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CLUSTER ECONOMIES, PRODUCTIVITY AND TECHNICAL EFFICIENCY – A NARRATIVE REVIEW

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ABSTRACT

Productivity and efficiency studies abound in research, academia, industry and business to facilitate the assessment of the efficiency and effectiveness of input-use, and to measure efficiency and output levels against an optimum production frontier. Empirical studies have established links between cluster economies, productivity and technical efficiency – links that enable investigations into correlations between industry-size and the implications/externalities that arise from clusters. This paper discusses the concept of cluster economies, the different proxies that have been used to represent the concept, the possible linkages between cluster economies, productivity and efficiency, and the different methods for measuring and analyzing these concepts.

CLUSTER ECONOMIES – AN INTRODUCTION

Clusters, also referred to as agglomerations/agglomerates/groupings, and the externalities that arise from them, have become an important feature of the economic landscape. They have become necessary due to an uneven distribution of both natural and artificial resources (Antwi and Onumah, 2020). These groupings/agglomerations have spillover effects referred to as externalities that arise from the interactions within them and have very important implications for industry. Cluster externalities can arise from proximity of firms/farms to each other and/or to customers. The advantages gained from these externalities have given firms some competitive edge by expanding production possibilities beyond restrictions that were erstwhile imposed by a number of exogenous factors inimical to high productivity (Maciente, 2013).

As pioneered by Marshall (1920) and developed by other authors on the subject, such as Ellison*et al.* (2010), in the Marshallian view, clustering reduces transportation cost, cost of moving goods and cost of transfer of ideas. By virtue of proximity therefore, firms would either locate near suppliers to save on shipping/transportation costs, or would situate themselves closer to a specialized labour pool to facilitate access to appropriate labour as and when needed, and also so they can benefit from local knowledge spillovers (Maciente, 2013).

Glaeser (2010) describes economies of clustering as those benefits that arise from people and firms locating and/or relocating in close proximity to one another. Puga (2009) says that cluster economies arise when there is a situation of aggregation of firms and workers in a given environment as opposed to disaggregation especially in location. Following Marshall's observations (Marshall, 1920) about cluster economies, many other authors have classified cluster economies as either being direct or indirect, either expressed through the market system or not (Scitovsky, 1954), either informal or institutionalized (Porter, 2000) and either internal or external to the firm (Parr, 2002a; 2002b). The existence of cluster economies is evidenced by the concentration of firms, people and industries and is further defined by the consequent interactions within these groupings and how they tell on certain parameters, such as cost, which inevitably affect the economy.

Sources of Cluster Economies

The concept of agglomeration revolves around clustering, and the objective of any researcher on the subject is to ascertain and understand the mechanisms that make this clustering productive and profitable. For instance, Krugman (1991) introduces the classic model of clustering that emphasizes agglomeration benefits that arise from a reduction in transporting goods over space. As such, the merit derived from these clusters (i.e. the supplier locating themselves closer to the customer) is a reduction in transportation cost (Glaeser, 2010).

The sources of or motivation for clustering could therefore arise from the cost of moving people (Glaeser, 2010). Krugman (1991) demonstrates how it would be more economically sound and productive for an input supplier to locate his business close to a final goods producer and thus save on cost of shipping of input (goods). There is however the element of moving people across space, where the value of time is considered in forming clusters. This encompasses people travelling across space to buy goods and ensure labour-matching, which makes it easier and cheaper to locate and match 'labourer and employer' especially when these clusters are effective. Cluster results are more impactful when the sectors that implement them are heterogeneous, to avoid correlation of shocks, but at the same time are similar enough so as to allow for movement of workers across the different firms (Glaeser, 2010; Overman and Puga, 2010).

Aside labour-pooling, another source of cluster economies is knowledge spillovers (Jacobs, 1969; Marshall, 1920) that come about as a result of a faster flow of ideas and information between people and firms due to proximity. Chinitz (1961) argues that a business community with a lot of smaller businesses and firms is more likely to flourish in comparison to one that has a few large firms. This, he says, is due to the fact that there is a more vibrant intellectual linkage in the former scenario than in the latter. There is the likelihood of a high incidence of learning, or knowledge-sharing, resulting in the adoption of technologies or practices. These end up creating cluster economies that could have positive implications for the sector, for agriculture and for the economy as a whole (Puga, 2009).

Puga (2009) outlines six main sources of cluster economies - firms sharing facilities, firms sharing suppliers, firms sharing gains from individual specialization, firms sharing a labour pool, better matching of employees and employers, and learning within firms (as mentioned earlier). This is made possible by the large size of the market where these firms interact. Larger markets allow for better efficiency in the sharing of local facilities, amenities and infrastructure. Clustering also creates a conducive environment for sharing of workers/labour with similar skill, and intermediate suppliers of input. Large clusters also facilitate linkages between business partners, suppliers and buyers, labourers and employers, and so on.

Classification of Cluster Economies

Cluster economies can be categorized into two broad groups – economies that are external and those that are internal to the firm (Parr, 2002a; 2002b). There is a strong linkage and parallelism between the two classifications. Parr (2002a) further classifies internal and external agglomeration economies into three other categories, based on their economic rationale (Maciente, 2013) and these are by *scale, scope* and *complexity* (Parr, 2002a; 2002b) (Table 1).

Internal economies of scale are seen to occur when large localized outputs within a production unit tend to reduce costs related to production, and whenever the production costs of more than one product within a firm is less than production costs incurred by separate firms (Maciente, 2013), or when production of multiple outputs translates into a more efficient combination of inputs, then there is Economies of scope or of lateral integration (Parr, 2002a). There is also vertical integration of local production which involves the clustering of the different stages of production in one firm, and this brings about internal economies of complexity.

