Assessing the impact of crop specialization on farms' performance in vegetables farming in Benin: a non-neutral stochastic frontier approach

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Abstract. A non-neutral stochastic distance function model is used to examine whether output specialization has an impact on the economic performance of vegetable producers in Benin. Specialization is assumed to have an effect on the production frontier and on the distance to the production frontier (technical inefficiency). The technology is found to exhibit diseconomies of scope, indicating that vegetable producers have an incentive for specialization. At the same time, the degree of specialization has a positive effect on technical efficiency. From a policy perspective, the findings imply that current government policies to encourage diversification may lead to a lower performance.

Keywords: Farm performance; Specialization; Impact; Input distance function; Non-neutral stochastic frontier; Benin

Introduction

Over the last four decades, agricultural productivity has been growing at fairly high rates in most regions of the world, reflecting the important role played by innovations in agriculture. However, Sub-Saharan African countries are still far behind (Chavas 2011; Fuglie 2008). The main cause of the low levels of agricultural productivity in Sub-Saharan Africa is the ineffective establishment of agricultural R&D institutions to sustain productivity growth. This suggests the need for a more selective strategy that can help to increase the competitiveness of agriculture and the viability of small-scale farms in Sub-Saharan Africa. It is worth noting that Sub-Saharan African countries are categorized as agriculture-based countries in which agriculture contributes to approximately one third of overall GDP (Byerlee et al 2009). Additionally, to reduce poverty and secure food needs in Sub-Saharan Africa, there is a growing interest in green revolution through diversifying production toward higher-value outputs. Vegetables in West Africa are an important crop and its importance is increasing over time. As fresh vegetables are characterized by high elasticity of demand, there is overwhelming evidence that vegetable production can contribute importantly to economic growth and food security. In Benin's vegetable sector, a large majority of farms produce both traditional and non-traditional vegetables, indicating that multi-output farms are the rule rather than the exception. By producing both categories of crops instead of only one, the farm may be able to reduce risk. For example, in some periods of the year, low revenues from traditional vegetables may be counterbalanced by relatively high revenues from non-traditional vegetables.

Another benefit associated with diversification is the complementary use of inputs on the farm (economies of scope). Diversification allows for more efficient use of inputs that can be used in different production processes (Teece 1980). However, other studies have shown that specialization in crops allows operators to exploit scale economies. Moreover, specialized operators have better opportunities to fine-tune their skills (Oude Lansink and Stefanou 2007). To the best of our knowledge no studies in West Africa explore the direct impact of horizontal crop choice strategies on producers' multi-output performance.

Most studies on the impact of specialization on technical efficiency regress the technical efficiency scores obtained from a stochastic frontier model on a specialization index using one- or two-stage procedures (Coelli and Fleming 2004; Rahman and Rahman 2008). This technique of measuring the effect of specialization on technical efficiency assumes a neutral effect of specialization, i.e. the composition of outputs is independent of the production process. The neutral specification ignores the adjustment of inputs with different output choices. In a multiple-output production technology the effects of specialization on technical efficiency may be related to input use, indicating that the effect of crop composition on technical efficiency is non-neutral. The non-neutral frontier model assumes that the method of application of inputs as well as the level of inputs (i.e. scale of operation) determine the potential output composition (Dinar et al 2007; Huang and Liu 1994; Karagiannis and Tzouvelekas 2009).

The objective of this paper is twofold. The first is to evaluate the causal effect of specialization on technical efficiency. The second objective is to investigate the presence or absence of economies of scope in vegetables farming. The non-neutral stochastic frontier approach is adopted to estimate the effect of specialization on production technology and technical efficiency. This flexibility of the model allows direct computation of a measure of economies of scope by exploiting the duality theory between the cost function and the input distance function.

The rest of this paper is organized as follows. Section 2 discusses the conceptual framework and our modelling approach. The data and the empirical specification are described in Section 3. The empirical results are discussed in Section 4 and the paper concludes in section 5.

Conceptual framework and Modeling approach

Distance Function

To explore the impact of crop diversification vs. specialization on the production process (i.e. on the shape of the production frontier) and on technical efficiency, we require a multi-output, multi-input specification of the technology. Distance functions developed by Shephard (1953; 1970) are shown to be a convenient way to represent a multiple-input multiple-output production technology (Coelli and Perelman 1996; Färe and Primont 1995; Morrison-Paul and Nehring 2005). Such a specification may be characterized from the output or input perspective. Vegetable producers are likely to have more control over inputs rather than outputs, so input orientation is used here.

The input requirement set $L(y)$ represents the set of all input vectors, $x \in \Re_+^K$, which can produce the output vector $y \in \Re_+^M$:

$$L(y) = \{x \in \Re_+^K \ : x\ can\ produce\ y\} \tag{1}$$

This relationship can be used to develop an estimable form of an input distance function. The input distance function $D^I(x,y)$ identifies the quantity of X necessary to produce Y, conditional on $L(y)$. More formally, as developed by Färe and Primont (1995):

$$D^I(x,y) = max\left\{\rho: \left(\frac{x}{\rho}\right) \in L(y)\right\} \tag{2}$$

where ρ is a positive scalar "distance" by which the input vector can be deflated.

