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Estimating farmers' productive and marketing inefficiency: an application to vegetable producers in Benin

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Abstract This paper estimates the technical and marketing inefficiency of a sample of urban vegetable producers in Benin. Marketing inefficiency is defined as the failure of farmers to achieve better marketing output and is reflected in lower output price indices. The study proposes a Russell-type measure of inefficiency using a directional distance function that accounts simultaneously for the expansion of outputs and price indices and the contraction of variable inputs. A truncated bootstrap regression is used in the second stage to consistently analyze factors that underlie differences in inefficiency. The first-stage results suggest that vegetable producers are more inefficient with respect to marketing than production. The second-stage results indicate that technical inefficiency is affected by the production environment and private extension services. Marketing inefficiency is affected by the type of marketing arrangements.

Keywords Vegetables · Inefficiency · Russell-type measure · Bootstrap · Benin

JEL Classification C34 · C61 · C67 · D24 · D49

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1 Introduction

Improving the performance of the agricultural sector remains an important issue in many developing countries. This topic has been addressed by a considerable volume of work that assesses technical efficiency relative to a production frontier representing the benchmark. However, producers are different not only with respect to efficiency in the production process, but also with respect to efficiency in marketing outputs. From a farm management perspective, producers are involved in three basic activities: production, marketing and investment activities. In developing countries, investment activities are a major constraint and are problematic due to a lack of bank institutions in the agricultural sector. Farm profitability, therefore, is related not only to production efficiency, but also to the farmers' marketing strategies. Charnes et al. (1985) were the first to apply data envelopment analysis (DEA) to measure marketing efficiency. Yet, thus far, no studies have integrated the measurement of technical and marketing efficiency (Rust et al. 2004). Doing so, however, could provide insights on the efficient utilization of resources that are used in the production process and in marketing outputs, such as labor and fuels. Such insights would help farmers better target improvement in their overall efficiency. Moreover, insight into the factors that underlie the differences in technical and marketing inefficiency are required, as such information would allow governments and extension services to assist farmers in improving their performance.

In West Africa, the rapid population growth, infrastructure development and urbanization require the

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intensification of agricultural systems in urban regions. The production of vegetables in urban zones has increased over the past several years in terms of the amount of area cultivated, the number of producers and the income generated. Urban vegetable producers are largely market oriented and, generally, grow a wide range of vegetables. Although there have been quite a large number of studies on technical and allocative efficiency in sub-Saharan Africa (rice, cereals and coffee are the most commonly analyzed products), there are only a few studies related to vegetable production and marketing in West Africa (Haji 2006; Haji and Andersson 2006).

The purpose of this paper is twofold. First, this paper develops an integrated approach to assessing technical and marketing inefficiency. Marketing inefficiency, in this study, reflects the failure of farmers to achieve better marketing outputs that yield higher prices. Marketing activities involve producing better-quality outputs, as well as obtaining better prices through negotiating and putting time and effort in choosing better marketing arrangements. Our paper is the first to measure marketing inefficiency simultaneously with output- and input-oriented technical inefficiency using a Russell-type measure of inefficiency. As the resources used for production and marketing activities are not separable at the farm level (i.e., the problem of production is not separable from marketing decisions), a Russell-type measure is straightforward for measuring technical and marketing inefficiency (Färe et al. 1994). In this paper, marketing activities refer to choices regarding product quality, the negotiation process and access to the marketing channels. The inefficiency measure reflects the maximum feasible equiproportionate reduction of inputs and expansion of physical and marketing outputs. We aim at measuring marketing efficiency, where farmers can become marketing efficient by obtaining a better price for their outputs. The conceptual model of the integrated measurement of marketing and technical inefficiency is applied to a sample of urban vegetable producers in Benin. Second, this paper analyzes the determinants of urban vegetable producers' marketing and technical inefficiencies. In recent years, the bootstrap technique has become a valid approach in the semi-parametric DEA method to correct for small sample bias. Therefore, in this paper, we apply the single truncated bootstrap procedure that enables statistical inference in the second-stage regression.

The remainder of the paper is organized as follows. Section 2 describes the conceptual framework of our approach. Section 3 describes the vegetable marketing channels of urban vegetable producers in Benin. This section also presents the data, the grouping method and the construction of the variables and identifies the factors that explain technical and marketing inefficiency. Section 4 presents and discusses the results, and Section 5 provides conclusions and policy implications.

2 Theoretical framework and empirical specification

We assume that producers simultaneously allocate resources to production and marketing activities. The marketing process in a farm involves allocating resources to improving product quality, resources for negotiation and resources for improving access to different marketing channels. It is assumed that the production process affects output quantity and that marketing activities have a direct effect on output price. Hence, we assume that producers seek to improve their output prices through their marketing activities. From the producers' perspective, selling products at the highest possible price constitutes efficient marketing (Abbott and Markeham 1981). The pricing decision is at the core of every business plan, as it directly impacts the critical components of a farm's marketing strategy. Furthermore, the marketing process is likely to affect production-related decisions, such as the area allocated to each crop and whether to purchase quality-improving inputs.

Let $y \in \Re_+^r$ denote the physical output vector, $x \in \Re_+^s$ the input vector and $M \in \Re_+^r$ a vector of marketing output. As producers are assumed to decide simultaneously on the allocation of resources to production and marketing activities, the reference production technology T is the collection of all feasible input–output:

$$T(x, y, M) = \{(x, y, M) : x \,\text{can produce}\, y, M\} \tag{1}$$

The technology set is nonempty, compact and convex. We assume that the technology set allows for variable returns to scale and strong disposability of physical outputs and inputs (see Chambers 1988; Färe et al. 1994). As stated by Chen (2008), in a highly competitive business environment, producers need to provide customized and innovative products and require innovative methods of performance measurement. Indeed, the essential function of a performance measure is to assess how well activities within a process, or the outputs of a process, achieve specified goals. This implies that the reference production technology T is the collection of all feasible input–output quantity and marketing output vectors similar to the graph of the technology defined by Färe et al. (1994). The production technology captures the differences in input use, quantity of output produced, as well as differences in marketing outputs. Hence, the technology is fully characterized by the (y, M) output possibilities set.