External economies however occur as a result of clustering through location, where the location of one firm can have positive implications and effects, such as minimizing production cost, on other privately owned and operated firms in the locality. *Marshall-Arrow-Romer* economies, better known as External economies of scale or localization economies, refers to and is made up of all cost savings to a firm that is attributed to the local scale of its own industry (Maciente, 2013). Knowledge spillovers lead to horizontal integration within firms and this results in localization economies.

Table 1: Classification of cluster economies

	Internal to the firm	External to the firm
Scale	Horizontal integration	Localization economies
Scope	Lateral integration	Urbanization economies
Complexity	Vertical integration	Activity-complex economies

Source: Parr, 2002a.

Diseconomies of scale could also occur where cost disadvantages arise due to increase in per-unit costs of inputs. This could be as a result of increase in firm size or output which results in production of goods at increased costs. This results in a negative cluster externality.

Firms that belong to different industries can also co-locate and this can result in External economies of scope (Beaudry and Schiffauerova, 2009; Fujita and Thisse, 2002); this is closely related to or present among firms located in markets with specialized units (Jacobs, 1969). There are also External economies of complexity which operate in a vertically integrated process and occur as a result of co-location of firms belonging to a specific production chain; industries linked through direct or indirect trade linkages (Parr, 2002b). These economies may become internal cluster economies if the firms merge into one or are subsequently owned by one single firm.

The different classifications give a better understanding of how they act independently but can also complement each other by incentivizing clustering and co-clustering of firms and industries respectively (Viner, 1932). Thus, the creation of cluster economies leads to externalities that can either be classified as positive or negative depending on the efficiency and effectiveness of the economies.

Cluster Externalities and Further Implications

Cluster externalities which arise from the presence of local markets specializing in one product/service or another, and also due to the presence of intermediate products (Larue and Latruffe, 2008), are cited by Duranton and Puga (2004) and Antwi and Onumah (2020) as having positive implications such as knowledge spillovers, demand-matching, labour-supply, and input-sharing.

Cluster externalities have a very vital function in the creation of economic agglomerations (Fujita and Thisse, 2002; Marshall, 1920). Unlike *concentration,* which describes different economic phenomena, agglomeration is more definitive and less ambiguous in describing clusters that are encouraged by the externalities that arise from them. Cluster externalities in agriculture could have negative influences on the members of the clusters and these could include spread of plant disease, water shortage problems among farms, widespread effects of bad farming practices and so on. Fujita and Thisse (2002) however outline four positive cluster externalities and conditions that are relevant for the formation of clusters:

1. Availability of a larger labour pool or force from which employers can recruit.
2. Availability and facilitation of effective information-sharing (made possible by clustering and proximity of firms to each other).
3. Demand-matching (leading to specialization).
4. Sharing of resources.

These merits come about especially as a result of proximity and a subsequent increase in the propensity of group members to interact with each other. Cluster externalities tend to give members of agglomerates a competitive edge over non-members. For instance, in agriculture, farmers are able to access tools and equipment that were erstwhile unavailable to them, from neighbouring farms, at no or very low costs. The Marshallian externalities concept captures the idea that cluster externalities arise from a snowball effect where firms would want to congregate with the main aim and purpose of benefitting from a large diversity of economic activities and a high degree of product specialization. According to Matsuyama (1995), cluster externalities result in increasing returns to scale and provides members with competitive advantage in the economy.

There are two main categories of cluster externalities. Scitovsky (1954) proposes that these two categories are;

(a) Technological externalities – knowledge externalities, and
(b) Pecuniary externalities.

Technological externalities identify the effects that non-market interactions have on firms, through some processes that have direct effect on the utility of a firm. These processes may also have effects on the production function of a firm and even on individual players in the industry (Fujita and Thisse, 2002). Pecuniary externalities on the other hand refer to the by-products of interactions within markets that are limited by the degree of involvement in exchanges between the members of these clusters. The market price mechanism regulates these systems. Pecuniary externalities are therefore most relevant when the markets involved are imperfectly competitive; that is to say that prices, and also the well-being of others in the market, are affected by the decisions of one agent (Fujita and Thisse, 2002).

More specifically, Thünen (2012) describes the following as some of the consequences and implications of cluster externalities:

1. Due to clusters, prices of raw materials are reduced on account of a reduction especially in cost of transport.
2. Low transportation costs translate into lower costs of production which lead to a decrease in prices of a firm's products, making it more competitive on the market.
3. There is a reduction in haulage costs of finished goods due to relative closeness of the firm to its consumer base.
4. Construction costs (incurred in building the firm, and so on) are reduced as the distance between raw materials and the site of construction is significantly shorter.

Cluster Externalities in Agriculture – Implications on Technical Efficiency and Productivity

The externalities that arise as a result of the creation of cluster economies, may have some effect on technical efficiency and also on the productivity of the farming sector (Antwi and Onumah, 2020; Battese and Tveteras, 2006; Maciente, 2013). Therefore, aside the variables that directly affect technical efficiency and productivity, such as input and socio-economic demographics of the farmers (Antwi *et al.,* 2017), cluster externalities also have direct effect on the efficiency of input combinations, and on the production frontier. Factors(both endogenous and exogenous factors) that affect technical efficiency and productivity may also influence the formation of clusters within an industry (Parr, 2002a).

In agriculture, cluster externalities may either be positive or negative based on spatial concentration. Positive spatial externalities are likely to occur from access to input units (factors) and services such as feed, farming tools, veterinary services, and so on. Positive externalities are also likely to occur as a result of dissemination of information and knowledge through interactions between the farmers, as discussed earlier. Cluster externalities have been closely linked to productivity gains (Larue and Latruffe, 2008).