$D^I(x,y)$ can be interpreted as a multi-output input-requirement function allowing for deviations (distance) from the frontier. It gives the maximum amount by which an input vector can be radially contracted while still being able to produce the same output. The input distance function is greater than or equal to one if the input vector is an element of the feasible set, $L(y)$. The distance function is equal to unity if x is located on the boundary of the input set. $D^I(x,y)$ is assumed to be non-decreasing, positively linearly homogenous and concave in inputs and non-increasing in outputs (Kumbhakar et al 2008). Thus, all the deviations from the frontier are interpreted in terms of technical efficiency, TE. The input-contracting view of technical efficiency leads to the following definition:

$$TE^I(x,y) = [D^I(x,y)]^{-1} \tag{3}$$

This measure assumes values in the interval $(0,1]$ and the points for which $D^I(x,y)=1$ define the boundary of the input requirement set and can be interpreted as the proportion of the observed inputs that could be used to produce the same amount of output (Kumbhakar and Lovell 2003, p. 50). To empirically estimate this function, linear homogeneity with respect to inputs must be imposed. This can be accomplished by normalizing by one input, i.e. $D^I(w x,y)=w D^I(x,y)$ for any $w>0$, so if w is set at $1/x_1$, $D^I(x,y)/x_1 = D^I(x/x_1, y) = D^I(x^*,y)$, where $x^* = x/x_1$.

Suppose that we have data on inputs and outputs for a sample of farms. Then, for producer i we get:

$$TE_i^I = [D^I(x_i,y_i)]^{-1}e^{-v_i} \Leftrightarrow lnD^I(x_i,y_i) = -lnTE_i^I - v_i \quad (4)$$

where v_i is a white-noise error term. From the above homogeneity property, we have:

$$lnD^I(x_i,y_i) = lnD^I(x_i^*,y_i) + lnx_1 \Leftrightarrow -lnx_1 = lnD^I(x_i^*,y_i) - lnD^I(x_i,y_i) \quad (5)$$

with $x_i^* = \frac{x_i}{x_1}$ and x_1 being the normalizing input. Substituting (4) in (5) we get an estimable form of the input distance function:

$$-lnx_1 = lnD^I(x_i^*,y_i) + lnTE_i^I + v_i = lnD^I(x_i^*,y_i) - u_i^I + v_i \quad (6)$$

where $u_i^I = -lnTE_i^I$ is treated as an one-sided error term. The equation can be estimated econometrically using maximum likelihood techniques, assuming that v_i is independently and identically distributed random variable, $N(0,\sigma_v^2)$. However, as output crop composition influences both the production frontier and the efficiency with which producers utilize the resources, a modified non-neutral approach developed by Huang and Liu (1994) has to be employed. In reality, technical efficiency is dependent on the input choices and the method of application of inputs. Some vegetables may need more inputs and require more management skills than other vegetables. Following Alvarez et al (2006) and Dinar et al (2007), u_i^I is modeled as:

$$u_i^I = g(z_i;\delta) + \varepsilon_i, \tag{7}$$

where z is a vector of explanatory variables which includes an output specialization index, interactions between this index and the elements of x_i, and farm-specific characteristics (e.g. demographic, socio-economic, etc.) (Dinar et al 2007; Huang and Liu 1994); δ is a vector of parameters to be estimated and ε is a random error referring to the unexplained or residual technical efficiency. The requirement that $u_i^I = g(z_i;\delta) + \varepsilon_i \geq 0$ is met by truncating ε_i from below such that $\varepsilon_i \geq -g(z_i;\delta)$, and ε_i is assumed to be an independently, but not identically distributed random variable with $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$[1]. Substituting equation (7) into equation (6) yields:

$$-lnx_1 = lnD^I(x_i^*, y_i) + v_i - [g(z_i;\delta) + \varepsilon_i], \tag{8}$$

The specification of the efficiency model allows for a non-neutral shift of observed input from the frontier. The assumptions imposed on u_i^I and ε_i are consistent with $u_i^I \sim N^+(g(z_i;\delta), \sigma_u^2)$ (Battese and Coelli 1995), and that v_i and u_i^I are distributed independently (Kumbhakar and Lovell, 2003 p. 267). The first term on the right-hand side of equation (8) is

[1] In the spirit of Huang and Liu (1994), ε_i is assumed to follow a normal distribution with zero mode, truncated from below at a variable truncation point $[-g(z_i;\delta)]$, which allows $\varepsilon_i \leq 0$, but enforces $u_i^I \geq 0$.

the change in the frontier quantity of inputs; the g(·) function gives the change in the distance to the frontier i.e. technical efficiency. The information contained in the first right-hand side term can be used to test whether economies of scope exist. The log likelihood function of the above model is a straightforward extension of the Huang and Liu (1994) and can be found in Kumbhakar and Lovell (2003 p. 270).

