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Efficiency and Farm Size in Philippine Aquaculture. Analysis in a Ray Production Frontier Framework

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Abstract. We investigate the existence of an inverse relationship (IR) between farm size and technical efficiency in Philippine brackishwater pond aquaculture. The study is motivated by the exemption of fish ponds from the Comprehensive Agrarian Reform Laws and suggestions in the literature of inefficient management of fish farms. The analysis of technical efficiency is based on the estimation of a multi-product ray production function estimated in a stochastic frontier framework. There is some evidence of an IR but of only limited strength. Hence, it is unlikely that agrarian reform is the key to unlocking the productive potential of brackishwater aquaculture in the Philippines.

Keywords. Aquaculture, inverse relationship, ray production function, efficiency, land reform, Philippines

JEL-codes. Q15, O13

As global production of capture fisheries stagnated over the last decade, output from aquaculture expanded steadily, making aquaculture one of the fastest growing food-producing sub-sectors globally (Ahmed and Lorica, 2002; FAO, 2002). This spectacular development has sometimes been described as a blue revolution, with the underlying idea that aquaculture has the potential to solve some aspects of the world's chronic hunger and malnutrition problems (Coull, 1993). While there is no arguing with the increase in aquaculture production, it is however necessary to acknowledge that this development has generated a number of social, environmental and economic problems. Hence, questions have been raised about the ecological impact of aquaculture, in particular with regard to biodiversity (Jana and Webster, 2003; Tisdell, 2003) and mangrove destruction (Primavera, 2000); about the equity of its development (Primavera, 1997; Alauddin and Tisdell, 1998; Coull, 1993) and about its food security benefits (Naylor *et al.*, 2000; Primavera, 1997).

Aquaculture development in the Philippines fits the global picture described above. Yap (1999) reports that aquaculture output in the country grew at the average annual rate of 5.4% in the 1990s and that its share of total fisheries production keeps increasing. Yet, its development has had a detrimental effect on mangroves, resulted in the salinisa-

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tion of previously productive agricultural land, generated conflicts over the use of natural resources (Yap, 1999) and some have even argued that it has been responsible for the marginalisation of some coastal communities and an increase in the rate of unemployment (Primavera, 1997). Against this background, the aim of this article is to address one equity aspect of aquaculture development in the Philippines that relates to the distribution of fishpond holdings.[2] We investigate whether there is evidence of an inverse relationship (IR) between farm size and technical efficiency in brackishwater aquaculture in order to evaluate the case, on efficiency ground, for reform of the existing tenurial system, land redistribution, or other policies aimed at improving the functioning of the land market.

The study is motivated first by a common perception that the vast areas of Philippine brackishwaters[3] represent a valuable resource that is not exploited optimally and is not contributing fully to the development process of coastal areas. We believe that it will make a contribution to an important and ongoing policy debate that emerges from the fact that, while the Philippines adopted several land reform laws in the late 1980s, aquaculture ponds have so far been exempted[4]. As a result, the distribution of holdings in brackishwater aquaculture remains very unequal as indicated by a Gini coefficient of 0.72 for the two regions that form the focus of our study[5]. Naturally, large fishpond owners and leaseholders believe that agrarian reform would, if anything, only worsen the severe problems of poverty and inequality in the communities where fish farming represents an important activity. Yap (1999) cites a telling extract from the newsletter of Negros Prawn Producers and Marketing Cooperative:

> The implementation of the (land reform) law is liable to cause widespread strife among the landowners…. There is no showing that land reform will enliven the plight of the poor. Without undermining their capabilities, it is also doubtful whether they (the farmers) can put up the necessary capital to maximize land use. Having been used to having a landlord on whom to call in times of need, this plunge to independence may have a crippling effect.

This view stands in sharp contrast with the common belief in agriculture that small farmers tend to achieve higher productivity and efficiency levels than large farmers, i.e. that there usually is an IR, as hypothesized in Sen's seminal paper (1962)[6]. Besides, the experience of Thailand, where the extremely dynamic prawn industry is supported by relatively small farmers (Yap, 1999), suggests that there is no particular impediment to the development of a competitive aquaculture sector based on smallholders. We therefore believe that testing the IR in Philippine brackishwater aquaculture will generate important policy insights; in particular, a strong IR would suggest that institutional changes leading to a more equal size distribution of holdings could increase both equity and efficiency.

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[2] Although it is not always specified, our study relates only to brackishwater pond aquaculture.

[3] Yap reports that there are 239,323 hectares of brackiswater fishponds in the Philippines. The electronic data that we obtained from the Bureau of Agricultural Statistics gives a total harvested area of 415,272 hectares in year 2000.

[4] The most recent one is the Comprehensive Agrarian Reform Law (CARL) of 1988 that imposes land redistribution with a five hectare retention limit set on all agricultural land.

[5] Source of data: Bureau of Agricultural Statistics' inventory of fishponds from 1997.