Studies carried out by Battese and Tveteras (2006), Larue and Latruffe (2008) and Roe *et al.* (2002) have led to the formulation of some theoretical expectations arising from cluster externalities in the agriculture sector. First of all, the concentration of farms tends to create positive impacts on their technical efficiency (Larue and Latruffe, 2008). The relationships that are created among farmers due to their spatial proximity further create knowledge spillovers. These relationships also allow these farmers to match labour.

Another expectation of cluster externalities in agriculture is the positive influence that the closeness of farms has on technical efficiency and productivity. There also may arise situations of negative influences on efficiency due to negative externalities that arise from clustering (Larue and Latruffe, 2008) and these take a toll on the productivity of the farms involved. These externalities could be due to an unfavourable increase in competition over raw materials or clientele, spread of diseases among crops, lack of water for irrigation, pollution, and so on.

Identification of externalities of clusters and the effect that they have in agriculture have undergone a revolution since very early empirical studies (Glaeser*et al.,* 1992; Henderson *et al.,* 1995). There is emphasis on three main indicators of clustering, according to Agovino and Rapposelli (2014), and these are as follows:

1. Marshall, Arrow, Romer (MAR) Externalities
2. Jacobs Externalities
3. Porter Externalities

MAR Externalities

These are usually created via spillovers of knowledge and information between farms that belong to the same sector. Knowledge spillovers between farms are therefore stimulated by spatial clustering and regional specialization and this leads to expansion and augmentation of the local industry (Cainelli and Leoncini, 1998) and this could have an influence on the way that inputs are combined to produce outputs (Agovino and Rapposelli, 2014). The MAR theory suggests a monopolistic market where players in the industry are allowed to protect their novelties and dispense them more efficiently. The MAR externalities are defined by an indicator specified as:

$$MAR = max_i(s_{ij}\, s_j)$$

where $s_{ij}$is the ratio of employed people within the *jth*sector in the *ith*region to the total employed in the *ith*region, $s_j$is the ratio of employed people in the *jth*sector at country level to the total employed at country level (Duranton and Puga, 2000).

Jacobs Externalities

Jacobs externalities are centered on the assumption that variety in industry can promote and enhance long-term development via the exchange of knowledge between diverse production units (Jacobs, 1969). The perfect competition market form is the most appropriate for this type of externality because it levels out the playing field and makes opportunities for growth equally available to all in the industry (Cainelli and Leoncini, 1998).

Porter Externalities

Porter externalities are a combination of MAR and Jacobs cluster theories. Like MAR, Porter argues that knowledge spillovers within specialized clusters can help improve decision-making which can in turn increase efficiency and stimulate growth. Local competition and input-sharing can foster the pursuit and adoption of technological innovation, such as the use of improved seeds. Porters externalities are maximized when there are specialized competitive firms that are in clusters.

Farm Associations and Farm Density as Indicators of/Proxies for Clustering

Empirical studies have been conducted over the years to find the effects of clustering on a diverse set of parameters including efficiency and productivity. These include studies by Caballero and Lyons (1992), Eberts and McMillen (1999), Paul and Siegel (1999), among others, that have tried to create linkages between industry size (industry concentration or agglomeration) and the externalities that exist among the firms that belong to these clusters. Battese and Tveteras (2006) are pioneers of such empirical studies, especially as is relevant to the agricultural sector, as they examined the effects of cluster externalities on efficiency and productivity in salmon farming in Norway. Battese and Tveteras (2006) captured cluster externalities as internal and external factors that have a tendency to influence productivity. The external factors that they modeled into the stochastic frontier and efficiency models are farm density (number of farms located within one square kilometer) and the size of the regional industry (which can also be captured by the number of farmers who belong in a farm association). These parameters were included in both the stochastic frontier and efficiency models to ascertain their effects on both output and efficiency.

Larue and Latruffe (2008) used the same concept to establish the effects of cluster externalities on the technical efficiency of French pig farms. They captured the cluster externalities by two indexes, the first as the concentration of farms measured by the farms' spatial proximity to each other (Larue and Latruffe, 2008). They also captured clustering as vertical and horizontal integrations arising from farmers' interactions with each other leading to better market-access, demand-matching and input-sharing. They then investigated the positive and negative effects of these indexes on the technical efficiency of the pig farms.

In recent times, Hailu and Deaton (2016) estimate the effects of a dairy farm's proximity to other dairy farms, captured as farm density, on its production efficiency. They do this using a stochastic input distant function and the results show that farm density has positive economic effect on the efficiency of dairy production in Ontario.

RETURNS TO SCALE, ECONOMIES AND DISECONOMIES OF SCALE

The production frontier can be characterized in relation to returns to scale (RTS). The RTS expresses the relationship that exists between the proportionality of change in inputs used in a production system to the resultant proportionality of change in output (Fried *et al.,* 2008). It expresses the impact of output expansion on average costs of production and is characterized by the effect of increased output on average cost when there is an equivalent increase of all inputs in the long run (Doll and Orazem, 1984).

There are 3 main categorizations of returns to scale and these are increasing returns to scale, decreasing returns to scale and constant returns to scale. Increasing returns to scale is said to occur when increases in output is proportionally greater than increase in inputs during production. This leads to efficiency of production as it exhibits the combination of fewer quantities of input to produce an output (Salim, 2006). The opposite is the situation of decreasing returns to scale, which shows a production system exhibiting increases in output in less than proportionate quantities to increases in input. Here, the output produced is less than the increased input even though there still is increase in the output (Fried *et al.,* 2008). Constant returns to scale is said to happen when the rate of increase in input used in production is equal to the increasing rate in the output. Fried *et al*. (2008) also describe the variable returns to scale (VRS) frontier as one that exhibits aspects of all the three types of returns to scale in different regions.