A few comments are in place here. First, our production frontier estimation in (8) yields two effects of crop specialization on input uses. The first partial derivative of the input distance function defined in (8) with respect to one output is assumed to be negative, implying that an extra unit of output *ceteris paribus* reduces the amount by which the input vector has to be deflated to reach the production frontier (Coelli and Fleming 2004). The dual relation between cost function and the input distance function can be exploited to derive a measure of economies of scope (or cost complementarities) without requiring estimates of the parameters of the cost function (Hajargasht et al 2008). This approach has the advantages that the estimation of an input distance function does not require behavioral assumptions, such as cost minimization, nor does it require access to input price data, which are not available in our case (especially capital and land).

Second, our non-neutral specification gives a marginal contribution of output specialization on technical efficiency and varies with the farm's input utilization. It is important to indicate that our model is different from the one used by Rahman (2009) to explain the effect of diversification on technical efficiency. Rahman assumed a neutral specification where the marginal effect of crop diversification on technical efficiency is constant. Since the Huang and Liu (1994) paper, in which a neutral specification is demonstrated to suffer from misspecification, the non-neutral stochastic frontier model is preferred to a neutral model in many empirical applications (Alvarez et al 2006; Dinar et al 2007; Karagiannis and Tzouvelekas 2009). These authors argued that the conventional formulation and estimation of the stochastic frontier production function may not be appropriate in identifying the sources of technical inefficiency in production. Also, Dinar et al (2007) have shown that the hypothesis of a neutral shift in the production frontier is strongly rejected.

For the empirical implementation, we assume that the input distance function is approximated by a Translog. The Translog is a flexible functional form which approximates any twice differentiable function without imposing a priori restrictions on the production technology. However, a complication arises with the ‘traditional’ Translog specification because some producers in the sample are perfectly specialized in one category of vegetables (i.e. traditional or non-traditional vegetables). For this reason a modified Translog function is used in which vegetable outputs are adjusted according to the Battese (1997) transformation (see Tsekouras et al 2004). Moreover, variables related to production conditions are included in the production frontier model (see e.g. Dinar et al 2007; Sherlund et al 2002). The empirical model is given by:

$$ln\, D_i^I/x_{1,i} = \beta_0 + \sum_d^D \beta_d F_{di} + \beta_1 D_{1i} + \beta_2 D_{2i} + \sum_k^K \beta_{k^*} lnx_{ki}^* + \frac{1}{2}\sum_k^K \sum_l^K \beta_{k^*l^*} lnx_{ki}^* lnx_{li}^* + \sum_m^M \beta_m lny_{mi} + \frac{1}{2}\sum_m^M \sum_n^M \beta_{mn} lny_{mi}\, lny_{ni} + \frac{1}{2}\sum_k^K \sum_m^M \beta_{km} lnx_{ki}^*\, lny_{ni} \qquad (9)$$

where x^*s are input quantities normalized by x_1, ys are outputs, Fs are physical production variables, and i indexes farms. D_1 is a dummy variable for traditional vegetable production with $D_1 = 1$ if $y_{Trad} = 0$ and $D_1 = 0$ if $y_{Trad} > 0$; and $y_1 = Max(y_{Trad}, D_1)$. Similarly, D_2 is a dummy variable for non-traditional vegetable production with $D_2 = 1$ if $y_{NTrad} = 0$ and $D_2 = 0$ if $y_{NTrad} > 0$; and $y_2 = Max(y_{NTrad}, D_2)$. Using (8), we obtain the following estimable form:

$$-lnx_{1,i} = \beta_0 + \sum_d^D \beta_d F_{di} + \beta_1 D_{1i} + \beta_2 D_{2i} + \sum_k^K \beta_{k^*} lnx_{ki}^* + \frac{1}{2}\sum_k^K \sum_l^K \beta_{k^*l^*} lnx_{ki}^* lnx_{li}^* +$$

$$\sum_m^M \beta_m lny_{mi} + \frac{1}{2}\sum_m^M \sum_n^M \beta_{mn} lny_{mi}\, lny_{ni} + \frac{1}{2}\sum_k^K \sum_m^K \beta_{km} lnx_{ki}^*\, lny_{ni} - u_i^I + v_i \qquad (10a)$$

The modified non-neutral efficiency regression with interactions is given by:

$$u_i^I = \delta_0 + \delta_I Spe_i + \sum_k^K \delta_{Ik} Spe_i lnx_{ki}^* + \sum_j^J \delta_{Ij} Spe_i A_{ji} + \varepsilon_i \qquad (10b)$$

Spe refers to specialization index and As are farm characteristics; x^*s are the same as defined in (9).