A non-radial representation of the technology is as follows:

$$T(x, y, M) = \{(x, y, M; -g_x, g_y, g_M) : Y'\lambda \geq y + g_y, X'\lambda \leq x - g_x, M'\lambda = M + g_M, \lambda \geq 0\} \tag{2}$$

where λ is a vector of intensity variables (producer weights), which identifies the producers who determine the

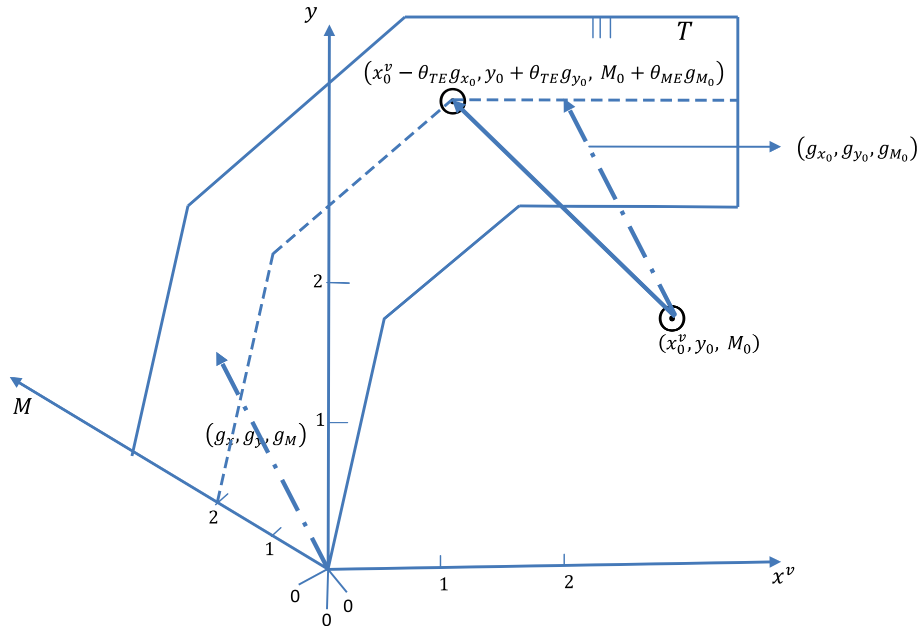

Fig. 1 Russell-type measure of technical and marketing inefficiency

production frontier. The vectors $g_x \in \Re_+^s$, $g_y \in \Re_+^r$ and $g_M \in \Re_+^r$ are directional vectors. The directional distance vector (g_x, g_y, g_M) reflects the direction in which efficiency is measured. It expands physical and marketing outputs in the directions g_y and g_M, respectively, and contracts inputs in the direction g_x. In this paper, we define technical and marketing inefficiency as a Russell-type of measure (Färe et al. 1994 p. 81, 115; Oude Lansink and Ondersteijn 2006). The Russell measure of technical and marketing inefficiency is based on maximum possible physical output, obtained marketing output and minimum required inputs in the (g_x, g_y, g_M) direction (see Fig. 1). The equality $M'\lambda = M + g_M$ in (2) implies weak disposability of marketing output. Specifically, the Russell measure of the directional distance function associated with the technology is defined as:

$$\vec{D}\left(x_i^v, y_i, M_i; g_x, g_y, g_M\right) = \max\{(\theta_{TE} + \theta_{ME}) : (y_i + \theta_{TE} g_y, x_i^v - \theta_{TE} g_x, M_i + \theta_{ME} g_M) \in T\} \tag{3}$$

where θ_{TE} is technical inefficiency $(\theta_{TE} \geq 0)$ for the i^{th} producer and θ_{ME} is marketing inefficiency $(\theta_{ME} \geq 0)$. All other variables are as defined in (1) and (2). As an efficiency measure, we are interested in the properties of the directional distance function. Following Färe and Grosskopf (2005 p. 8–10), our directional distance function satisfies the translation property and is homogeneous of degree—1 in the directional vector (g_x, g_y, g_M). The translation property condition guarantees that if output is expanded by αg_y, input is contracted by αg_x and marketing output is expanded by αg_M, then the value of the distance function will increase by 2α with $\alpha \in \Re$, i.e., $\vec{D}\left(x_i^v - \alpha g_x, y_i + \alpha g_y, M_i + \alpha g_M; g_x, g_y, g_M\right) = \vec{D}\left(x_i^v, y_i, M_i; g_x, g_y, g_M\right) - 2\alpha, \alpha \in \Re$. The homogeneity property implies that $\vec{D}\left(x_i^v, y_i, M_i; \lambda g_x, \lambda g_y, \lambda g_M\right) = \lambda^{-1} \vec{D}\left(x_i^v, y_i, M_i; g_x, g_y, g_M\right)$.[1] It is important to note that our directional distance function is a complete characterization of the technology T, that is, $\vec{D}\left(x_i^v, y_i, M_i; g_x, g_y, g_M\right) \geq 0 \Leftrightarrow (x, y, M) \in T$ (Chambers et al. 1998). As the technology T is convex, $\vec{D}\left(x_i^v, y_i, M_i; g_x, g_y, g_M\right)$ is concave in (x^v, y, M), M) (see Chambers et al. 1996 for proofs). Having established some of the properties of our measure of technical and marketing inefficiencies, we can define a producer as fully efficient in the (g_x, g_y, g_M) direction if $\vec{D}\left(x_i^v, y_i, M_i; g_x, g_y, g_M\right) = 0$, that is, if $(\theta_{TE} = 0)$ and $(\theta_{ME} = 0)$. This implies that a producer is fully efficient in the (g_x, g_y, g_M) direction if he/she is simultaneously technically and marketing efficient.