[6] A recent review of the IR literature is Fan and Chan-Kang. It concludes to the lack of consensus on the validity of the IR hypothesis.

Our analysis is based on a sample of 127 farms in two of the three main regions for brackishwater aquaculture in the Philippines and investigates the level and determinants, including farm size, of their technical efficiency. Although our focus lies primarily with the analysis of a policy issue, we also believe that the article makes a modest methodological contribution to the agricultural economics literature by establishing two methods to measure the explanatory power of the inefficiency effect variables in the widely used composed error model of Battese and Coelli (1995). This is useful in the empirical section to establish by how much inefficiencies would decrease and output rise if aquaculture land was distributed more equally in the Philippines.

The paper is organized as follows. The next section develops the conceptual framework, emphasizing the advantages of the estimation of a ray production function over alternative approaches. Section three presents the estimation strategy and proposes an approach to quantify the explanatory power of the inefficiency effect variables in the econometric model. The remaining sections discuss the data and empirical model, present the empirical results, and offer conclusions.

1. Measuring the efficiency of polyculture farms. A conceptual framework

1.1 Choice of approach

The IR literature started with the simple observation that yields, defined as output per unit of surface area, differed according to the size of farms. However, output per hectare is only a partial productivity indicator which cannot satisfactorily measure overall farm productivity (Jha, Chitkara and Gupta, 2000), and economic optimality usually differs from yield maximisation. To address this concern, albeit only partially, one can investigate the relationship between gross margin and farm size, but this again fails to account for the input of primary factors when comparing farm performance. There is also a concern that gross margins depend on the price environment in which farms operate (Coelli, Rahman and Thirtle, 2002). There is therefore a strong case to investigate the IR within the confines of production economics, which can accommodate the multi-dimensional aspect of farm production.

Aquaculture production in the study area involves the polyculture of prawns, fish (tilapia and/or milkfish) and crabs, which are produced simultaneously in the same ponds so that the inputs (e.g. feeds, labour) with the exception of the fry and fingerlings, are non-allocable. This introduces a first linkage among the different outputs of the aquaculture farm. Second, it is necessary to recognize the possibility of output jointness as it is likely that the different species interact with each other in the aquaculture pond. For instance, biologists and aquaculture experts often consider that the association prawn/tilapia tends to reduce the rate of prawn mortality because tilapias, through their filtering activity and consumption of organic matter lying at the bottom of the pond, improve the bacteriological quality of the pond water (Corre *et al.*, 1999). We therefore conclude that the production process relies on a truly multiple-output technology, and that it is not possible to specify different production functions for each output.

The most common approach to measure efficiency in a multi-output setting involves the estimation of dual cost, revenue or profit functions (Löthgren, 2000). However, this group of methods relies on relatively restrictive behavioural assumptions of economic optimization, such as static revenue or profit maximisation, that are not expected to hold in developing country aquaculture as farmers are likely to adopt complex livelihood strategies in the face of multiple market failures. For instance, prawn production in the Philippines, though profitable on average, is also inherently risky due to the presence of diseases that are not easily controlled but have the potential to wipe out entire harvests. This type of risk is unfortunately not insurable due to the poor development of insurance and credit markets. Furthermore, at a more practical level, estimation requires data on prices of inputs and/or outputs with a minimum of variability, but such data is unfortunately not easy to obtain at a given point in time because input and output markets are relatively well integrated within regions. Hence, a primal approach seems better suited to the analysis of efficiency and productivity for this particular study.

In a primal setting, a transformation function can be re-written so as to express one output as a function of the input vector and the quantities of all other outputs, but the resulting efficiency scores then depend on the particular output that is chosen as dependent variable, with no guarantee of consistency of the resulting efficiency rankings of farms for alternative formulations of the model. The efficiency literature has addressed the problem by developing models based on input and output distance functions (Coelli and Perelman, 2000; Morrison-Paul, Johnston and Frengley, 2000; Brümmer, Glauben and Thijssen, 2002) or ray production functions (Löthgren, 2000). Both types of functions appear equally satisfactory from a theoretical point of view, but the ray production function seems superior for the problem considered in our paper for two reasons. First, the output distance function is linear homogenous in outputs, which is imposed globally through the use of a logarithmic functional form that cannot accommodate zero values[7]. In response to that problem, a common practice consists of replacing zero values with small numbers (see Morrison-Paul, Johnston and Frengley, 2000 as well as Fousekis, 2002 for two examples) but this seems highly unsatisfactory as the logarithmic function goes asymptotically to minus infinity at zero. Battese (1997) explores this problem in the context of a Cobb-Douglas production function to conclude that it can seriously bias the parameter estimates. Given that most farms in our sample do not produce all four outputs, this problem represents a major obstacle to the estimation of an output distance function from our data. The second issue with the distance function arises from the fact that its value is unobservable so that the estimation equation is derived indirectly by exploiting the homogeneity properties of the distance function. However, it is feared that the resulting estimable equation leads to possible endogeneity problems (Grosskopf *et al.*, 1997; Löthgren, 2000). By contrast, no homogeneity restriction needs to be imposed on the ray production function, which can therefore be represented by non-logarithmic functional forms and hence accommodate zero values. Furthermore, it is also believed that the endogeneity problem highlighted above for the distance function does not apply to the ray production function (Löthgren, 2000). Hence, we choose to pursue our investigation of efficiency of aquaculture farms in the Philippines based on the estimation of a ray production function.