Economies of scale are closely linked to returns to scale (Doll and Orazem, 1984) as they describe output levels with respect to input quantities used and also incorporate a cost component. Reduction in average costs of production with increases in output size or quantity leads to economies of scale. Diseconomies of scale occur as the scale of production continues to increase leading to increase in average cost of production with increase in output. This leads to inefficiency especially in large organizations. Economies and diseconomies of scale are therefore the advantages and disadvantages of large-scale production in the long-run. It is critical to examine these phenomena as they invariably tell on the efficiency of production.

Economics and diseconomies of scale could either be internal or external. Internal economies of scale are merits enjoyed by the firm as it expands or increases quantum of output, and these advantages are due to certain adjustments made within the firm. External economies are therefore the benefits enjoyed by the firm as the industry it operates in grows larger. The same applies for diseconomies of scale, only that in this case it refers to the cost disadvantages that the firm experiences as a result of expansion within the firm (internal diseconomies of scale) or expansion in the industry that the firm belongs to (external diseconomies of scale) beyond the optimal size (Doll and Orazem, 1984; Fried *et al.,* 2008).

Productivity Measurement

The classical definition of productivity is that it is the ratio between an output of a production system and all the factors that contribute to this output. Productivity of any production unit is the ratio of (or relationship between) its output to its input (Lovell, 1993). Productivity is therefore the output realized per input used in production and can either be estimated as Marginal Physical Productivity (MPP) or Average Physical Productivity (APP), also referred to as Partial Factor Productivity. Marginal Physical Productivity deals with per unit increments and is defined as the rate of change in output per unit change in the quantity of input. The Average Physical Productivity however describes the ratio of quantity of total output per unit to variable input when all other inputs are held fixed. It is also the ratio of total physical product to quantity of variable input. To illustrate the functional forms, the APP and MPP can be mathematically represented as:

$$APP_{Input} = \frac{Output\ (Y)}{Input\ (x)} = \frac{Y}{L}$$

$$MPP_{Input} = \frac{\delta Y}{\delta x} = f_L$$

Diminishing marginal productivity will however set in when an upsurge in the use of any additional input leads to lower output levels per unit input (productivity) or translates into a less than proportionate increase in quantity produced. This may occur when an input is indefinitely employed while all other inputs of production are held constant (Kibaara, 2005; Lovell, 1993).

Productivity is easiest calculated when a single output is produced from a single input in a production system. It however becomes necessary to aggregate the inputs and outputs if several inputs in differing quantities are used to produce several outputs. This makes it possible therefore to measure productivity as the ratio of two scalars.

Productivity can further be categorized into Partial and Total Factor Productivity. Productivity is described as Partial Factor Productivity when only one production factor is concerned, and it takes into consideration the contribution of one input to total output. Total Factor Productivity (TFP) on the other hand refers to all the factors of production and measures the total output of a production process to all inputs used. This productivity measure does not show the interactive process between the individual inputs and output as it aggregates all inputs and output. Partial Factor Productivity is relatively easier to compute due to the absence of aggregation complications.

$$PFP = \frac{Y}{X_i}$$

$$TFP = \frac{\sum_{i=1}^{n} Y_{it}}{\sum_{i=1}^{n} X_{it}}$$

where Y denotes output, $X_i$denotes the input levels and X_{it} represent the quantity of inputs used over a period of time (t).
The Multiple Factor Productivity (MFP) also measures productivity as a ratio of combined inputs to the total output produced (Fried*et al.*, 2008; Kibaara, 2005). For this aspect of productivity to be possible, all inputs must be expressed in the same unit of measurement. The MFP can be generally specified as;

$$MFP = \frac{Y}{\sum_{i=1}^{n} X_i}$$

where $\sum_{i=1}^{n} x_i$ is the sum of all inputs used in the production system.

EFFICIENCY

Issues often arise as to exactly what efficiency is as some authors do not make a distinction in the definition of efficiency and productivity. Cooper *et al.* (2000) and Sengupta (1995) define both technical efficiency and productivity as a ratio of output to input. Fried *et al.*(2008) state that productivity and efficiency are conjoining terms but rather than describe efficiency as the output-input quotient of a firm, it can be described as the differences in the quantities of input and output which describes the best possible production frontier for the firm in its industry.
Efficiency of production can thus be expressed as comparisons between the actual (observed) and peak values of the firm's input and output levels (Lovell, 1993). This can be expressed as the ratio of the actual to the optimal levels of the firm's output and input. Lovell (1993) also describes the efficiency of a firm as the relationship between the minimum or maximum obtainable potential output and the input needed to produce the output expressed as a ratio. The optimum output is therefore expressed in terms of production possibilities and the efficiency is described as being technical (Fried *et al.,* 2008).
Koopmans (1951) describes an input-output vector as being technically efficient only when it is possible to increase some output in the production system by decreasing some other output, or decreasing an output is only possible by increasing some other output in the same production system. Thus, technical efficiency describes the combination of input variables in a way in which no higher output levels can be realized from such a combination without negatively affecting the output of another product (Koopmans, 1951). Farrell (1957) describes Koopmans' observations about technical efficiency as being relevant when considered in relation to the best observed production practice in the sector, by virtue of which there can be differentiation between efficient and inefficient production systems.
Fried *et al.* (2008) put forward that the efficiency of the firm is very closely related to Pareto optimality. If during (of intermediate goods) or after production (of final goods) there is still the possibility of increasing output levels or decreasing input levels, then the production bundle is not Pareto optimal.
Farrell (1957) also observes that efficiency of production relies on the ability and skill with production managers to identify and choose the most efficient input-output bundle considering existing input and output prices, also taking into consideration the overall objective of the producer. He also argues that it is possible to empirically estimate a firm's efficiency and suggests a pioneering technique of estimating the efficiency frontier by observing real situations of production. Parametric estimation methods, as used by Berger and Mester (1997) and Farrell (1957), non-Parametric estimation methods as used by Seiford and Thrall (1990) and semi-Parametric estimation methods as used by Simar and Wilson (2007) have evolved from the studies on relative measure of efficiency developed by Farrell.