The Russell-type measure in the case of a directional distance function (DDF) model of DMU i, under the assumption of variable returns to scale, can be computed as the solution to the linear programming problem:

[1] Proof of the translation property $\vec{D}\left(x_i^v - \alpha g_x, y_i + \alpha g_y, M_i + \alpha g_M; g_x, g_y, g_M\right) = \max\{(\theta_{TE} + \theta_{ME}) : (y_i + \alpha g_y + \theta_{TE} g_y, x_i^v - \alpha g_x - \theta_{TE} g_x, M_i + \alpha g_M + \theta_{ME} g_M; g_x, g_y, g_M) \in T\} = \max\{(\theta_{TE} + \theta_{ME}) : (y_i + (\alpha + \theta_{TE}) g_y, x_i^v - (\alpha + \theta_{TE}) g_x, M_i + (\alpha + \theta_{ME}) g_M; g_x, g_y, g_M) \in T\} = -2\alpha + \max\left\{(2\alpha + \theta_{TE} + \theta_{ME}) : \left(y_i + (\alpha + \theta_{TE}) g_y, x_i^v - (\alpha + \theta_{TE}) g_x, M_i + (\alpha + \theta_{ME}) g_M; g_x, g_y, g_M\right) \in T\right\} = \vec{D}\left(x_i^v, y_i, M_i; g_x, g_y, g_M\right) - 2\alpha$. Q.E.D.

$$\vec{D}(x_i^v, y_i, M_i; g_x, g_y, g_M) = \max_{\theta_{TE}, \theta_{ME}, \lambda} (\theta_{TE} + \theta_{ME})$$

s.t.

$$\begin{aligned} & Y\lambda \geq y_i + \theta_{TE} g_y \\ & X^v \lambda \leq x_i^v - \theta_{TE} g_x \\ & M\lambda = M_i + \theta_{ME} g_M \\ & X^f \lambda \leq x_i^f \\ & N1'\lambda = 1 \\ & \lambda \geq 0 \end{aligned} \tag{4}$$

where $x^v \in \Re_+^{s_1}$ is a vector of variable inputs and $x^f \in \Re_+^{s_2}$ is a vector of fixed inputs with $s = s_1 + s_2$. All other variables are as defined in (1), (2) and (3).

Measuring marketing output (M), however, poses a serious challenge for the simple reason that it is not directly observed. Since our framework is applied to farm level data, we assume that marketing output is measured by prices. As indicated above, a higher price for outputs is obtained through better output quality and by allocating resources to improve access to higher value added markets, negotiation for higher prices and in search for better marketing channels. Hence, we assume that vegetable producers can become more marketing efficient by obtaining a better price for their outputs. This is particularly true in the case of highly perishable food products as indicated by Sexton et al. (2005), where a commodity must be sold in the current market period. We are aware that apart from marketing activities, other sources of price variation that are not accounted in the model can play a role.

In order to define the distance function, output prices are assumed to be weakly disposable, as prices cannot be expanded freely due to certain market regulations (for instance, producers and buyers agreed on the maximum output price in the previous year or period). As suggested by Färe and Grosskopf (2005 p. 52), the weak disposability assumption is used to indirectly model regulations on specific outputs. Relative to this technology, we can define a measure of inefficiency in which output quantity and prices are expanded, while, simultaneously, inputs are contracted. In our analysis, the inputs and outputs are in monetary units and prices are measured using a price index in order to reflect farmer's success in marketing outputs.

Our analysis incorporates data on multiple inputs and multiple outputs. Since there are more than 30 vegetable crops that are produced, we cannot compare farmers' marketing inefficiency based directly on the price they sell their outputs. We resolve this issue by transforming each farmer's output prices using the weighted average price index (more details are provided in the data description section). The idea of our model is to construct an appropriate reference set for each producer. The purpose of this index is to reflect prices that result from differences in market segmentation (differences in the quality of output and differences in crops produced) and differences in marketing arrangements.

The directional vectors (g_x, g_y, g_M) used in this study are the observed variable inputs, outputs and output price indices, respectively, as this allows for the inefficiency score to be given the convenient interpretation of a percentage (Chambers et al. 1998; Färe and Grosskopf 2005 p. 141). In this specification, technical efficiency refers to the achievement of the maximum potential output and the minimum potential use of variable inputs, taking into consideration physical production relationships. Marketing efficiency represents the maximum potential marketing output—measured by output price indices—a producer could obtain through his/her marketing activities given physical production relationships. The model consists of a convex combination of inputs, outputs and output price indices of the most efficient farms.

To determine why inefficiencies are present, we add a second stage to our model to account for nondiscretionary factors that influence the inefficiency scores. We add to our first-stage model a truncated bootstrap regression of the estimated inefficiencies on the environmental factors for purposes of statistical inference. A major problem in a standard two-stage approach is the dependence of the inefficiency scores, which violates the dependency assumption within the sample required by regression analysis. To resolve this problem, Simar and Wilson (2007) developed two complementary consistent procedures in the two-stage DEA approach: the double bootstrap and the single truncated bootstrap. The double bootstrap procedure facilitates statistical inference in the first and second stages. However, this technique is too complex, and it is not yet developed for the DEA estimators of the directional distance function approach. Therefore, in this paper, we adapt the single bootstrap technique, thus enabling statistical inference in the second-stage regression. The description of the algorithm of this paper is similar to Singbo and Oude Lansink (2010). The truncated bootstrap regression is defined as:

$$\begin{aligned} \hat{\theta}_{TE_i} &= z_i'\beta + \xi_{TE_i} \geq 0, \\ \hat{\theta}_{ME_i} &= w_i'\delta + \xi_{ME_i} \geq 0, \end{aligned} \tag{5}$$

where $\hat{\theta}_{TE_i}$ and $\hat{\theta}_{ME_i}$ are, respectively, technical and marketing inefficiency scores for the ith producer obtained in (4); z and w are environmental variables ($z \neq w$); β and δ are parameters to be estimated; and ξ are the error terms. The error components in this second-stage truncated bootstrap regression are probably not identically and independently distributed, since the technical and marketing inefficiency scores are derived simultaneously from the first stage non-radial Russell-type measure model. Thus, it might be preferable to stack the two regressions and estimate the parameters via seemingly unrelated regressions (SUR), allowing for the two error terms to be correlated. This would be feasible within a conventional error structure. However, the truncated-bootstrap framework that would account for possible correlation of the error terms is complex and extremely demanding from a computational perspective (Hajivassiliou 1993). As the truncated bootstrap regression consistently corrects for the correlation between the error terms and the explanatory variables in (5), we estimate each model separately to control for the within correlation in each model.