[7] In fact, all the published papers on distance functions of which we are aware use a transcendental logarithmic functional form, in order to impose homogeneity while conferring sufficient flexibility to the parametric function.

1.2 Theoretical model

The main insight of Löthgren (2000) is to express the output vector y of dimension M in polar coordinates:

$$y = \|y\| m(\theta(y)) \tag{1}$$

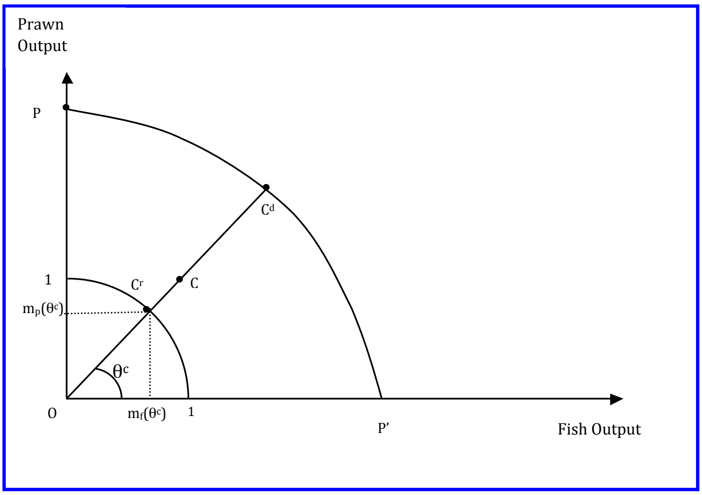
where denotes the Euclidian norm of vector y ($\|y\| = \sqrt{\sum_{i=1}^{M} y_i^2}$), $\theta(y)$ is an *(M-1)* vector of polar coordinate angles of the output vector y, and the M functions m_i: $[0, \pi/2]^{M-1} \rightarrow [0,1]$ define the coordinates of the normalized output vector. This is illustrated in the two-output case in Figure 1. The output vector of farm C is expressed in terms of its norm, OC/OC^r, and a single angle θ^c measuring the relative proportions of fish and prawn outputs, i.e. the output mix. The two functions m_f and m_p of the polar-coordinate angle θ^c simply define the (regular) coordinates of the normalized output vector OC^r obtained by radial projection of vector OC on the circle of radius 1. The *(M-1)* polar coordinate angles are obtained recursively as in Löthgren (1997), from which the coordinates of the normalized output vector can easily be recovered.

This set up allows us to represent any technology by a multi-output ray production function $f(x,\theta(y))$ as follows:

$$f(x,\theta(y)) = \max\{\rho > 0 : \rho.m(\theta(y)) \in P(x)\} \tag{2}$$

This function gives the maximum norm of the output vector that the firm can produce, given a vector of inputs x and the existing production set $P(x)$, and assuming that any increase in production would involve a proportional increase in all individual outputs.

Figure 1. Graphical presentation of the ray production function



Hence, any technologically feasible input-output combination *(x, y)* is defined by the inequality. In terms of Figure 1, the value of the ray production function is simply equal for farm C to the ratio OC^d/OC^r. Under the assumption of strong input disposability, the ray function is positively monotonic in inputs (Löthgren, 2000).

The usefulness of the ray production function in measuring efficiency derives from its relation to the output distance function. It follows from equation (2) that, for any observed output vector *y*:

$$D_o(x, y) = \|y\| / f(x, \theta(y)) \tag{3}$$

This is indeed observed in our graphical example, as ratio OC/OC^d is obviously equal to OC/OC^r divided by OC^d/OC^r. This relationship is most important because we know that virtually all the properties of a multi-output technology can be recovered from the distance function. For instance, Brummer, Glauben and Thijssen (2002) use it to characterize technological change and productivity growth, while Kim (2000) derives measures of output substitutability from it. Equation (3) therefore implies that the same can be done from the ray production function. For our purpose, it is sufficient to recognize that output elasticities are easily derived from the ray production function as:

$$\varepsilon_{y,x_j} = \frac{\partial \ln\|y\|}{\partial \ln x_j} = \frac{\partial f(x;\theta(y))}{\partial x_j} . \frac{x_j}{f(x,\theta(y))} \tag{4}$$

This expression gives the percentage change in all outputs resulting from a one percent change in input *j* and is expected to take a positive value (Fousekis, 2002). Alternatively, Appendix 1 demonstrates that because the ray production function entertains some duality with both the maximum revenue and minimum cost functions, this elasticity can be interpreted as the revenue elasticity or the scale-adjusted cost share of input *j*. The scale elasticity follows immediately (Löthgren, 2000):

$$\varepsilon_{scale} = \frac{\nabla_x f(x;\theta(y)).x}{f(x,\theta(y))} \tag{5}$$

This elasticity should be compared to unity to establish whether the firm operates under decreasing, constant or increasing returns to scale.

