indicated desirable levels of macro-business environment and negative value indicated undesirable levels of macro-business environment. As shown by Pastor (1996); scaling of variables using a constant does not affect the result of the DEA model. The DEA models in Equations (6) and (7) were estimated using General Algebraic Modeling System (GAMS) software (McCarl et al., 2010).

The results of the two DEA models were used to estimate unbiased capacity utilization for each enterprise in the sample as explained above. The unbiased capacity utilization variable and observed revenue were then used to estimate revenue gap percentage. The measure of revenue gap percentage was regressed on all inputs (both desirable and undesirable inputs) to quantify the impact of micro-business environment. The Tobit model (Long and Freese, 2006) was used for the regression analysis. This is because the revenue gap percentage was censored from below (at 0%).

3. Results and Discussion

3.1 Results of the Rasch Model

Since our major interested is on the impact of macro business index and due to space limitation, not all results from the Rasch Model are reported. We report the distribution of the estimated macro business environment indexes in Table 1.

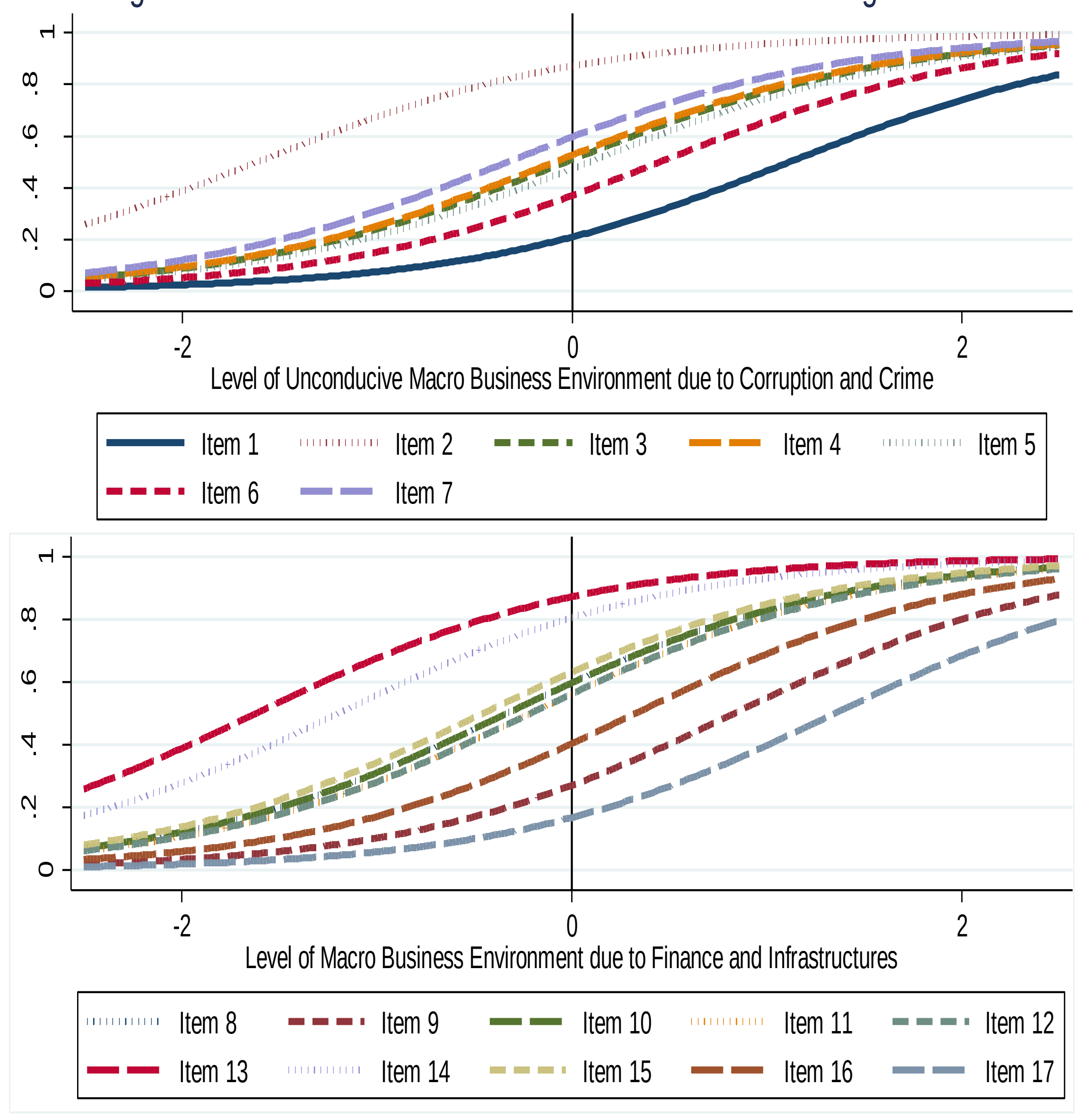
In Table 1, the first part shows the summary statistics for the enterprises that registered unconducive macro business environment (i.e., the estimated score was positive). For the 43 enterprises out of 73, the index ranged from 0 to 2.492 with the mean and standard deviation of 0.758 and 0.617. The coefficient of variation was therefore 81.4%. The second part of Table 3 shows the summary statistics of the remaining 30 enterprises with conducive macro business environment (i.e., the estimated score was negative). For these enterprises the index ranged from -2.271 to -0.245. The coefficient of variation was 44.6%. Therefore, there was higher dispersion in enterprises with unconducive macro business environment.