3 Data and background description of vegetable marketing channels in Benin

Data for this study were obtained from a survey conducted among 186 producers in six cities and towns in Benin. Urban vegetable production is one of the higher-value agriculture food activities in Benin. Marketing of vegetables plays an important role in the economic development of the country as the major portion of vegetables is sold in rural and urban markets through a range of marketing arrangements. Pepper, tomato, amaranth, carrot, cabbage, cucumber, solanum plants (black morelle), lettuce, onion, corchorus, okra and bitterleaf are the major vegetable crops cultivated year round on mostly small, scattered pieces of land ranging from 0.005 to 12 ha.

The distribution of vegetables is based on a private market system. Vegetables are available in the market every month of the year with significant variations in the quantity supplied. While most transactions between producers and buyers occur at the farm gate, vegetables are transferred from producers to the final consumers through conventional marketing channels, where fresh products are traded between actors who are involved in recurrent trade relationships. In contrast to the cereal market (Kuiper et al. 2003), vegetable retailers prefer to obtain their products either from the wholesaler or directly at the farm gate, as production occurs closer to the consumer. Vegetable producers market much of their produce in bulk at harvest time because of the highly perishable nature of their products. In general, producers conduct all of their sales immediately after harvest.

The supply chain of vegetables in urban areas involves two types of intermediaries, i.e., the wholesalers and the retailers. These two groups serve as the link between producers and consumers and other buyers of vegetables, though producers may also sell a portion of their products directly to consumers. As a result, farmers primarily use three channels to market their products, that is, the wholesalers, retailers and consumers.

During the last 25 years, vegetable production and marketing in Benin has experienced two significant changes. First, the sector has become increasingly concentrated. Vegetable producers are more specialized in producing traditional and non-traditional vegetables. In addition, many producers have become much larger on average. However, the market conditions in the study areas are similar and there are no differences between large and small producers in terms of being able to influence prices. This implies that differences in prices will reflect (to some extent) differences in marketing efficiency rather than simply differences in competitive conditions. Second, for the procurement of market vegetables, the buyers (wholesalers and retailers) increasingly rely on alternative marketing arrangements (AMAs), such as contracts, thus decreasing their dependency on the spot market (Akplogan et al. 2007).

The data were collected during the agricultural production year of 2009/2010 using a two-stage stratified random sampling procedure. A structured questionnaire was used and was designed in such a way that the data for specific crops and activities could be collected. To avoid or minimize measurement errors and non-response bias, specific aspects of the questionnaire were addressed two or three times in each household. With respect to farm size, our sample consists of small, medium and large farms, with medium and large farms being the majority. Questionnaire design and data collection were conducted under the supervision of the first author.

Data were obtained on more than 30 vegetable crops. Vegetables are aggregated into two groups: traditional vegetables and non-traditional vegetables. This grouping strategy is based on the classification given by Achigan-Dako et al. (2009), who asserted that traditional vegetables refer to all plant species that have been used by communities for several generations and are integrated as part of the cultural habits. Our grouping method identifies 23 non-traditional vegetables and 10 traditional vegetables, implying that vegetable farms are well diversified.[2] Our grouping method is also consistent with the categorization according to the managerial practices used by Haji and Andersson (2006).

Two outputs (traditional vegetables and non-traditional vegetables), five inputs (operating costs, land, labor, capital and water), and two Paasche weighted-average output price indices are distinguished. Output in each category consists

[2] The term non-traditional vegetables refers to species such as lettuce, cabbage, courgette, cucumber, beet, carrot, radish, turnip, french bean, melon, squash, watermelon, celery, chicory, chives, coriander, dill, fennel, garden mint, leek, overripe, parsley, rocket and thyme. Species such as tomato, solanum plants, okra, pepper, amaranth, corchorus, bitterleaf, African basil, cockscomb and onion are considered as traditional vegetables.

of the average price of crops times the quantity produced. Variable inputs represent the operating costs that include fertilizers (mineral and organic), pesticides, seeds, and other miscellaneous expenses. Fixed inputs are land, labor, capital and water. Land is measured in hectares, while labor consists of family labor and hired labor and is measured in hours. Labor is assumed to be a fixed input, as a large share of total labor consists of family labor and permanent contract labor. Capital consists of machinery and equipment and is assessed in terms of replacement cost. As water is one of the major constraints in vegetable production in urban areas, the quantity of water used for irrigation is included as a fixed input in order to make a correct representation of the production technology.

The model for computing marketing inefficiency requires output price indices that reflect the farmer's success in marketing outputs. We constructed a farm-specific price index which reflects price differences that result from differences in the quality of output as well as differences due to the negotiation process and the choice of the marketing channel. Thus, a farmer that produces high quality vegetables receives higher prices than the average farmer and is using a marketing strategy that addresses the upper market segment. For each output category, we constructed a Paasche price index P_{ik} for producer i and aggregate output $k\,(=1$ for traditional vegetables, and 2 for non-traditional vegetables); furthermore, j reflects a crop in category $j = 1, \ldots, N$. The Paasche weighted average price index of each category of producer $i\,(P_{ik})$ is computed as follows:

$$P_{ik} = \frac{\sum_{j\in k}^{n} P_{ij} q_{ij}}{\sum_{j\in k}^{n} \bar{P}_j q_{ij}} \tag{6}$$

where q_{ij} is the output quantity in kg of crop j for producer i and $\bar{P}_j$ is the average output price of crop j. For vegetable crops that are produced several times in each year, the average price in each year is collected from the producers. Price data are constructed as the average price of each crop in the last two years. It is important to notice that we fail to find a difference in price levels for the two years covered by the data. To account for the possible monthly variation in prices, we need to collect higher frequency data, but it is very difficult, in our context, to obtain this type of data.