2. Estimation Strategy

2.1 The econometric model

The estimation of firm-level efficiency scores from a ray production function follows the stochastic frontier methodology initially proposed by Aigner, Lovell and Schmidt

(1977). Accordingly, a scalar-valued composed error term is introduced in the empirical ray production function[8]:

$$\|y\| = f(x,\theta(y);\beta) + v - u \tag{6}$$

where β is a vector of parameters to be estimated; v is a symmetric random variable that is independently and identically distributed across individuals; and u is a non-negative random variable. This specification recognizes the fact that production is first affected by random shocks and measurement errors, which are captured by the disturbance term v. However, the productive performance of farms is also determined by the quality of managerial decisions and it is likely that some farmers make mistakes, i.e., that they are technically inefficient. This is formally captured by the random variable u that describes the deviation of the norm of the observed output vector y from the maximum achievable norm, which is conditional on the exogenous shock v.

Given a parameterisation of the ray production function and distributional assumptions on the random terms, equation (6) can be estimated by the maximum likelihood methods that have now become commonplace in the stochastic frontier literature[9]. We adopt the specification of Battese and Coelli (1995) who relax the assumption of identically distributed inefficiency terms by considering that u_i is obtained by truncation at zero of a normal variable $N(\mu_i; \sigma_u^2)$ where[10]:

$$\mu_i = z_i\delta \tag{7}$$

The term z_i denotes a vector of potential determinants of inefficiencies, including farm size, while δ is a vector of parameters to be estimated. Note that because the inefficiency effects enter the model in a highly non-linear way, there is no identification problem when using the same variable in the specification of the ray production function and as an inefficiency effect.[11] The likelihood function is derived algebraically as in Battese in Coelli (1993) and it can then be maximized numerically to produce estimates of both the ray production function and the vector of parameters δ. Further, while the individual inefficiency levels are not directly observable, the method allows for calculation of their predictors by applying the procedure first proposed by Jondrow *et al.* (1982). As the expressions for these predictors are presented in Battese and Coelli (1993) only for the multiplicative model, while ours is additive, they are worth reporting here. First, the conditional expectation of the inefficiency term u given a total residual $e=v-u$ is derived from

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[8] Notice that the error term is introduced in an additive rather than multiplicative way because, as explained earlier, we do not want to use a logarithmic functional form due to the 'zero value' problem.

[9] See Coelli, Rao and Battese (1998) for an introductory presentation of this literature and Kumbhakar and Lovell (2000) for a more detailed and technical one.

[10] The individual subscript i was ignored up to this point for notational clarity.

[11] An example of a stochastic production frontier where land appears both as an input and as an inefficiency effect is Ngwenya, Battese and Fleming, cited on page 212 of Coelli, Rao and Battese (1998). The issue of identification is also discussed in Battese and Coelli (1995) where a time trend is used to capture both technological change and inefficiency change over time.

the expression of the conditional density function of u given e presented in full in Battese and Coelli (1993)[12]:

$$E(u|e) = \mu_* + \sigma_* \phi(\mu_* / \sigma_*) / \Phi(\mu_* / \sigma_*) \tag{8}$$

where:

$$\begin{aligned} \mu_* &= (\sigma_v^2 z\delta - \sigma_u^2 e)/(\sigma_u^2 + \sigma_v^2) \\ \sigma_*^2 &= \sigma_v^2 \sigma_u^2 /(\sigma_u^2 + \sigma_v^2) \end{aligned} \tag{9 a and b}$$

and *f(.)* and *F(.)* denote the density and distribution functions for the standard normal random variable. These expressions express mathematically that the random variable u, conditional on e, is simply obtained by truncation at zero of the normal variable $N(m_*,s_*^2)$. The Farell output-oriented efficiency score follows immediately:

$$\hat{TE} = (\hat{y} - E(u|\hat{e}))/\hat{y} \tag{10}$$

where denotes the fitted output norm and is the estimated residual.

2.2 Quantifying the strength of the inefficiency effects

Next we turn to the issue of quantifying the explanatory power of the inefficiency effects introduced in vector z, which is motivated by our primary aim of exploring the robustness of any potential IR by introducing farm size as an efficiency effect. This problem has been largely ignored in the literature, as the only attempt at tackling it of which we are aware is Pascoe and Coglan (2002). Their procedure simply involves regressing the estimated technical efficiency scores against the vector of inefficiency effect variables z by OLS. This approach is ad hoc and seems unsatisfactory because it fails to recognize the highly non-linear way in which the inefficiency effects enter the model. From equation (7), it is evident that the mean of the normal variable truncated at zero to model inefficiencies is a linear function of the z variables but this implies that the relationship between predicted efficiencies (10) and these variables takes a complex non-linear form. We therefore prefer to investigate this question differently.