Table 1 Distribution of the estimated macro business environment in absolute value

Enterprises with unconducive macro business environment	
Number of enterprise	43
Mean score	0.758
Standard Deviation	0.617
Maximum	2.493
Minimum	0.00
Enterprises with conducive macro business environment	
Number of enterprise	30
Mean score	1.086
Standard Deviation	0.484
Maximum	2.271
Minimum	0.245
Sample	
Number of enterprise	73
Mean score	0.447
Standard Deviation	0.619
Maximum	2.271
Minimum	0.00

In order to compare items across domains we used the estimated macro business environment index (θ_n) and indicator location parameters (δ_i) to construct item characteristics curves as shown in Figure 1. Item Characteristic Curves (ICCs) are also known as trace-lines, category response curves, or probability curves. The assumption behind the ICC is that each enterprise has an underlying level of macro business environment. At each level of macro business environment, there is a certain probability that an enterprise will be scored present or not present for each indicator. The probability is low when the score is not present and the probability is high when the score is present. This means that enterprises with high score will have a higher probability of observing unconducive macro business environment (i.e., high frequency of present score).

Figure 1: Item Characteristics Curves for the Manufacturing Sector



In Figure 1, the probability of scoring "present" to any of the indicators is near zero, for an enterprise with the lowest levels of score on unconducive macro business environment. The probability increases and at the highest levels of unconducive macro business environment, the probability of scoring “present” approaches one. The curves in Figure 1 therefore show the relationship between the probability of scoring “present” to an item and the unconducive macro business rating by the enterprise. In addition, Figure 1 shows two technical properties of an item characteristic curve. The first is the difficulty of the indicators, which describe, in this case, the position of the indicator along the macro business environment scale on the horizontal axis. A high difficulty score will appear among respondents with high unconducive macro business environment (easy item or high score on present) and low score among enterprises with low levels of unconducive macro business environment.

The second technical property is discrimination, which describes how well an indicator can differentiate between enterprises having macro business environment scores below the indicator location and those having the score above the indicator location. This property essentially reflects the steepness of the item characteristic curve in its middle section. The steeper the curve, the better the indicator can discriminate and the flatter the curve, the less the item is able to discriminate since the probability of “present” score at low level of unconducive macro business environment is nearly the same as the higher level.