PRODUCTION FUNCTION ANALYSES AND EFFICIENCY-MEASUREMENT

The notion of production involves the transformational process that a given set of inputs goes through to be turned into an output(s). The production process churns out both waste and the actual product, the latter being the most beneficial to the producer. According to Coelli*et al.* (2005), the production function explains the relationship that is present between the input and output, and represents the optimum output level that can be achieved from each input factor. The productivity-efficiency relationship is such that if firms are technically efficient, then they operate on the production frontier. Firms are said to be technically inefficient when they operate below this frontier (Coelli*et al.,* 2005).
The main input variable classifications in agriculture, land, capital, labour and management, are what are usually combined to produce an output, with the aim of maximizing profit, utility, or output, or minimizing cost (Olayide and Heady, 1982). In production, the variability in the quantity of input used determines invariably the variability in the quantity of output. The continuous and differenti-

able nature of the production function enables the estimation of rates of returns (Olayide and Heady, 1982) based on output levels.

Types of Efficiency

Technical efficiency is identified as being only one of the three main types of efficiency, the other two being Allocative and Economic efficiency (Farrell, 1957).

Technical Efficiency

Under any given technology, technical efficiency is the capacity of firms to produce the required quantity of output using minimum quantity of inputs (Fried *et al.,* 2008; Shalma, 2014). From a combination of different sets of input, a more technically efficient firm is able to produce larger quantities of output than other firms using the same quantities of input. In the situation where the output is predetermined, the ability of the firm, while producing the output, to minimize its input in the production system is also said to be technical efficiency.

The measurement of the technical efficiency of a firm relies on the distance between the actual output produced of a firm and the most optimum production frontier (Pascoe and Mardle, 2003; Fried *et al.,* 2008; Farrell, 1957). By comparing and contrasting the actual output and potential output, the technical efficiency levels can be ascertained (Greene, 1993).

Some socio-economic factors may have significant impact on the efficiency of a production unit. These factors include human and monetary capital, socio-economic characteristics and demographics, and institutional factors (Bhosale, 2012). These factors may either be endogenous or exogenous, putting a clear differentiation between factors that are within and outside of the firm's control (Battese and Tveteras, 2006).

Technical efficiency studies are very key to ensuring higher productivity in industry and also in agriculture. Several studies including Onumah*et al.* (2010), Battese and Tveteras (2006), and Mohammed *et al.* (2016) have adapted technical efficiency studies across several agricultural sectors of fisheries and crop production.

There are three main classifications of technical efficiency employed especially in farm efficiency studies - these are deterministic parametric estimation, non-parametric mathematical programming, and the stochastic parametric estimation. The non-parametric method of measuring efficiency is further divided into two. Chavas and Aliber (1983) and Chavas and Cox (1988) employ the first type by measuring efficiency basing their measurements on the neoclassical theories of consistency, recoverability and extrapolation, and restriction of the production form (Shalma, 2014).

The second measure (non-parametric estimation), as developed by Farrell (1957), broke efficiency down into two constituents of technical and allocative efficiency, which was further expanded by Fare *et al.* (1985), in which disposability of inputs was linked to the restrictive supposition of constant returns to scale. Farrell (1957) postulates that there are multiplicative interactions between the technical and allocative components and this provides a means by which economic efficiency can be measured.

In order to estimate economic efficiency therefore, technical efficiency measurements are a necessary but not sufficient condition (Farrell, 1957). Therefore, it is necessary that both the allocative efficiency and technical efficiency of a firm are estimated to ascertain the economic efficiency of firms and industries.

Allocative Efficiency

The work of Farrell (1957) also introduced another type of efficiency - allocative efficiency. As technical efficiency investigates the maximum output that is attainable from the combination of available inputs, allocative efficiency conversely investigates the capacity of the production firm to utilize available inputs in optimal proportions. Allocative or price efficiency deals with how well a firm mixes its factors of production and allocates resources to input factors considering prevailing market prices. For inputs used in production, allocative efficiency assumes fixed market prices. It also assumes that output is fixed. Thus, the ability of the producer to coalesce input factors in optimal quantities and proportions (which is constrained by the prices of factors of production) constitutes allocative efficiency. Therefore, allocative efficiency measures the success with which a firm chooses optimal sets of inputs for production, given the prices of the inputs (Fried *et al.,* 2008). Unlike technical efficiency, allocative efficiency does not necessarily measure a firm's success against the production frontier but rather its capacity to generate the most optimum output level from a given set of inputs (Fried *et al.,* 2008).

According to Adinya and Ikpi (2008) and Badunenko*et al.* (2008), it is critical that extensive studies in allocative efficiency be undertaken in Africa since the majority of farmers are allocative inefficient due to their inability to make the most of the resources at their disposal. Such studies are however difficult to carry out due to the difficulty in obtaining the prices of input factors, which are very key requirements in estimating allocative efficiency. Apart from information on prices of factor inputs, it is also necessary to be willing to assume that the major objective of the firm is cost minimization (Uri, 2001).

Efficiency studies are incomplete without allocative efficiency studies especially for developing countries with relatively higher scarce resources. In recent times there have been studies that have tried to estimate allocative efficiency by obtaining and using upper and lower bounds of economic efficiency especially when information about input prices are incomplete or not readily accessible or available (Kuosmanen and Post, 2001). It is therefore an important allocative efficiency measure especially for countries that do not have readily available and/or reliable input price information.