From (10b), the marginal effect of output crop specialization on the expected production efficiency is a function of the normalized inputs, farm characteristics and environmental variables. The marginal effect is given in Huang and Liu (1994), Kumbhakar and Lovell (2003, p. 270) and Wang (2002), and is:

$$\frac{\partial lnE(-u_i^I|\varepsilon_i)}{\partial Spe} = \psi\left[\delta_I + \sum_k^3 \delta_{Ik} lnx_{ki}^* + \sum_j^4 \delta_{Ij} A_{ji}\right] E(exp\{-u_i^I\}|\varepsilon_i) \qquad (11)$$

where

$$\psi = \left[\sigma_\varepsilon + \frac{\phi(\xi)}{1-\Phi(\xi)} - \frac{\phi(\sigma_\varepsilon+\xi)}{1-\Phi(\sigma_\varepsilon+\xi)}\right]\frac{1}{\sigma_\varepsilon},$$

$$\xi = \frac{\delta_0+\delta_I Spe_i+\sum_k^3 \delta_{Ik} Spe_i lnx_{ki}^* + \sum_j^4 \delta_{Ij} Spe_i A_{ji}}{\sigma_\varepsilon},$$

$$E(exp\{-u_i^I\}|\varepsilon_i) = exp\left[\sigma_\varepsilon\left(\xi + \frac{1}{2}\sigma_\varepsilon\right)\right]\frac{1-\Phi(\sigma_\varepsilon+\xi)}{1-\Phi(\xi)},$$

where E is the expectation operator, ϕ and Φ are the probability and cumulative density functions of a standard normal distribution, respectively.

Economies of scale and Economies of scope

From equation (10a), the input elasticity for output y_m, $-\varepsilon_{D^I,y_m} = -\partial lnD^I/\partial lny_m = \partial lnx_1/\partial lny_m = \varepsilon_{x,y_m}$, represents the percent change in x_1 from a 1% change in y_m, holding all input ratios x^* (and thus input composition) constant. The scale elasticity can be calculated as the negative sum of the input-output elasticities; that is, $-\varepsilon_{D^I,y} = -\sum_1^M \partial lnD^I/\partial lny_m = \sum_1^M \partial lnx_1/\partial lny_m = \sum_1^M \varepsilon_{x,y_m} = \varepsilon_{x,y}$. The measure of scale economies is indicated by the short-fall of $\varepsilon_{X,Y}$ from unity.

In a multiproduct production technology, economies of scope exist when for outputs y_1 and y_2, the average cost of joint production is less than the cost of producing each output separately (Cowing and Holtmann 1983; Panzar and Willig 1981; Teece 1980). That is, economies of scope are measured by:

$$EOS = C(y_1, 0) + C(0, y_2) - C(y_1, y_2) \tag{12}$$

where $C(y_1, y_2)$ is the variable cost of producing both outputs simultaneously and $C(y_1, 0)$ and $C(0, y_2)$ denote the variable costs of producing the two outputs separately. Economies of scope exist if *EOS* > 0, in which case the costs of producing both outputs separately is higher than the cost of producing them jointly.

More generally, a sufficient condition for the presence of economies of scope between outputs i and j is:

$$\frac{\partial^2 C(\cdot)}{\partial y_i \partial y_j} < 0, \text{ for } i \neq j \tag{13}$$

where $C(\cdot)$ is the variable cost function. This expression implies that the cost function exhibits cost complementarities.

The input distance function and the cost function are dual to one another, meaning that the information contained in the input distance function about the production technology is identical to the cost function (Färe and Primont 1995, p. 47-48). In this study, economies of scope are measured using a primal input distance function. Consequently, we use the dual measure of economies of scope approach developed by Hajargasht et al (2008). In this paper, the derivative-based measure of economies of scope is obtained by exploiting the duality between the shadow cost function and the input distance function. Focusing on the sufficient condition in (13), they derived a general expression to calculate the economies of scope between outputs i and j using the derivatives of the input distance function as follows:

$$C_{yy} = C\{D_y^I D_y^{I\prime} - D_{yy}^I + D_{yx}^I[D_{xx}^I + D_x^I D_x^{I\prime}]^{-1} D_{xy}^I\} \quad (14)$$

where subscripts denote partial differentiation.

From this equation, one can find that information on the sign of the second cross partial derivatives of outputs, $D_{yy}^I(i,j)$, is not sufficient to conclude if scope economies exist or not. As shown by Hajargasht et al (2008), if the technology satisfies certain restrictions, such as input homotheticity or global constant returns to scale, simpler expressions are obtained. A value of (14) less than zero (i.e., $C_{yy}/C < 0$) indicates the presence of economies of scope, meaning that the vegetable producer has an incentive to diversify. In contrast, a value greater than zero (i.e., $C_{yy}/C > 0$) represents diseconomies of scope, implying that the producer has an incentive to specialize in the production of one output category.