A first approach compares the full specification of the model to a restricted one where the inefficiency effect variable z_k is dropped from vector z. The comparison is based on the decomposition of the total variance term e into its random shock and inefficiency components u and v (Coelli, 1995):

$$\gamma^* = \gamma/[\gamma + (1-\gamma)\pi/(\pi-2)] \tag{11}$$

[12] In the remainder of this section, we again omit the farm subscripts for notational clarity but note that e, u, μ*, z, z_k, y and TE are all farm-specific.

where parameter $\gamma=\sigma_u^2/(\sigma_u^2+\sigma_v^2)$. This quantity γ* measures the variation in production not accounted for by physical factors that is attributed to inefficiencies rather than random shocks. Hence, the difference between this quantity for the full model and the restricted model gives us directly a measure, in percentage terms, of the explanatory power of the inefficiency effect variable z_k.

We would also like to be able to measure the strength of the relationship between any z_k variable and technical efficiency by calculating a standard elasticity but, once again, the literature seems to have ignored this issue. From equations (8) and (9), one can derive the responsiveness of the conditional predictor of u to a change in any inefficiency effect variable z_k:

$$\frac{\partial E(u|e)}{\partial \ln z_k} = \frac{z_k \delta_k (1-\gamma)}{(\Phi(\mu^*/\sigma^*))^2}[\Phi(\mu^*/\sigma^*)(\Phi(\mu^*/\sigma^*) - \frac{\mu^*}{\sigma^*}\phi(\mu^*/\sigma^*)) - \phi^2(\mu^*/\sigma^*)] \tag{12}$$

Using this expression in equation (10) defining the efficiency score, one obtains:

$$\frac{\partial TE}{\partial \ln z_k} = -\frac{z_k \delta_k (1-\gamma)}{\hat{y}(\Phi(\mu^*/\sigma^*))^2}[\Phi(\mu^*/\sigma^*)(\Phi(\mu^*/\sigma^*) - \frac{\mu^*}{\sigma^*}\phi(\mu^*/\sigma^*)) - \phi^2(\mu^*/\sigma^*)] \tag{13}$$

This elasticity gives the percentage change in efficiency resulting from a unit percentage change in variable z_k. Note that it depends not only on the parameter estimates but also on the data so that it can be estimated at any sample point or at the sample mean. The empirical section of the paper uses this expression to derive what we call the technical efficiency elasticity of farm size.

3. Data and empirical model

Two main regions of the Philippines for brackishwater pond aquaculture were selected for this particular study. The northern Central Luzon region has brackishwater fish ponds in the four provinces of Pampanga, Bulacan, Bataan and Zambales. The Western Visayas region is located in the central Philippines, and includes the provinces of Iloilo, Capiz, Negros Occidental and Aklan. The sample was stratified by farm size and by province, based on census data from 1997 provided by the Bureau of Agricultural Statistics. Production and socio-economic data were then collected by interviews with farm operators and caretakers (salaried supervisors). A total of more than 150 farms were initially surveyed but several observations were dropped because of inconsistencies and/or missing values, so that our analysis is based on a sample of 127 individuals.

Table 1 presents the summary statistics of the production variables. The farms in the study area are relatively large, with an average surface area of more than eleven hectares, and land is unequally distributed, as indicated by a Gini coefficient of 0.67. The main intermediate input corresponds to the seeds[13], followed by the feeds and, finally, fertilizers.

[13] This means the "fry" for prawns, "juveniles" for crabs and "fingerlings" for milkfish and tilapia.

This cost structure reflects the extensive nature of brackishwater aquaculture in the Philippines, as even in semi-intensive production systems, the feeds account for the major share of cash costs. Also, the substantial cost of fertilizers reveals that farm operators attempt to bolster the natural productivity of aquaculture ponds, while the production process in intensive aquaculture relies solely on the provision of feeds from an external source for the growth of the cultivated species. Finally, the summary statistics also suggest that labor represents an important cost of production, as, on average, the total wage bill exceeds the cost of any individual intermediate input[14].

Table 1. Summary Statistics*

Variable	Mean	Standard Deviation	Minimum	Maximum
OUTPUTS (Kg)				
Milkfish	4,356	1,098	0	80,000
Tilapia	674	230	0	25,600
Prawns	691	202	0	22,240
Crabs	311	79	0	8,000
INPUTS				
Land (ha)	11.5	1.9	0.1	130.0
Labor (man days)	1,160	220	187	26,312
Feeds (Pesos)	95,259	39,617	0	4,420,893
Fert (Pesos)	33,578	5,867	0	403,260
Seeds (Pesos)	183,770	46,518	0	4,140,000

*All variables are expressed on a per year basis.