The second stage of our procedure involves explanatory variables that influence our inefficiency estimates. This figure implies that changes in the environmental variables do not affect the shape of the distribution of inefficiency scores, but that they affect the level of inefficiency. Several variables have been considered in previous studies as possible determinants of technical and marketing inefficiencies. Among the variables used in this analysis are the following: (a) market competition, where distance to the central market is used as a proxy, (b) alternative marketing arrangements, (c) output specialization index, (d) extension services such as public and private extension visits, (e) soil fertility index, (f) amount of credit received and its squared value, (g) farm characteristics (age, gender, education and experience in farm management) and (h) city dummies. The distance between the production site and the main market-place is assumed to reflect the impact of more distant production areas on efficiency.[3] To determine whether heterogeneity in selling outlets affects marketing inefficiency, the main target of the environmental variables is the effect of alternative marketing arrangements on inefficiency. As a proxy for this variable, we use the proportion of vegetable outputs sold to wholesalers, retailers and consumers. As the proportions add up to one, two variables are included in the regression, that is, the proportion sold to the wholesaler and to the consumer. Hence, the proportion sold to the retailer serves as the reference level and the interpretation of the parameters is relative to this reference.

The specialization variable used in our inefficiency effects model is specified as a normalized Hirschman index of the concentration of output shares for each vegetable crop. This index discriminates between producers who are relatively more specialized. It is a widely used measure of concentration and was used, for example, by Al-Marhubi (2000) to specify the concentration of output shares in his analysis of export diversification and growth. Following Al-Marhubi (2000 p. 561), the normalized Hirschmann index is defined as follows:

$$H_i = \frac{\sqrt{\sum_j^{33}\left(\frac{q_j}{\sum_j^{33} q_j}\right)^2} - \sqrt{1/33}}{1 - \sqrt{1/33}} \tag{7}$$

where i is the producer index, q_j represents the producer output quantity of vegetable crop j, and 33 is the number of vegetables produced in the data set. The Hirschmann index is normalized to assume values ranging from 0 to 1. Note that a normalized Hirschmann index of 1 indicates perfect specialization. Likewise, a value closer to 0 signifies a more diversified vegetable crop production.

Agricultural extension services are considered as a single mechanism by which information on new technologies, more effective management options, and better practices can be transmitted to farmers (Owens et al. 2003). In Benin, there are two types of extension services: the national public extension services and the private extension services provided by NGOs. In general, the two types of extension agencies work separately, though in some cases, they collaborate to extend programs. Public and private

[3] Distance to market can also capture higher transportation cost.

Table 1 Descriptive statistics

	Unit	Mean	SD
Variable			
Aggregate output for traditional vegetables	10^3 CFA	2,546	6,659
Aggregate output for nontraditional vegetables	10^3 CFA	1,674	3,531
Paasche weighted average price index for traditional vegetables	Index	1.1086	0.4204
Paasche weighted average price index for nontraditional vegetables	Index	0.9145	0.3225
Variable input: Operating costs	10^3 CFA	435.583	694.455
Fixed inputs: Labor	Man-hour	313.573	129.271
Capital	10^3 CFA	509.470	829.234
Land area	ha	0.539	1.347
Water	10^3 L	4,137	1.06E+04
Environmental variables			
Gender of household head (1 = male, 0 = female)	Dummy	0.892	0.311
Years of management experience in vegetable production[a]	Year	15.102	9.459
Number of years of formal education by the producer	Years of schooling	7.344	5.335
Concentration of output shares	Hirschmann normalized index	0.530	0.137
Number of public extension service visits to the producer during the campaign 2009–2010	Number	6.41	13.184
Number of private extension service visits to the producer during the campaign 2009–2010	Number	0.866	3.547
Best soil fertility index (1 = best, 0 = others)	Dummy	0.151	0.359
Medium soil fertility index (1 = medium, 0 = others)	Dummy	0.667	0.473
Amount of credit received by the producer during the campaign 2009–2010	10^4 CFA	24.559	68.399
Distance of the farm to the central market	km	15.738	17.561
Fraction of vegetables output sold to Wholesaler	Number	0.307	0.416
Fraction of vegetables output sold to Retailer	Number	0.687	0.413
Fraction of vegetables output sold to Consumer	Number	0.006	0.042

$1US = 494.030 CFA franc in 2010 or 1 Eur = 655.957 CFA franc

[a] As the correlation of the explanatory variables showed that the Pearson partial correlation coefficients between the variable age of the household head and the number of years for management experience of the household head is high, we remove the variable age of the household head from both models

extension services are found by many authors to have complementary effects on inefficiency (Dinar et al. 2007). Since extension services focus on providing technical advice and not on the farmers' marketing strategy, we assumed a priori that extension only affects technical inefficiency. We include the number of extension visits in the specification of technical inefficiency without any prior hypothesis. We include the amount of credit received by vegetable producers and its squared value to control for size effects. We finally include city dummies as explanatory variables to control for unobserved heterogeneity across cities.[4] Since the data were collected in six cities, we set one city (city of Ouidah) as a reference and included the remaining five city dummies in both regressions.

[4] We are thankful to a referee for pointing out the importance of incorporating city dummies as explanatory variables in the regressions.

Summary statistics of the data used in this research are presented in Table 1. This table shows the inputs, outputs and the Paasche weighted average price index for each output category, as well as the summary statistics for the environmental variables that affect the magnitude of technical and marketing inefficiencies.

4 Empirical results and discussion

4.1 Inefficiency results

Table 2 provides the technical and marketing inefficiency scores. The directional vector we have chosen for g_x, g_y, and g_M consists of the observed values for x^v, y, and M, respectively, as suggested by Chambers et al. (1998). A particular advantage of our global measures of inefficiency is that they do not impose a single orientation (e.g., output-oriented or input-oriented). The outcome gives an estimate of the maximum feasible expansion in physical outputs and marketing output and the contraction in variable inputs, implying a radial interpretation of our inefficiency measures. In general, the first-stage estimates indicate that vegetable producers appear to be less technically inefficient than marketing inefficient.