Economic Efficiency

Farrell (1957) defines economic efficiency as the capability and capacity of a firm to churn out a predefined output while incurring the least cost. Economic efficiency describes the state in which every resource at the disposal of the firm is optimally allocated in the production process while waste and cost are minimized. It describes a situation where it is impossible to generate more output (welfare) from the resources available (Lovell, 1993). Economic efficiency therefore includes both technical and allocative efficiency. It is however worth noting that in a real-life setting, there is a difficulty in determining the optimal output obtainable by a production system (Kumbhakar and Lovell, 2003).

The principles of economic efficiency are based and bound by the theory of scarce resources indicating that it is not possible for any economy to function at its highest capacities at all times. This is because of the scarcity of resources to do that. One important advantage of economic efficiency studies is the comprehensive evaluation of production units taking into consideration input and output factors (Coelli, 1995).

Other Considerations for Efficiency

Scale Efficiency

A firm is considered as scale efficient when the extent and size of its operations are optimal so that when the size is modified in any way, the production unit is rendered less efficient. It indicates whether or not a firm is operating and functioning at its optimal size and capacity. This type of efficiency has been developed over the years in three distinct ways (Fried *et al.,* 2008). Farrell (1957) used the most restrictive technology that had a strong disposability of inputs and exhibited constant returns to scale. Charnes*et al.* (1978) expressed Farrell's model as a framework of linear programming while showing that measuring efficiency by virtue of constant returns to scale can further be expressed as the product of a scale efficiency measure and a technical efficiency model. The third model of scale specifies the production function as a non-linear function (example a translog or Cobb-Douglas function) from which one can directly compute the scale measure (Sengupta, 1994).

Structural Efficiency

This was developed by Farrell (1957) to determine the extent to which an industry keeps up with the production performance of its own best practice firms (Fried *et al.,* 2008). It therefore measures the level of the degree of an industry at which its farms are of maximum potential size and also the degree to which production level of that industry is optimally allocated, in the short-run. An industry is therefore comparatively efficient structurally if the distribution of its best firms is more concentrated closer to its efficiency frontier for the entire industry. Bjurek*et al.* (1990) proposed a computation for structural efficiency measurements by developing an average unit for the entire cluster of firms and then computing the individual measures of efficiency for this unit (Fried *et al.,* 2008).

MEASUREMENT OF EFFICIENCY

Efficiency (including farm efficiency) studies have incorporated several approaches of efficiency studies under the parametric (statistical) and non-parametric concepts, one of these approaches being to estimate the efficiency frontier, where producing at any point below this frontier is regarded as production that is inefficient.

Efficiency studies have further categorized parametric measures of efficiency into neutral and non-neutral frontiers. Aigner *et al.* (1977) and Meeusen and van den Broeck (1977) used the neutral frontier parametric method in their measure of maximum output and production efficiencies. They did this by specifying a composed error term to the conventional production function. The non-neutral approach employs the use of a production function form of varying coefficients.

Non-Parametric Approach

This approach estimates production efficiency without imposing any structure on the distribution of the population. The general assumption of this approach is that the failure to reach optimum output is not due to errors but rather to inefficiency. This method does not require the specifying of a functional relationship between outputs and inputs (Fried *et al.,* 2008). Unlike in the parametric approach, this approach does not require defining the frontier line and stochastic error term. Also, no assumptions are made about the functional form of the density of efficiency values.

The non-parametric approach is oriented by an input framework which is based on the input efficient boundary and the input requirement set (Aigner and Chu, 1968; Fried *et al.,* 2008). This approach aims at minimizing input levels while maintaining present output levels. The main non-parametric estimators are the Data Envelopment Analysis (DEA) and the Free Disposal Hull (FDH).

Charnes*et al.* (1978) developed the DEA as an extension of Farrell's relative efficiency concept, and it assumes the production set's free disposability and convexity. This approach constructs a non-parametric frontier for sample data using linear programming while efficiency measures are computed in relation to the frontier (Coelli*et al.,* 2005). In using the DEA estimator, unnecessary restrictions about the functional form that may distort efficiency measures and affect the analysis can be avoided. This is because the analysis can proceed without necessarily having knowledge of the algebraic form of the input-output relationship (Coelli*et al.,* 2005; Fraser and Cordina, 1999).

Deprins*et al.* (1984) proposed the FDH estimator and it is meant to represent a more general form of the DEA estimator in that it is dependent on the assumption of free disposability (Fried *et al.,* 2008). Thus, the FDH does not restrict itself to convex technologies and this gives it an advantage due to the scarcity of empirical and theoretical justification for using convex production axioms in efficiency studies.

Parametric Approach

This analytical approach to efficiency measurement is described by a known mathematical production frontier function which depends on some unknown parameters. Efficiency frontier models are classified according to how the functional form has been specified for the frontier function, the type of data that is to be analyzed and the presence of *noise* in the data (Fried *et al.,* 2008). The advantages of this approach include the fact that the estimators used have statistical properties and also there is economic interpretation of the parameters. The parametric frontier estimation is categorized into deterministic and stochastic techniques depending on how the error term is specified (Aigner *et al.,* 1977; Aigner and Chu, 1968). The stochastic technique is estimated by an econometric technique while the deterministic technique can be estimated with either mathematical programming (Aigner and Chu, 1968) or an econometric approach.

THE DETERMINISTIC FRONTIER MODEL

The non-parametric method of the deterministic approach to efficiency measurement is mostly used in efficiency studies. Following this approach means that models employed in the estimation do not account for statistical noise. The deterministic frontier production function as developed by Aigner and Chu (1968) is expressed as:

$$Y_i = f(X_i\!:\beta).\exp(-u_i)\,, u_i \geq 0$$

where $u_i$represents the technical inefficiency effect of the *ith*firm. $Y_i \leq f(X_i : \beta)$ when $u_i \geq 0$. Therefore, the technical efficiency of the deterministic frontier model is expressed as:

$$Y_i = \frac{f(X_i\!:\beta).\exp(-u_i)}{f(X_i\!:\beta)} = \exp(-u_i)$$

The foremost merit of the deterministic frontier model is that it is easy to use. However, Fried*et al.* (2008) identify the impact of super-efficient outliers as one of the main demerits of the model, stating that this could tell on the overall outcome of the analysis.