Data and Specification of the model variables

Data used in this study are part of a broader survey on the structural characteristics of the vegetable sector in southern Benin. The survey is based on farm-level cross-section data for the agricultural year 2009/2010. A multistage stratified random sampling technique was employed to locate the departments, the cities/towns in each of the four departments, and the sample households. Data are available for a total of 239 households[2]. Vegetable producers are usually involved in producing two categories of vegetables, i.e. traditional vegetables and non-traditional vegetables. The data set contains 23 non-traditional (y_{NTrad}) vegetable crops and 10 traditional (y_{Trad}) vegetable crops (see Achigan-Dako et al 2009 for detail on vegetables grouping). Four inputs are distinguished: material cost (x_{Mat}) that include fertilizer, pesticides, seeds, and other miscellaneous expenses; farm labour in hours (x_{Lab}); capital (x_{Cap}) measured in replacement cost and farmland in hectares (x_{Land}). Two soil fertility indicators (dummy) variables are used as additional variables in the specification of the distance function.

The specialization variable 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:

[2] The sample producers were selected based on the information on the total number of vegetable producers including their farms size categories, which were obtained from a census survey in each city/town. Then a stratified random sampling procedure was applied using a formula from Whitley and Ball (2002) with a 5% error limit.

$$H_i = \frac{\sqrt{\sum_j^{33}\left(\frac{q_j}{\sum_j^{33} q_j}\right)^2} - \sqrt{1/33}}{1-\sqrt{1/33}} \quad (15)$$

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.

Based on the existing literature, farmers' socio-economic characteristics are included in the model. These are: producers' education ($EDUC$), and farming experience (EXP). Most empirical studies found that farm experience and producer education have the strongest impact on the producer management practices. For example, Pope and Prescott (1980) found that less experienced farmers (or younger farmers) are more specialized as they may start small and specialized operations, and perhaps become more diversified as they expand their operations. Katchova (2005) found that more educated farmers have higher excess farm values. The ratios of the amount of credit received by producer over total revenue ($MCRED$), and the proportion of vegetables sold to wholesaler ($WHOLE$) are included to represent socioeconomic characteristics of farms. Vegetable cultivation requires more purchased inputs such as fertilizers, pesticides, and irrigation water, increasing the need for liquidity in hand. Vegetable cultivation also demands more labour than field crops, such as cereals and a large proportion of labour in vegetable cultivation is hired labour (Ali and Abedullah 2002). All these conditions increase the demand for liquidity in vegetable production. Consequently, more loans are required to finance vegetable production. Vegetables have a shorter shelf life than cereal crops, so strong relationships between producers and buyers are essential to ensure a timely delivery to the market. Hence, the proportion of vegetable output sold to wholesaler is included in the model as an explanatory variable. Table 1 presents summary statistics for all farms. Aggregate non-traditional vegetable outputs represent 55% of the total vegetable output share, meaning that producing non-traditional vegetables is one of the strategic decisions made by producers.

In our model specification (10a), capital is set as the normalizing input x_1 so that all other inputs are represented relative to capital. All input and output variables were mean-corrected prior to estimation, so that the coefficients of the first-order terms can be directly interpreted as distance elasticities evaluated at the geometric mean of the data. That is, each output and input variable has been divided by its geometric mean.

Table 1. Descriptive statistics of the variables[a] ($n = 239$)

Variable	Variable	Mean[b]	St. dev.	Min.	Max.
Economic data					
Aggregate output for traditional vegetables[c] (10^3 F CFA)	y_{Trad}	2,269	3,767	5.136	2.40E+4
Aggregate output for non-traditional vegetables[c] (10^3 F CFA)	y_{NTrad}	1,574	3,386	24.355	3.42E+4
Total output (10^3 FCFA)	-	3,818	6,585	141.70	4.67E+4
Materials (10^3 F CFA)	x_{Mat}	367.431	488.614	14.750	4,712
Labour (Hours)	x_{Lab}	314.861	125.472	83.294	912.307
Capital (10^3 F CFA)	x_{Cap}	465.844	525.613	1.350	2,739
Land area (ha)	x_{Land}	0.4879	0.9824	0.0048	10.5
Specialization index	SPE	0.5748	0.1677	0.2407	1
Dummy for traditional vegetables	d_Trad	0 = 02.09% 1 = 97.91%			
Dummy for non-traditional vegetables	d_NTrad	0 = 18.83% 1 = 81.17%			
Farm characteristics					
Years of management experience in vegetables production (Year)	EXP	14.0042	9.2757	1	40
Number of years spent in formal education by the producer (Year)	$EDUC$	6.9539	5.2574	0	21
Ratio of credit received over revenue (Ratio)	$MCRED$	0.0758	0.1372	0	0.8241
Fraction of vegetables output sold to Wholesaler	$WHOLE$	0.39361	0.4470	0	1

[a] Descriptive statistics calculated for non-zero output observations.
[b] Frequencies are reported for dummy variables.
[c] Aggregate output consists of the average price of crops times the quantity produced.
$1US = 494.030 F CFA in 2010 or 1 Eur = 655.957 F CFA.

Empirical results

Economies of scale and Economies of scope

The parameter estimates of the Translog specification of the input distance are presented in Table 2. The results show that all elasticities (first-order terms for input and output variables) are between zero and one and possess the expected signs at the geometric mean. Hence, the input distance function satisfies the property of monotonicity, i.e. the input distance function is non-decreasing in inputs and non-increasing in outputs.