With respect to outputs, milkfish is the dominant production in volume. This is not surprising as the polyculture production system described here represents a recent evolution of the traditional milkfish monoculture system (Chong *et al.*, 1984). The average milkfish yield of less than 500kg per hectare confirms the extensive nature of production. The volumes produced of the other species appear relatively small compared to that of milkfish but the relative importance of the species is different in value terms. Given that prawns fetch a price nearly ten times as high as that of milkfish per weight unit, they actually represent the dominant production in terms of revenue share[15]. This price differential is explained in part by the fact that milkfish and tilapia are consumed domestically, while an important proportion of the prawns are exported to the high-income markets of Japan and the United States. However, notice that crabs, which are also exclusively sold on domestic markets, also receive high prices and are therefore important productions in

[14] The wage rate for farm labor is approximately 150 PhP/day in Central Luzon and 100 PhP/day in the Western Visayas.

[15] The average prices per kilogram for our sample are 45PhP for milkfish, 31PhP for tilapia, 412PhP for prawns and 210 PhP for crabs.

economic terms. Finally, we note that, although not apparent in Table 1, the farms in the sample choose different associations of species. First, a large majority of farms (82) practice the polyculture of at least two species, hence justifying our earlier discussion on multi-product technologies. And second, the association of all four species is only adopted by a relatively small fraction of the sample farms (11), implying that there is a large number of zero output values in the sample.

We choose a quadratic functional form as a first step in estimating the output ray function defined in equation (6):

$$\|y\| = \alpha_0 + \sum_{j=1}^{M+K-1} \alpha_j w_j + \sum_{j \le k} \sum_{k=1}^{M+K-1} \beta_{jk} w_j w_k + D - u + v \tag{14}$$

where the vector w includes each of the $(M\text{-}1)$ polar coordinate angles $\theta(y)$ and the K inputs, and D is a regional dummy taking a value of unity for the farms located in the Western Visayas[16]. The quadratic production function is a flexible functional form in the sense that it can serve as a local second-order approximation to any unknown production function. This specification therefore gives flexibility to the model which can accommodate zero values on both inputs and outputs. The empirical specification includes the three following inputs: land and labor, defined as in Table 1 as the total surface area of the aquaculture farm and the number of man days of labor used on the farm; and intermediate inputs, expressed in value terms, and hence representing an aggregate of the feed, seed and fertilizer inputs. On the output side, all four productions were used to define the three polar coordinate angles for tilapia, crabs and prawns. The last step in specifying the model involves choosing the inefficiency effects z, which should include variables susceptible of influencing the adoption of particular management practices or the determinants of their adoption (Irz and McKenzie, 2003). Given the focus of this paper on the IR, farm size is included as it is our aim to establish whether small and large farms adopt different management practices that lead to differences in efficiency. It is also possible that management differs across regions, and we therefore include the regional dummy as well as inefficiency effect. Other variables, such as training and experience of the operator, probably have an influence on efficiency but our data unfortunately does not allow for their inclusion.

4. Empirical Results

4.1 Partial productivity indicators

We start our analysis of the IR by investigating the relationship between farm size and land productivity as, although imperfect, partial productivity indicators have played an important role in the development of the IR literature. Table 2 presents the results of three OLS regressions relating a measure of land productivity to farm size and, in order to account for possible regional effects, the regional dummy D. The first regression uses the

[16] We introduce the regional dummy because the preliminary OLS regressions discussed below suggest that there might be technological differences between the two regions.

crudest measure of land productivity, i.e. harvest weight per hectare, and the results seemingly indicate a significant and positive relationship between farm size and productivity. However, it makes little sense to add weights of species that fetch widely different prices and the second regression tackles this problem by measuring land productivity in terms of revenue per hectare. The regression has a surprisingly large explanatory power, as indicated by a R-squared value of 0.42 and reveals a significant and negative relationship between farm size and revenue per hectare. The coefficient of the farm size variable is an elasticity and indicates that a 10% increase in farm size results in a 2.2% decrease in revenue per hectare. Finally, the coefficient of the regional dummy is also negative and significant, indicating that farms tend to be substantially less productive in the Western Visayas than in Central Luzon. The last regression accounts for differences in use of intermediate inputs when comparing farms as it measures land productivity by gross margin per hectare[17] but, although it confirms the results of the previous regression, its explanatory power is too low to draw definite conclusions.

Table 2. Farm Size and Partial Productivity

	Dependent Variable		
Regressors	Log(harvest weight per hectare)	Log(harvest value per hectare)	Gross Margin per hectare
Constant	6.52	11.60	90,94
	(37.32)	(71.78)	(6.78)
Log(Farm size)	0.87	-0.22	-8,95
	(11.91)	(-3.30)	(-1.60)
Western Visayas	-0.85	-1.69	-63.53
dummy	(-4.04)	(-8.69)	(-3.93)
R^2	0.55	0.42	0.13

Note: t-values in parenthesis

The difference in results between the first two regressions imply that, on a per hectare basis, larger farms tend to produce more in weight but less in value terms than smaller ones. Hence, it is likely that larger farms tend to choose output combinations with greater emphasis on lower value species (tilapia, milkfish). The difference in results between the last two regressions is more difficult to interpret. It could indicate that smaller farms make a more intensive use of intermediate inputs, or rely more on family labour, than larger farms. We conclude from this preliminary analysis that there is only weak evidence of an inverse relationship between land productivity and farm size.