Russell and Young (1983) also criticized the deterministic frontier model for its underlying assumption that the firm decision-maker or manager controls all deviations from the efficient frontier and that these deviations are endogenous.

THE STOCHASTIC FRONTIER MODEL

The stochastic frontier model was developed by Meeusen and van den Broeck (1977) and Aigner *et al.* (1977) and it incorporates both endogenous and exogenous factors in the estimation of the efficiency of a firm. Thus, the stochastic frontier model decomposes the error term of the specified production function into two parts. One part of the error term caters for random shocks while the other accounts for the inefficiency effects (Aigner *et al.,* 1977). The advantage of the stochastic frontier model over the deterministic frontier model is that it identifies and makes a clear distinction between deviations occurring as a result of stochastic noise resulting associated with production and deviations occurring as a result of inefficiency.

Model Specification for the Stochastic Frontier Function

The stochastic frontier model specifies a stochastic frontier for cross-sectional data as:

$$Y_i = f\,(x_i;\beta)\exp\,(\varepsilon_i) = f\,(x_i;\beta)\exp(v_i - u_i), i = 1,2,\ldots..N$$

where Y_i represents the output level, $x_i$represents the vector of inputs and other explanatory variables that are associated with the firm, *β* is the vector of unknown parameters to be estimated and *ε* is the error term ($V_i – U_i$). $V_i$is the noise error term that is outside the firm's control (capturing other random effects) and $U_i$captures the non-negative inefficiency error term.

To ensure that all of the observations of efficiency lie on the stochastic production frontier or below it, U_i is non-negative ($U_i \geq 0$) (Aigner *et al.,* 1977; Coelli*et al.,* 2005; Onumah*et al.,* 2010). The technical inefficiency effect, with reference to Battese and Coelli (1995), is specified as:

$$U_i = Z_i\delta + W_i$$

where U_i represents the endogenous error term, $Z_i$the vector of explanatory variables that is associated with technical inefficiency effects, *δ* the vector of unknown parameters, and W_i the random variables, such that $W_i \geq Z_i\delta$. The technical efficiency can further be expressed as the ratio of observed output to the potential maximum output, assuming that any deviations are stochastic (Boshrabadia*et al.,* 2008).

FUNCTIONAL FORMS FOR PRODUCTION FRONTIER ESTIMATIONS

Mathematical models employed by empirical studies for estimation purposes may be specified diversely depending on the objective of the researcher. The specification of an economic model is therefore guided by the objectives and goals of the study and the conditions underlying the research. Some commonly used functional forms for production frontier analysis include the Cobb-Douglas, Translog, Leontief, Logarithmic and Spillman production functions (Griffin *et al.,* 1987). This review considers two of the most common functional forms.

The Cobb-Douglas Production Function

The Cobb-Douglas production function is a double-logarithm production model that expresses input and output variables as logarithms. The Cobb-Douglas model can be expressed generally as:

$$Y = aX^b \quad \text{(x)}$$

where *Y* represents the output, *X* the input variables with *a* and *b* being unknown parameters to be estimated. In its general form the Cobb-Douglas function is a non-linear multiplicative function that can be linearized by taking the logarithms of the variables used in the model. After applying the logarithmic transformations to linearize it, the generalized Cobb-Douglas function in equation x is expanded into:

$$In\,Q = \beta_0 + \sum_{i=1}^{n}\beta_1 In\,X_i$$

The Cobb-Douglas production function assumes constant returns to scale with elasticity of substitution equal to one. It is however limited by the assumption of constant returns to scale and this can be problematic (Hassani, 2012). Also, the function assumes a market form of perfect competition. Some efficiency studies have however employed the Cobb-Douglas production function successfully. Hassani (2012) employed the Cobb-Douglas function in time-cost analysis in the construction sector while Onumah and Acquah (2010) employed it in the estimation of productivity differentials between family and hired labour aquaculture in Ghana.

The Transcendental Logarithmic (Translog) Production Function

This production function is a generalized form of the Cobb-Douglas production function in which the number of parameters expands with increases in the number of production factors (Pavelescu, 2011). The transcendental logarithmic production function provides a second order approximation to an arbitrary twice differentiable function. This enables the testing of structural hypotheses like separability with fewer maintained restrictions than necessary. The merits of the translog function include the absence of any restrictions on the elasticities of substitution of the inputs used in production. The general translog functional form is specified as:

$$In\, Y = \beta_0 + \sum_{j=1}^{n} \beta_j \; InX_j + \frac{1}{2}\sum_{j=1}^{n}.\sum_{k=1}^{n} \beta_{jk} \; InX_j \; InX_k$$

The translog production function cannot give a second order approximation to an arbitrary weakly separable function given any input, and so is referred to as separable-inflexible (Coelli*et al.,* 2005). The translog function produces fewer parameters after imposing separability and this does not allow it to maintain flexibility. The contribution of flexible forms depends on their ability to place fewer restrictions prior to estimation and not in their approximation properties.