The directional distance function model yielded average inefficiency scores of 0.137 and 0.25 for technical and marketing inefficiency, respectively. Approximately 54 % (101 out of 186) of the farmers are technically efficient, and 45 % (84 out of 186) attain full marketing efficiency. Only 40 % (77 out of 186) of the vegetable producers are located in the economically efficient frontier, meaning that they are simultaneously technically and marketing efficient.[5]

The average technical inefficiency score of 0.137 means that, on average, vegetable producers can simultaneously reduce their variable input use by 14 % and increase their physical output levels by 14 % if they were to become technically efficient. One can briefly compare this set of results to those reported by Singbo and Oude Lansink (2010) in their study on lowland farming system inefficiency in central Benin. In their study, Singbo and Oude Lansink (2010) applied a directional distance method to a sample of 72 lowland producers and found an average technical inefficiency score of 0.20 for integrated rice and vegetable farming system. The same results are noted by Haji (2006) when addressing the technical efficiency of 150 smallholders' vegetable farming systems of eastern Ethiopia using a non-parametric DEA method. This result is also consistent with the findings of Iráizoz et al. (2003) in their study on 46 horticultural farms in Navarra (Spain) using both a non-parametric DEA method and a parametric stochastic frontier approach. However, Rao et al. (2012) found relatively large technical inefficiency scores (average values of 0.29 and 0.44) when comparing 133 supermarket vegetable producers' to 269 traditional-channel producers in Kenya using stochastic production frontier and propensity score matching methods. The conclusion is that most of the producers who cultivate vegetables demonstrate high managerial skills on the production side, though to some extent, they over-utilize fertilizers, pesticides and other variable inputs.

Table 2 Technical and marketing inefficiency scores

Parameters	Ineff. scores ($\hat{\theta}$)	Minimum	Maximum
Technical inefficiency (TE)	0.137 (0.191)	0.000	0.695
Marketing inefficiency (ME)	0.250 (0.309)	0.000	0.971

As the DEA estimators are generally known to be sensitive to extreme observations, we also implemented the method for detecting outliers developed by Tran et al. (2010). After dropping from the sample 26 observations that have a high level of the defined weights (efficient farms), the technical inefficiency scores still range from 0 to 0.695 and the marketing inefficiency scores from 0 to 0.971, showing that the data do not contain extreme observations that could drive the frontier far from the inefficient farms

The average marketing inefficiency score of 0.25 means that, on average, vegetable producers can increase their marketing output levels by 25 % if they were to become marketing efficient. In addition, the distribution of the marketing inefficiency scores suggests that approximately a fourth (48 out of 186) of the vegetable producers relinquish at least half of the average output price. First, the result suggests that, given the level of the resources they use, vegetable producers in the urban areas of Benin are facing marketing problems. Second, the result captures the major differences in the quality of vegetables available in the markets, assuming that the best-quality vegetables bring higher prices. The high-level marketing inefficiency suggests the need for producers to incorporate a better profitable pricing strategy into their overall marketing strategy. Vegetable producers must be well prepared to develop and reinforce profitable pricing strategies, that is, to develop a proactive pricing approach. The above findings confirm, to a large extent, the normative recommendations that have been proffered within the existing marketing literature (e.g., Monroe 2003; Nagle and Holden 1995).

Our findings suggest that vegetable producers must pursue not only a high productive performance but also a profitable marketing strategy. The producers need to engage in a better profitable pricesetting behavior by paying more attention to market conditions. This implies that producers have to search for other marketing outlets or conduct better negotiations, as indicated by Jaleta and Gardebroek (2007) in their study of the tomato market in Ethiopia where farmers succumb three times more often in reducing prices from their initial price quotes. Producer organizations must assume a major role by becoming proactive actors in assisting their members to improve their marketing strategies (crop and quality differentiation).

[5] To check whether the most technically efficient producers are also the most efficient with respect to marketing, we use the Pearson partial correlation statistic. The result gives a coefficient value of 0.21 with a p value of 0.035, indicating significant correlation between technical inefficiency scores and marketing inefficiency scores. This result implies, to some extent, that technically efficient farms also have a good marketing strategy.

Table 3 Second-stage coefficients and confidence intervals at 5 % (L = 2,000)

	Coefficients	Std. Err.	Intervals, 5 %
Technical inefficiency ($\hat{\theta}_{TE}$)			
Constant	0.6807	0.1328	[−0.2092;0.5142]
Gender of the household head	−0.0244	0.0396	[−0.0276;0.1372]
Years of management experience of the household head	−0.0037**	0.0015	[−0.0071;−0.0006]
Number of years of formal education	−0.0049**	0.0024	[−0.0106;−0.0003]
Concentration of output shares	−0.2306	0.1028	[−0.2386;0.1835]
Number of public extension visits per year	−0.0012	0.0012	[−0.0046;0.0006]
Number of private extension visits per year	0.0124***	0.0038	[0.0029;0.0205]
Best soil fertility	−0.0947**	0.0460	[−0.2189;−0.0228]
Medium soil fertility	−0.1539***	0.0324	[−0.1948;−0.0558]
Amount of credit received	−0.0032***	0.0005	[−0.0044;−0.0019]
Square of amount of credit received (10^{-4})	0.132***	0.0147	[0.1007;0.161]
Distance of the farm to the central market	0.0006	0.0009	[−0.00034;0.0037]
City of Cotonou (dummy)	0.0105**	0.1004	[0.0416;0.6713]
City of Porto-Novo (dummy)	−0.4045	0.1288	[−0.5206;0.2210]
City of Sèmé-Kpodji (dummy)	0.0713***	0.1158	[0.1090;0.7980]
City of Grand-Popo (dummy)	−0.3047	0.1166	[−0.2949;0.3862]
City of Agoué (dummy)	0.0287**	0.1059	[0.0153;0.6747]
Statistics: Wald χ^2 (16) = 233.50***			
Marketing inefficiency ($\hat{\theta}_{ME}$)			
Constant	0.6866***	0.1162	[0.5159;0.9698]
Gender of the household head	−0.0798	0.0388	[−0.1403;0.0113]
Years of management experience of the household head	0.0064***	0.0014	[0.0021;0.0079]
Number of years of formal education	0.0091***	0.0023	[0.0044;0.0139]
Concentration of output shares	0.1232	0.0932	[−0.0978;0.2758]
Amount of credit received	−0.0021***	0.0004	[−0.0034;−0.0014]
Square of Amount of credit received (10^{-4})	0.0511***	0.0122	[0.0342;0.0820]
Distance of the farm to the central market	−0.0009	0.0008	[−0.0012;0.0023]
Fraction of vegetables sold to the wholesaler	−0.2032***	0.0553	[−0.4012;−0.1694]
Fraction of vegetables sold to the consumer	0.9539***	0.2636	[0.5748;1.6397]
City of Cotonou (dummy)	−0.6623***	0.0925	[−0.8929;−0.5207]
City of Porto-Novo (dummy)	−0.3910***	0.1008	[−0.6181;−0.2191]
City of Sèmé-Kpodji (dummy)	−0.2995***	0.0967	[−0.5505;-0.1582]
City of Grand-Popo (dummy)	0.1091	0.0977	[−0.1215;0.2741]
City of Agoué (dummy)	0.1508	0.0983	[−0.0486;0.3417]
Statistics: Wald χ^2 (14) = 390.23***			

*** Significance at 1 % level, ** Significance at 5 % level, * Significance at 10 % level

4.2 Determinants of inefficiency

The second stage of the model uses the inefficiency scores and regresses them on non-discretionary variables. The truncated bootstrap regression model results are presented in Table 3. The two models are strongly significant with a Wald χ^2 value of 390.23 and 233.50 for the marketing inefficiency and technical inefficiency models, respectively.