Figure 1 shows that all items have the same level of discrimination (i.e., the curves do not cross) but differ with respect to the power of discrimination, which is expected in the Rasch model. The left hand curves represent an easy indicator (because the probability of “present” is low for enterprises with low scores and approaches one for enterprises with high scores). This means that most enterprises responded that this indicator was present. The center curves represent indicators with medium impact on macro business environment. The right-hand curve represents a hard item-few enterprises scored the indictor as “present”. For these indicators, the probability of “present” is low along the macro business environment scale and increases only when the higher levels are reached. Even at the highest level shown (+4), for most of these indicators, the probability of “present” as indicated by some enterprises is less than 0.7.

In general, for corruption, theft and security domains the most limiting indicators were from the corruption domains: gifts to public officials are expected to get an operating license and enterprises are expected to give gifts when meetings with tax officials. For financial and infrastructure domains, the most limiting indicators were: enterprises not having line of credit or loans from financial institutions and lack of electricity; therefore, generators were used most of the time to generate electricity.

3.2 Estimates of Technical Efficiency and Capacity Utilization

Estimated Technical Efficiency and capacity utilization measures are summarized in Table 2 on the next page. The last column indicates the summary statistics of optimal value of (ϕ) as estimated using Equation (5). The last but one column shows the summary statistics of the optimal value of (h) as estimated using Equation (4). The production gap was estimated using optimal value of (h) and optimal value of (ϕ) as explained above. On average, for enterprises experiencing unconducive macro business environment could increase revenue by about 34% by operating at the efficient frontier. The value was 14% for enterprises not experiencing unconducive macro business environment. It can be clearly seen that on average most enterprises experiencing unconducive macro business environment were technically inefficient and produced below capacity. Notice that for enterprises experiencing unconducive macro business environment, average technical efficiency under variable returns to scale was 2.21. After adjusting for capacity utilization the average technical efficiency score was 3.09. Therefore, most of the inefficiencies were from capacity utilization rather than inefficiency due non-optimal allocation of inputs.

Table 3 on the next page shows the estimated coefficients, their standard errors, and the associated t-statistics. The model fit was evaluated by comparing the predicted values based on the Tobit model to the observed values in the dataset. The correlation between the predicted and observed values of the revenue gap percentage was 0.81. If we square this value, we get the squared multiple correlation of about 0.66. This implies that the predicted values share about 66% of their variance with the observed values of the revenue gap, which implies better fit.

Table 2 Distribution of Estimated Output-Oriented Efficiency Measures

Summary Statistic	**Revenue Gap (%)**	**Technical Efficiency VRS**	**Technical Efficiency CU**
Enterprise with unconducive macro business environment			
Number of enterprise	43.00	43.00	43.00
Mean score	34.17	2.21	3.09
Standard deviation	52.77	2.19	3.73
Maximum	237.45	8.87	21.46
Minimum	0.00	1.00	1.00
Enterprise with conducive macro business environment			
Number of enterprise	30.00	30.00	30.00
Mean score	14.02	2.59	2.27
Standard deviation	20.26	2.29	1.89
Maximum	73.92	9.73	8.05
Minimum	0.00	1.00	1.00
Sample			
Number of enterprise	73.00	73.00	73.00
Mean score	25.89	2.37	2.75
Standard Deviation	43.47	2.22	3.12
Maximum	237.45	8.87	21.46
Minimum	0.00	1.00	1.00

Table 3 Results of the Tobit Model

Variable	Est. Coef.	Std. Error	t-Stat	
Labor cost	0.081	0.025	3.181	***
Cost of materials and intermediate inputs	-0.026	0.034	-0.743	
Net book value of equipment and machinery	0.058	0.095	0.608	
Net book value of land and building	-0.019	0.023	-0.842	
Variable for conducive macro business environment	0.827	0.282	2.932	***
Variable for unconducive macro business environment	-0.523	0.257	-2.033	***
Intercept	10.01	2.988	3.353	***
Sigma	65.63	8.331	49.05	***