Criteria for Choosing Functional Forms

The purpose of analysis determines the choice of functional form; however, it is impossible to determine for any given relationship, the true functional form (Griffin *et al.,* 1987). In choosing a functional form therefore, one needs to be sure of which one is the best suited for the job at hand. One of the most important criteria for selecting a functional form is by considering how a production technology aligns with specific theoretical properties. In choosing a functional form, some hypothesis governing the analysis are chosen for testing while the other hypotheses are assumed to be true and remain testable. Therefore, in making a choice of a functional form, the model is considered useful if the hypotheses governing it is acceptable and useful. An unrestrictive functional form may however be used especially when a strong empirical or theoretical basis for the adoption of a hypothesis is absent.

Another criterion for the selection of a functional form is the availability of data and resources for computing the estimates. For instance, for functional forms that do not follow linear least square procedures for estimations, absence of adequate data for analysis may be problematic. In choosing a functional form, one may also consider issues of conformity to the data (goodness-of-fit) where a model is chosen based on data-specific considerations (Griffin *et al.,* 1987). Another method of finding the model that best fits the data is by testing nested and non-nested models (Judge *et al,* 1985).

Application-specific features of the functional form can be a quality looked into for consideration as an appropriate model. For instance, for optimization and simulation purposes, researchers might look for certain desirable features in considering the choice of a functional form. Some properties to look out for in choosing a functional form include the linearity, robustness, parsimony, and regularity of that model.

DETERMINANTS OF INEFFICIENCIES

Kumbhakhar and Lovell (2000) outline three major approaches to incorporating exogenous variables to measure technical efficiency variations. These are the initial approach, the two-stage approach and the single stage approach.

The Initial Approach

The assumption governing this approach to measuring the determinants of inefficiencies is that the exogenous factors have an effect on production. The stochastic frontier model for the initial approach is specified as:

$$InY_i = In\, f(x_i, z_i;\, \beta) + v_i - u_i$$

where Y_i, x_i,z_i and β represent the output, input variables, exogenous variables and the production parameters respectively. The vector of the exogenous variables (z_i) is assumed to influence the structure of the production function by directly influencing output. Due to the assumption that exogenous variables are uncorrelated with the error terms (v_i and u_i), variations in efficiency are not explained adequately by this model.

The Two-Stage Approach

The two-stage approach tries to link variations in the estimated efficiency to production-specific variations in the exogenous variables. The first stage of the two-stage approach estimates the production frontier parameters under independence and distributional assumptions and then regresses the estimated inefficiency effects on the exogenous variables in the second stage. This is represented as:

$$E(u_i|v_i - u_i) = g(z_i; \gamma) + \varepsilon_i$$

The two-stage approach imposes the assumption that the exogenous variables have an indirect effect on the output variable by virtue of their effect on efficiency. Unlike in the initial approach, the structure of the production technology is not influenced by the exogenous variables. the exogenous variables are deemed to affect the efficiency of production. The Ordinary Least Squares estimation method is not appropriate in this approach since the dependent variable is bound by zero and one. The two-stage approach is limited by the violations of the identical distribution of the $u_i$when the technical inefficiency effects are regressed on some specific firm's characteristics.

The Single Stage Approach

In this approach, the effects of inefficiency are defined as an explicit function of some known factors to production (Kumbhakar and Lovell, 2000). The Maximum Likelihood Estimate procedure estimates all the parameters of the productivity and inefficiency models and explains variations in the inefficiency. This approach circumvents the problem of identical distribution. Using the single stage approach, Battese and Coelli (1995) specify an inefficiency model as:

$$\mu_i = \delta_0 + \delta_i Z_i$$

where Z_i represents some socioeconomic factors that influence technical inefficiency and the δs are the parameters to be estimated.

EXOGENOUS FACTORS

Exogenous factors have implications on firm efficiency and productivity. In agriculture studies, we identify farm specific factors, farmer specific factors and institutional factors as some of the main exogenous factors. Farm and farmer specific factors include some identified socioeconomic and exogenous factors that influence the efficiency of farmers positively or negatively. These factors could either be statistically significant or otherwise depending on the data collected during the study. They include the gender, age, educational level and experience of the farmer, the farm size, seed, fertilizer and labour. Onumah*et al.* (2013) identify some other farm specific factors as access to credit, household size, extension contact and the distance between the farm and residence of the farmer.
Due to extensive efficiency studies conducted in agriculture, the relationship between some farm specific factors and efficiency are almost always predictable in their *a priori* expectations. For instance, level of education, access to credit and membership to farmer associations usually have a positive influence on efficiency and productivity.
Institutional factors are also significant determinants of farming. These are factors related to social institutions, tenancy issues and land ownership and they have bearings on the size of the field, the farming system/type and invariably the productivity.

ECONOMETRIC PACKAGES FOR EFFICIENCY ANALYSIS

In estimating different kinds of efficiency, researchers have employed the use of a diverse list of econometric tools some of which include Ox-SFAMB (as used by Onumah*et al.* (2010)), STATA, LIMDEP, GAUSS and SAS. The FRONTIER 4.1 (Coelli, 1996) and LIMDEP (Greene, 1995) are very commonly used econometric packages for efficiency analysis. The Ox-SFAMB software (Brümmer, 2003) specified under the FRONTIER 4.1 is also being widely considered for efficiency estimations. The FRONTIER 4.1 is designed specifically for stochastic frontier estimations. The LIMDEP is however more general in its usage for diverse non-standard econometric computations. For the FRONTIER 4.1 econometric tool, the estimates of efficiency are produced as a direct output from the package and this is advantageous as one can specify the assumptions of distribution for the inefficiency term estimates in a program control file (Coelli, 1996).

Conclusion

Efficiency and productivity studies are necessary in production to enable the assessment of input-use and the effectiveness of output production. Also very important in today's society, is the study of cluster economies that help to determine other endo- and exogenous factors that affect the efficiency and productivity of production. The study of the implications of clustering on efficiency and productivity leads to knowledge on how to better access positive cluster externalities and reduce negative externalities in farming, business and in industry.

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