Technical inefficiency in urban vegetable production is strongly related to ten variables: soil fertility (best and medium soil fertility types), amount of credit received by producers and its squared value, private extension service visits, years of management experience of the household head, the number of years of formal education by the producer along with three city dummies. The estimated coefficients of the soil fertility index are statistically significant and negatively related to the technical inefficiency measure. The best fertility type reduces technical inefficiency, implying that farmers producing vegetable crops on sandy soil use more variable inputs (especially fertilizers) and achieve lower output levels than farmers producing crops on loamy soil.

The results in Table 3 also show that private extension services contribute positively to technical inefficiency. This finding could be attributed to private extension service agents who mainly focus on the worst-performing producers and provide less attention to farmers who perform well. In practical terms, this suggests that vegetable producers who are not performing well are those searching for solutions to specific management problems, such as disease control or yield management, and that they need advice. The insignificant effect of public extension services is surprising but could be interpreted as an indirect effect of farmers' behavior against public extension services[6] or the selection bias in targeting farmers. In addition, this result may suggest that public extension services do not provide useful technology messages due to a shortage of qualified staff. In addition, the negative effect of the amount of credit the producer receives implies that access to credit reduces technical inefficiency. This result suggests that credit allows vegetable producers to purchase better quality inputs and services or to close the technology gap by investing in new technologies. Furthermore, the positive effect of the squared value of the amount of credit received by vegetable producers on technical inefficiency yields an U-shaped relationship and indicates the presence of an internal optimum of credit. This result implies that there is a size effect of the credit and increasing the amount of credit ultimately leads to overinvestment in inputs and technology (increasing technical inefficiency). As the average amount of credit received in the agricultural year 2009–2010 by producers was 245 10^3 CFA franc and ranged from 0 to 5 10^6 CFA franc, this finding means that the loan must be adapted and be compatible with vegetable production constraints in order to control for the overinvestment effect. This result is in line with a criticism of the role of microfinance in agricultural production, that is, credit does not really improve agricultural production (Cole 2009). Furthermore, the results indicate that formal education and additional years of management experience in vegetable farming resulted in lower technical inefficiency. This result implies that upgrading the producers' level of education and farming skills would lead to better performance in vegetable production as found by Singbo and Oude Lansink (2010). With respect to technical inefficiency effects, three out of the five city dummies have large significant effects. This result is consistent with the finding of Rao et al. (2012) and Sherlund et al. (2002) that region dummies capture differences in environmental conditions that likely affect agricultural production. Specialization has an insignificant effect on technical inefficiency, although a negative effect was expected, a priori (see also Coelli and Fleming (2004) for Papua New Guinea).

Marketing inefficiency is strongly related to nine variables: marketing arrangements (fraction of output sold to wholesaler and fraction of output sold to consumer), years of management experience, number of years spent in formal education, amount of credit received by producers and its squared value, and three out of the five city dummies. The negative effect of selling to wholesalers suggests that increasing the share of output sold to wholesalers while reducing the share to retailers (and keeping the share to consumers fixed) would lead to lower marketing inefficiency. In contrast, the positive effect of selling to consumers indicates that increasing the share of output sold to consumers while reducing the share to retailers (and keeping the share to wholesalers fixed) would lead to an increase in marketing inefficiency. As retailers are in direct contact with consumers (and they know the preferences of final consumers), this result implies that better quality products go to retailers, and the long-term relationship with wholesalers results in higher prices to producers. This is because resellers (wholesalers and retailers) have long-term contracts with producers and can sell their products on time. This result implies that vegetable producers should diversify their marketing outlets to increase their marketing efficiency. As indicated by many authors, producers who rely completely on wholesalers may have weak bargaining power (Haji and Andersson 2006; Jaleta and Gardebroek 2007). As producers are often concerned about maintaining a good relationship with their customers to secure their selling opportunities in the long term, the customers may take a lower price for granted (Lancioni 2010). The negative effect of the city dummy indicates that marketing inefficiency is lower in most of the main vegetable production areas relative to the base category. In fact, Cotonou, Sèmé-Kpodji, Porto-Novo and Grand-Popo are the main vegetable production cities in Southern Benin. The result implies that vegetable producers who are located in minor zones have a weakened bargaining position due, in part, to the short-term life of the products.

In addition, we found that years of management experience of the household's head and the number of years spent in formal education positively affect marketing inefficiency, thus implying that more experienced producers have decreased bargaining power and generate a lower price for their products. Singbo and Oude Lansink (2010) also found the same results on allocative inefficiency for lowland producers in Central Benin. The negative impact of the amount of credit received suggests that microfinance in agriculture helps farmers improve their market

[6] We also experimented with the joint effect of public and private extension services to search for the complementary effect on technical inefficiency, but the results are not statistically significant.