The two output dummy variable parameters are both statistically significant at the 5% critical level, showing that the hypothesis that the intercepts are equal for both types of vegetable producers (specialized in one output and not) is rejected. This result implies that a considerable bias would be introduced in the parameter estimates if the distance function was estimated without addressing explicitly this "zero" observation problem (Battese 1997; Tsekouras et al 2004).

The returns to scale calculated as the negative of the sum of the first-order output coefficients is 0.23, indicating possible presence of increasing returns to scale economies at the sample mean. The null hypothesis of constant returns to scale (CRS) is tested using a Wald test on the sum of the two output coefficients. The resulting χ^2 statistic shows that the null hypothesis of CRS is rejected at the 1% critical level. Additionally, the inverse of this sum is equal to 4.43, providing a measure of Ray scale economies, suggesting the presence of increasing returns to scale. Thus, the transformation process described in our model may be thought of as exhibiting increasing returns to scale. This is important for computing the economies of scope in the next paragraph as the calculation of economies of scope are based on an input distance function that exhibits variable returns to scale. This finding is consistent with results in many other empirical analyses of small-scale farms (e.g. Coelli and Fleming 2004) and implies that vegetable farms are likely to benefit from scale increases. The individual output contributions underlying the scale elasticity show that both categories of output contributed significantly to input use. The result indicates that traditional vegetables require a greater input share than non-traditional vegetables. However, both outputs appear to have almost similar output share (45% for traditional vegetables and 55% for non-traditional vegetables) (Table 1). The Pearson correlation test indicates that the two outputs are not correlated. However, the theory of diversification pointed out that even though a Pearson correlation test shows that two outputs are not correlated, the production of one can be reduced if uncertainty over the second output rises (Just and Pope 1978).

To further investigate the implications of our estimates about output complementarities, we focus on the economies of scope equation in (14). Since the data are mean-corrected prior to the estimation of the distance function, the presence of economies of scope is evaluated at the means of the sample data. The expression of $C_{yy}(1,2)/C$ evaluated at the sample means of the data is equal to 0.085. This value implies that vegetable producers have 8.5 per cent higher costs by producing traditional vegetables together with non-traditional vegetables compared to producing the two categories of outputs separately. Therefore, vegetable producers have a strong incentive for specialization in the production of one of the two outputs defined in this study. This result is in line with the finding of Oude Lansink and Stefanou (2001) who found substantial diseconomies of scope in the Dutch arable farms when considering dynamic adjustments of areas of crops. The incentive for specialization in traditional vegetables is relatively higher than the incentive for specialization in non-traditional vegetables, since the scale effect of traditional vegetables is higher than the scale effect of non-traditional vegetables (Table 2). An explanation of the presence of diseconomies of scope is that the two groups of outputs are produced in the same period and have the same input requirements.

Table 2. MLE estimates of the Translog input distance function frontier

Variable name[a]	**Variable**	**Estimates**	**S.E.**	$P > \|z\|$	**Variable name**[a]	**Coefficients**	**Estimates**	**S.E.**	$P > \|z\|$
Constant	β_0	0.7321***	0.1547	0.000	ln(Traditional veg.) × ln(Non-Traditional veg.)	β_{Trad_NTrad}	-0.0256	0.0247	0.300
ln(Materials/Capital)	β_{Mat}	0.1613**	0.0642	0.012	ln(Traditional veg.) × ln(Materials/Capital)	β_{Trad_Mat}	0.1196***	0.0327	0.000
ln(Labour/Capital)	β_{Lab}	0.6954***	0.0655	0.000	ln(Traditional veg.) × ln(Labour/Capital)	β_{Trad_Lab}	-0.1261***	0.0313	0.000
ln(Land/Capital)	β_{Land}	0.1237*	0.0647	0.056	ln(Traditional veg.) × ln(Land/Capital)	β_{Trad_Land}	0.0108	0.0209	0.604
ln(Materials/Capital)^2	β_{Mat_Mat}	0.0423	0.0279	0.129	ln(Non-Traditional veg.) × ln(Materials/Capital)	β_{NTrad_Mat}	-0.0257	0.0351	0.465
ln(Labour/Capital)^2	β_{Lab_Lab}	-0.04756	0.0355	0.181	ln(Non-Traditional veg.) × ln(Labour/Capital)	β_{NTrad_Lab}	-0.0016	0.0427	0.969
ln(Land/Capital)^2	β_{Land_Land}	0.0012	0.0186	0.947	ln(Non-Traditional veg.) × ln(Land/Capital)	β_{NTrad_Land}	0.0809**	0.0336	0.016
Dummy for Traditional veg.	β_{d_Trad}	-0.3316***	0.1274	0.009	ln(Materials/Capital) × ln(Labour/Capital)	β_{Mat_Lab}	0.0533	0.0496	0.283
Dummy for Non-Traditional veg.	β_{d_NTrad}	-0.2095***	0.0642	0.001	ln(Materials/Capital) × ln(Land/Capital)	β_{Mat_Land}	-0.1987***	0.0606	0.001
ln(Traditional veg.)	β_{Trad}	-0.1379***	0.0221	0.000	ln(Labour/Capital) × ln(Land/Capital)	β_{Lab_Land}	0.1804***	0.0491	0.000
ln(Non-Traditional veg.)	β_{NTrad}	-0.0878***	0.0250	0.000	Dummy_Best soil fertility	β_{B_Soil}	0.0016	0.0591	0.978
ln(Traditional veg.)^2	β_{Trad_Trad}	-0.0337***	0.0112	0.003	Dummy_Medium soil fertility	β_{M_Soil}	0.0119	0.0429	0.780
ln(Non-Traditional veg.)^2	β_{NTrad_NTrad}	-0.0056	0.0191	0.770					
Model diagnostic									
Log likelihood	-2.5714								
Wald χ^2_{24}	3506.26***								
$RTS = \|\beta_{Trad} + \beta_{NTrad}\|$	0.2257								
Number of obs.	239								