*** Statistically significant at 1% level of significance

The coefficients for labor cost and variables representing unconducive and conducive macro business environment are statistically significant. Therefore, for a one unit increase in labor cost, there is a 0.08% increase in the revenue gap. As shown in Table 1, the value of a variable representing conducive macro business environment varied from negative 2.27 to negative 0.25, with small values showing conducive macro business environment and large value representing increase in unfavorable macro business environment. Therefore, a one unit increase in favorable macro business environment is associated with a 0.83% decrease in the predicted value of revenue gap. Also, a one unit increase in unfavorable macro business environment is associated with a 0.52% increase in the predicted value of revenue gap percentage.

In Table 3, the estimated sigma (65.63%) is equivalent to the standard deviation of the errors and can be compared to the standard deviation of revenue gap which was 43.47%, a substantial increase. Also, the estimated sigma is statistically significant. This implies that the estimated coefficient (65.63%) is statistically significantly different from 0. In Table 3 note that the variable that represent net book value of equipment and machinery is positive and not statistically significant and net the book value of land and buildings variable is negative not statistically significant. For equipment and machinery, this can be attributed to undercapitalization associate with lack of credit to acquire new capital to replace old equipments and machinery. This is common in many SMEs in developing countries. For land and buildings variable this can be attributed to overcapitalization especially on land. Due to land policy uncertainties and availability of cheap land, firms in developing countries tend to acquire more land than necessary as a risk management strategy and as an investment.

4. Summary and Conclusion

In this study, we use different models to estimate the impact of macro business environment on productive efficiency of manufacturing enterprises in Liberia. A two parameter Rasch model was used to develop an index of macro business at the firm level. The index was developed from 17 items that represented presence or absence of unconducive macro business environment. The estimated index was divided into two sub-indexes: conducive macro business environment scores (negative value); and unconducive (positive value) macro business environment scores. These two indexes were used as inputs in an output-semi-oriented radial Data Envelopment Analysis (DEA) model. Other inputs were: cost of raw materials and intermediate goods, cost of electricity and other energy use, net book value of machinery, vehicle and equipments and net book value of land and buildings. Output was measured as total annual sales. The DEA model was used to estimate technical efficiency and capacity utilization measures. The estimated capacity utilization measure was regressed on all inputs used in the DEA model using a Tobit model framework.

Results from the Rasch models indicated that corruption by public officials, lack of line of credit or loans from financial institutions and inadequate supply of electricity were major contributors to unconducive macro business environment. Results of the Tobit model shows that labor cost and indexes of macro business environment have statistically significant influence on capacity utilization and therefore technical efficiency. While labor cost can be influenced by the managers or operators; macro business environment can be effected by the government and or government policies. Government laws and policies aimed to combat corruptions need to be implemented effectively. Investment in financial institution and electricity supply is paramount towards improving capacity utilization among manufacturing enterprises in Liberia.

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Appendix

Major indicators of macro business environment in Liberia

Corruption	
1	Informal payment to public officials is expected to get things done
2	Gifts to public officials are expected to get an operating license
3	Firm is expected to give gifts when meetings with tax officials
4	Firm is expected to give gifts to secure a government contract
Crime and theft	
5	Firm is paying for security
6	Firm experiencing frequent losses due to theft, robbery, vandalism, and arson
7	Firm experiencing frequent losses of products shipped to supply domestic markets
Finance	
8	Firm do not has line of credit or loans from financial institutions
9	Firm do not use banks to finance investments
10	Enterprises do not use banks to finance operating expenses
11	Value of collateral needed for a loan is higher than 50% of the loan amount
Infrastructure	
12	Reported revenue loss due to power outages
13	Generator used most of the time to generate electricity
14	Delay in obtaining an electrical connection
15	Incidence of water shortage and insufficiency
16	Experience in obtaining a water connections
17	Delay in obtaining a mainline telephone connection