Table 4 Marginal effects of inefficiency effects model variables

	Coefficients	Std. Err.	$P > \|z\|$
Technical inefficiency $(\hat{\theta}_{TE})$			
Years of management experience of the hozusehold head	−0.0034**	0.0013	0.013
Number of years of formal education	−0.0071**	0.0022	0.001
Number of private extension visits per year	0.0058*	0.00348	0.091
Best soil fertility	−0.0929**	0.03605	0.010
Medium soil fertility	−0.0809**	0.03049	0.008
Amount of credit received	−0.0031***	0.00053	0.000
Square of Amount of credit received (10^{-4})	0.128***	0.0	0.000
City of Cotonou (dummy)	0.2592**	0.1088	0.017
City of Sèmé-Kpodji (dummy)	0.5065***	0.1486	0.001
City of Agoué (dummy)	0.3206**	0.1355	0.018
Marketing inefficiency $(\hat{\theta}_{ME})$			
Years of management experience of the household head	0.0052***	0.0015	0.000
Number of years of formal education	0.0070**	0.0023	0.003
Amount of credit received	−0.0029***	0.0005	0.000
Square of Amount of credit received (10^{-4})	0.075***	0.0	0.000
Fraction of vegetables sold to the wholesaler	−0.2978***	0.0573	0.000
Fraction of vegetables sold to the consumer	1.5172***	0.2603	0.000
City of Cotonou (dummy)	−0.6266***	0.0664	0.000
City of Porto-Novo (dummy)	−0.2358***	0.0605	0.000
City of Sèmé-Kpodji (dummy)	−0.2312***	0.0639	0.000

The marginal effect of each variable is evaluated at their mean value and discrete change of the dummy variable from 0 to 1

*** Significance at 1% level, ** Significance at 5% level, * Significance at 10% level

participation. The positive effect of the squared value of the amount of credit producers receive, however, points out the size effect of credit.

As the parameter estimates for the inefficiency model presented in Table 3 only indicate the direction of the effects these variables have upon inefficiency levels, we estimate the contributions of these variables to the levels of inefficiency. The contributions are determined by the marginal effects, and we use the partial differentiation of the inefficiency predictors with respect to each of the inefficiency variables (Wilson et al. 2001; Zhu and Oude Lansink 2010). Following Cameron and Trivedi (2009 p. 527), the marginal effect of a variable that is left-truncated at 0 is defined as follows:

$$\frac{\partial E\left(\hat{\theta}_{TE}\middle|z,\hat{\theta}_{TE}>0\right)}{\partial z} = \left\{1-\frac{z'\hat{\beta}^*_{TE}}{\hat{\sigma}^*_{TE}}*\frac{\phi\left(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE}\right)}{\Phi\left(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE}\right)}-\left[\frac{\phi\left(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE}\right)}{\Phi\left(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE}\right)}\right]^2\right\}\hat{\beta}^*_{TE} \tag{8}$$

where $\hat{\theta}_{TE}$ is the technical inefficiency estimate, z is an explanatory variable, $\hat{\beta}^*_{TE}$ are the consistent coefficients of the explanatory variables obtained from the truncated bootstrap regression, $\hat{\sigma}^*_{TE}$ is the standard deviation of the error term, $\phi(\cdot)$ is the standard normal distribution, and $\Phi(\cdot)$ represents the standard normal cumulative distribution function. We also compute the marginal effects for the case of marketing inefficiency. In Table 4, we only report the contributions of the variables that are statistically significant in Table 3.

First, the marginal effect of the soil fertility index on technical inefficiency scores is −0.09 and −0.08 for best and medium soil fertility, respectively, suggesting that producers who farm poor land have an expected increase of approximately 0.08 in their technical inefficiency, most likely because they use more mineral and organic fertilizers to facilitate intensive cultivation. Second, for each additional private extension visit, the expected technical inefficiency of a producer would increase by 0.5 %. As previously indicated, this suggests that private extension addresses practical problems associated with the use of inputs, indicating that extension visits help the worst performing producers focus on their management strategy. Our finding is consistent with the finding of Dinar et al. (2007). The policy implication of the results on extension services is that private extension improves the management skills of the worst-performing producers. Third, farm debt is found to enhance technical efficiency, indicating a unit increase in the amount of credit to producers would decrease technical inefficient by 0.31 %. However, producers must pay attention to the size effect of the amount of the credit receives as there is an internal optimum level.

The marginal effect of the variable fraction of vegetables sold to wholesalers is −0.29, implying that a unit increase in fraction of vegetable sold to wholesalers associated with a unit decrease in fraction of vegetable sold to retailers (while keeping the fraction of output sold to consumers fixed) would decrease marketing inefficiency by 0.29. The marginal effect of the variable fraction of vegetables sold to the consumer indicates that a unit increase in the share of vegetables sold to consumers associated with a unit decrease in the share of output sold to retailers (while keeping the share of vegetables sold to wholesalers fixed) would increase largely marketing inefficiency. This result could be one of the reasons justifying the fact that the quantity of output sold to consumers is lower than the quantities sold to wholesalers and retailers. Because the vegetable market is characterized by a large number of retailers, this result implies that the long-term relationship of producers with wholesalers and retailers helps producers obtain higher prices. The results of this paper stress the evidence that marketing activities are also important for vegetable producers in their production management strategy.

5 Conclusions

This study estimates the technical and marketing inefficiency of a sample of urban vegetable producers in Benin. Marketing inefficiency is defined as the failure of farmers to achieve better marketing output. Marketing activities involve producing better quality output, as well as better prices obtained through negotiating and putting time into choosing better marketing arrangements. In this paper, the differences in marketing inefficiency capture major differences in the marketing activities, with better marketing output bringing higher prices. A price index is constructed to measure marketing output. The study proposes a Russell-type measure of inefficiency using a directional distance function that accounts simultaneously for the expansion of outputs and marketing output and the reduction of variable inputs. The results indicate that producers are more inefficient in marketing (25 %) than in production (14 %). Additionally, the results suggest that farmers vary widely in their technical and marketing inefficiency.

The truncated bootstrap regression of the determinants of the two inefficiency terms shows that soil fertility negatively affects technical inefficiency. However, it should be noted that decreasing technical inefficiency by improving soil fertility will be a tedious and costly process that may take up to several years. Another important finding that emerges from our analysis is that producers using wholesaler and retailer marketing arrangements are more marketing efficient than those selling directly to consumers. The result also suggests that private extension service agents mainly focus on the worst-performing producers.

The results imply that agricultural policies can improve the capacity of producers to use the available technology more efficiently. In conclusion, even though it is important to reduce the technology gap and improve the managerial skills of producers, agricultural policy must be accompanied by increasing market participation of farmers and market access to increase the economic feasibility of farming.

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