[a] RTS stands for the returns to scale; veg. for vegetables.
*** Significance at 1% level, ** Significance at 5% level, * significance at 10% level.

Impact of specialization on technical efficiency

Table 3 provides the results of the estimation of the non-neutral technical efficiency effect model. The estimated variances σ^2 and σ_u^2 are 0.086 and 0.047, respectively. The parameter γ is positive and significant at the 5% critical level, indicating that technical inefficiency is likely to have an important role in explaining variability in performance among vegetable producers in the sample. The value of γ in Table 3 indicates that about 54.2% of the variability of the disturbances is due to technical inefficiency.

Table 3. MLE estimates of the efficiency effect model (Non-neutral specification)[3]

Variables[a]	Coefficients	Estimates	S.E.	$P > \|z\|$
Constant	δ_0	0.1985	0.2211	0.369
Specialization	δ_{Spe}	-0.7449*	0.4493	0.097
Specialization × ln(Materials/Capital)	δ_{Spe_Mat}	-0.2422	0.2525	0.338
Specialization × ln(Labour/Capital)	δ_{Spe_Lab}	-0.0430	0.1622	0.791
Specialization × ln(Land/Capital)	δ_{Spe_Land}	0.4258**	0.1689	0.012
Specialization × Experience	δ_{Spe_Exp}	0.0023	0.0077	0.770
Specialization × Education	δ_{Spe_Educ}	0.0244*	0.01269	0.054
Specialization × Credit	δ_{Spe_Mcred}	0.00067	0.00086	0.438
Specialization × Wholesaler	δ_{Spe_Whole}	0.5883**	0.27489	0.032
$\sigma^2 = \sigma_v^2 + \sigma_u^2$		0.08646	0.0282	
$\gamma = \sigma_u^2/\sigma^2$		0.5416	0.2536	
σ_u^2		0.0468	0.0364	
σ_v^2		0.0396	0.0112	

[a] Specialization stands for Specialization index; Experience for Years of management experience in vegetable production; Education for Number of year spent in formal education by the producer; Credit for ratio of amount of credit received over total revenue; Wholesaler for fraction of vegetable sold to wholesaler.
*** Significance at 1% level, ** Significance at 5% level, * significance at 10% level.

[3] We have also experimented an alternative model by adding the four farm characteristics variables standing alone into the above model to check the individual effects of these variables and encounter omitted variable bias. But this model couldn't converge because of high multicollinearity problems.

Table 4 reports the results of the likelihood-ratio (LR) test of several hypotheses on the technology and technical efficiency. First, the null hypothesis that a distribution of u^I has a mode at zero, that is $\delta_0 = \delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$ is rejected at the 5% critical level. This implies that the technical efficiency specification in (10b) cannot be reduced to the half-normal model as proposed by Aigner et al (1977). Second, we tested for the effect of output specialization on technical efficiency. The null hypothesis is, $\delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$ (i.e. the specification is truncated normal stochastic frontier model with constant mode δ_0). This hypothesis is rejected at the 5% critical level implying that technical inefficiency follows a truncated normal distribution with variable mode depending on vegetable crop specialization. Third, in specifying the model we assumed that specialization in output production has a non-neutral effect on technical efficiency. The null hypothesis is, $\delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$, is rejected at the 5% critical level indicating that the non-neutral effect of specialization on technical efficiency in (10b) cannot be reduced to a neutral specification that was used by e.g. Coelli and Fleming (2004) and Rahman (2009). This outcome implies that crop specialization does not have a constant impact on technical efficiency. The result shows that specialization has a positive effect on vegetables farmers' technical efficiency. These results are consistent with the results of Alvarez et al (2006) and Dinar et al (2007) who found that restrictions on the general non-neutral model are rejected.