[17] Note that for this regression, the dependent variable is the level of the gross margin and not its logarithm. This is so because some farms have negative gross margins, which prohibits the use of a log-log functional form for this regression.

4.2 Specification tests and the structure of the technology

The stochastic ray production frontier described above was tested against simpler alternatives in order to gain some insights into the structure of the technology and inefficiencies. A second objective is to define a more parsimonious specification as the full model requires estimation of a relatively large number of parameters given the sample size[18]. The results of likelihood ratio tests are presented in Table 3[19].

Table 3. Specification Tests

	Log-likelihood	LR statistic	Critical Value		Outcome
Null Hypothesis			5%	1%	
1 No inefficiencies	-113.0	39.2	8.8	12.5	Reject
2 No inefficiency effects	-104.3	21.9	6.0	9.2	Reject
3 No regional effects	-94.1	1.6	6.0	9.2	Accept
4 No farm size effect	-100.0	13.4	3.8	6.6	Reject
5 Input-output separability	-195.2	203.8	16.9	21.7	Reject

First, we test the composed error specification against the hypothesis of absence of inefficiencies by comparing the log-likelihood of our model against that obtained by standard OLS regression. The likelihood ratio statistic of 39.2 exceeds by far its critical value and we therefore conclude to the presence of substantial inefficiencies across our sample farms[20]. This implies that the modelling of the technological relationship between inputs and outputs as a stochastic ray production function rather than a deterministic one is strongly supported by the data. The second test investigates the explanatory power of the inefficiency effect variables. It is also strongly rejected, implying that the regional dummy and farm size variables have, jointly, a statistically significant influence on efficiency. The third test considers the null hypothesis that the regional effects, introduced into the model through the regional dummy in the ray production function and in the inefficiency effect component of the model, are inexistent. The hypothesis is accepted, which stands in sharp contrast to the results obtained earlier based on partial productivity indicators. There is no inconsistency here, however, because the ray production function can accommodate possible differences in output mix across regions, while partial productivity indicators fail to do so[21]. Next, the explanatory power of farm size on inefficiencies is tested and the null hypothesis of no farm-size effect is strongly rejected. We conclude from these four tests that the regional dummy variable can be dropped from the speci-

[18] The total number of parameters in specification (14) is equal to 34, for a sample size of 127.

[19] The test statistic is $LR=-2*\{ln(L(H_0))-ln(L(H_1))\}$, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null and alternative hypotheses (Coelli, Rao and Battese, 1998).

[20] Note that the null hypothesis includes the restriction $\sigma u=0$. As this parameter is necessarily positive, the test statistic follows a mixed chi-square distribution, the critical values of which are found in Kodde and Palm (1986).

[21] In terms of Figure 1, the efficiency of farm C is measured radially, which means that this farm is implicitly compared to farms with a similar output mix. By contrast, gross margin or revenue per hectare measures fail to account for possible differences in output combinations when comparing farms.

fication of the model, while farm size as an inefficient effect should be retained. The last test investigates whether inputs and outputs are separable by comparing our model to a restricted version where the parameters of all cross-terms between inputs and polar coordinates angles in (18) are set equal to zero. The null hypothesis is rejected at any sensible level of significance, which implies that it would not be possible to aggregate consistently the four outputs into a single index. This is why the ray production frontier is used rather than a frontier production function, which requires output aggregation prior to estimation. Altogether, we conclude from this series of tests that there are substantial inefficiencies among the sample farms, which are partially explained by farm size, while the regional dummy can be dropped from the model's specification. Further simplification of the specification is not possible as the tests indicate that the technology is truly multi-product and the relationship among inputs and outputs is a complex one.

Table 4. Estimated stochastic ray production frontier

Parameter	Estimate	t-ratio
Ray frontier		
α_0	0.569	0.68
α_a	0.018	0.01
α_l	0.965	0.83
α_i	-0.890	-1.40
$\alpha_{\theta t}$	-0.685	-0.64
$\alpha_{\theta c}$	0.417	0.36
$\alpha_{\theta p}$	-0.858	-1.87
β_{aa}	0.047	1.27
β_{ll}	0.001	0.08
β_{ii}	-0.092	-13.76
$\beta_{\theta t\theta t}$	0.140	0.20
$\beta_{\theta c\theta c}$	-0.320	-0.48
$\beta_{\theta p\theta p}$	0.448	2.00
β_{al}	0.034	0.98
β_{ai}	0.403	11.72
$\beta_{a\theta t}$	-0.689	-0.69
$\beta_{a\theta c}$	0.588	0.34
$\beta_{a\theta p}$	0.998	1.88
β_{li}	-0.218	-5.16
$\beta_{l\theta t}$	0.103	0.11
$\beta_{l\theta c}$	-0.920	-0.86
$\beta_{l\theta p}$	-0.031	-0.09
$\beta_{i\theta t}$	0.843	1.53