Table 4. Tests of hypotheses for parameters of the efficiency frontier model for vegetable producers in Benin

No.	Hypothesis	LR-test	Critical value at 0.05
1.	Ho. Aigner et al (1977) formulation (i.e. $\delta_0 = \delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$)	42.77	$\chi_9^2 = 16.27$[*]
2.	Ho. Stevenson. (1980) formulation (i.e. $\delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$)	21.93	$\chi_8^2 = 15.51$
3.	Ho. Coelli and Fleming (2004) neutral specification (i.e. $\delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$)	31.13	$\chi_7^2 = 14.07$

[*] The critical value is obtained from Kodde and Palm (1986, Table 1) as the LR-test statistic follows a mixed chi-squared distribution.

Column 2 of Table 5 shows the average technical efficiency and its quartile distribution. The result reveals a positive skewness in the distribution of technical efficiency. The average technical efficiency of the sample is 79.40%, implying that the same output can be produced with 79% of the observed inputs. In addition, Table 5 reports the quartile distribution of the marginal effects of crop specialization on the technical efficiency, (computed using (11)). The results suggest a positive effect of specialization on technical efficiency. This result seems to corroborate the decreasing technical efficiency of most diversified farms. As indicated by Wang (2002), the opposite marginal effects in these two quartiles show that specialization in vegetable outputs production affects technical efficiency non-monotonically in the sample. Consequently, the results cannot tell more about when the impact of crop specialization turns from negative to positive. Since we cannot interpret directly the meaning of the marginal effects, we also compute the elasticity of technical efficiency with respect to specialization using the method described in Cameron and Trivedi (2009, p. 335). On average, the contribution of vegetable output specialization to technical efficiency is found to be quite low, but different from zero at the 5% level of significance. Specifically, the result shows that a 1% increase in specialization is associated with a 0.02% increase in technical efficiency. The result implies that, on average, specialization generates gains in technical efficiency. This suggests that the costs of diversifying outweigh the benefits, and specializing is the preferred strategy. The results are consistent with the findings in many empirical works, indicating that diversification often requires specialized equipment and that diversified farms accumulates fewer assets than specialized farms (Harwood et al 1999). In line with Katchova (2005), the results suggest that diversified vegetable farms had a lower excess value than specialized farms. The results are also in line with the finding of Llewelyn and Williams (1996) for irrigated farms in Indonesia, that greater diversification is associated with lower technical efficiency. Since vegetables are cash crops, the result stresses that diversification increases costs by the presence of diseconomies of scope and by decreasing technical efficiency. The reason for our finding is that the two categories of vegetables are grown in the same period and compete for the same inputs (labour, pesticides, fertilizers and water) and require similar managerial skills. Like in Rahman's (2009) study of smallholders in Bangladesh, the worsening evidence of diversification economies observed between traditional and non-traditional vegetables is largely due to the practice of producing both categories of crops. From the survey results, it turns out that vegetable production is generally input intensive regardless of the type of vegetable in consideration. However, this result is in contrast with Coelli and Fleming (2004) who found that greater specialization leads to lower technical efficiency.

Table 5. Distribution of technical efficiency and the marginal effect and elasticity of technical efficiency with respect to specialization

	Mean efficiency (TE)	Marginal effect of Specialization (ME)	Elasticity with respect to Specialization (EL)[a]
First Quartile	0.3458	-0.1941	-0.1405
Median	0.8514	0.0281	0.2035
Third Quartile	0.9086	0.0580	0.4200
Mean	0.7940	0.0169	0.0123

[a] $EL = ME \times \frac{\overline{TE}}{\overline{Spe}}$, where $\overline{TE}$ refers to mean of technical efficiency; $\overline{Spe}$ mean of specialization index (Cameron and Trivedi, 2009, p. 335)

Conclusion and implications

This paper provides an empirical evaluation of the impact of crop specialization on vegetable producers' economic performance in Benin. The challenge in this study was to assess whether changes in farm orientation through diversification or specialization can be attributed to the search for greater performance. We based our estimation on a non-neutral stochastic frontier model to test and consider the adjustment of inputs utilization with output choices and estimate the effect of specialization on production technology and producer management performance. The article employs a parametric method in estimating an input distance function using a modified Translog specification and a truncated efficiency regression, representing efficiency in production. The results show a prevalence of increasing returns to scale. Compared to non-traditional vegetables, traditional vegetables have greater returns to scale. The results also provide evidence for diseconomies of scope, indicating that vegetable producers have a strong incentive for specialization in either traditional or non-traditional vegetables. The production of traditional and non-traditional vegetables jointly at the farm-level induces 8.5 per cent higher costs compared to producing the two output categories separately.

The contribution of vegetable output specialization to technical efficiency is found to be quite low, but significant. Specifically, a 1% increase in crop specialization is associated with a 0.02% increase in technical efficiency.

Our results suggest that policy makers aiming at food security and agricultural growth may enhance specialization. The policy implication of this paper is that the current government agricultural policy to encourage diversification may lead to larger costs and greater technical inefficiency of production.

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