$\beta_{i\theta c}$	0.580	0.69
$\beta_{i\theta p}$	0.368	1.14
$\beta_{\theta t\theta c}$	0.120	0.22
$\beta_{\theta t\theta p}$	0.084	0.27
$\beta_{\theta c\theta p}$	0.066	0.24
Inefficiency Model		
δ_0	-2.356	-2.26
δ_a	2.292	4.43
Variance Parameters		
$s^2=s_u^2+s_v^2$	1.052	3.02
$g=s_u^{2}/s^2$	0.944	32.46
Log-likelihood	-94.147	

Subscript notations: a = land input, l = labor inputs, i = intermediate inputs, (θt, θc, θp) =three polar coordinate angles corresponding to tilapia, crabs and prawns respectively; α_0 and δ_o are the constant parameters.

The results of the maximum likelihood estimation for our preferred specification are presented in Table 4. We note that many of the coefficients present relatively low levels of statistical significance but this should be expected as there is a high level of collinearity among the covariates[22]. The individual parameters of the technology are not directly interpretable and we therefore compute in Table 5 the elasticities of the production ray function at the sample mean, together with their standard errors. Most straightforward to interpret are the input elasticities described in equation (4). First, there is a significant and positive relationship between land input and production, as a one percent increase in farm size results in a 0.58% increase in all outputs. Hence, land stands out as a key production factor which can be explained by the extensive nature of the technology. Second, the elasticity with respect to intermediate inputs is also highly significant, with a one percent increase in that aggregate resulting in a 0.36% increase in production. Finally, the elasticity with respect to labor is very small, negative and not statistically significant, which means that the model fails to capture a positive relationship between labor input and production. There are several possible explanations for this negative result. It is difficult to measure labor input properly, in particular as far as farm operators are concerned and the labor variable presents a high degree of collinearity with the other inputs. We also note that the finding of a negative and/or insignificant labor elasticity, although paradoxical, represents almost an empirical regularity (Whiteman, 1999). The scale elasticity is obtained by summation of all three input elasticities to give a value of 0.92, with a standard error of 0.11. Hence, the technology exhibits slightly decreasing returns to scale at the sample mean but the hypothesis of constant returns to scale cannot be rejected. On the

[22] This is not unusual when using flexible functional forms. For instance, in the full translog specification of his model, Löthgren (2000) reports only five significant coefficients (5%) from a total of 21 in the specification of the technology.

output side, the elasticities of the ray function with respect to the polar coordinate angles are more difficult to interpret. We conclude, however, that the representation of the technology that we obtain appears reasonably consistent with theoretical expectations.

Table 5. Elasticities of estimated ray production function at sample mean

Elasticity w.r.t.	Estimate	t-ratio
Land	0.58	4.51
Labor	-0.03	-0.43
Intermediate Inputs	0.36	7.90
q_t	0.03	0.12
q_c	0.08	0.34
q_p	0.61	7.37

4.3 Inefficiencies and the inverse relationship

The large t-ratio on parameter *g* in Table 4 confirms that inefficiencies are statistically significant. The mean efficiency score for the sample is equal to 0.37[23], which is very low and implies that the sample farms could potentially increase production 2.7 times without any increase in inputs or change in technology. This finding suggests that there is considerable room for managerial improvement of the farms in the study area and represents an empirical validation of Yap's contention that many brackishwater ponds are underdeveloped and under-productive (Yap, 1999). It can also be explained by the fact that extensive production systems have not been the focus of much research and extension activity in the Philippines. The interviews carried out with farmers confirmed that formal extension services are simply not regarded as an important source of technical information by the operators of extensive farms. Finally, it is also necessary to recognize that the extensive production systems considered here are intrinsically complex and offer numerous opportunities for farmers to make mistakes. This is so because these systems are open, due to the frequent exchange of the pond's water, which limits the farmer's control of the production process. Furthermore, the production process depends on the natural productivity of the pond, which itself relates to populations of various plankton and filamentous algae species that are difficult to manage and sensitive to temperature, salinity, soil conditions and the chemical and nutrient composition of the culture water (Arfi and Guiral, 1994)[24]. The situation is very different in intensive production where the growth of the target spe-

[23] In the additive model presented here, the predicted efficiency scores can take negative values, which is theoretically impossible. We therefore replaced negative values by zeros when that occurred (in only a few cases) prior to calculating this average.
[24] We are thankful to Pierre Morrisens for this idea.

cies depends primarily on the feeds brought from outside of the farm and the pond has little biological function beyond the provision of oxygen to the fish/crustaceans (Kautsky *et al.*, 2000)[25].

Figure 2. Frequency Distribution of Efficiency Scores

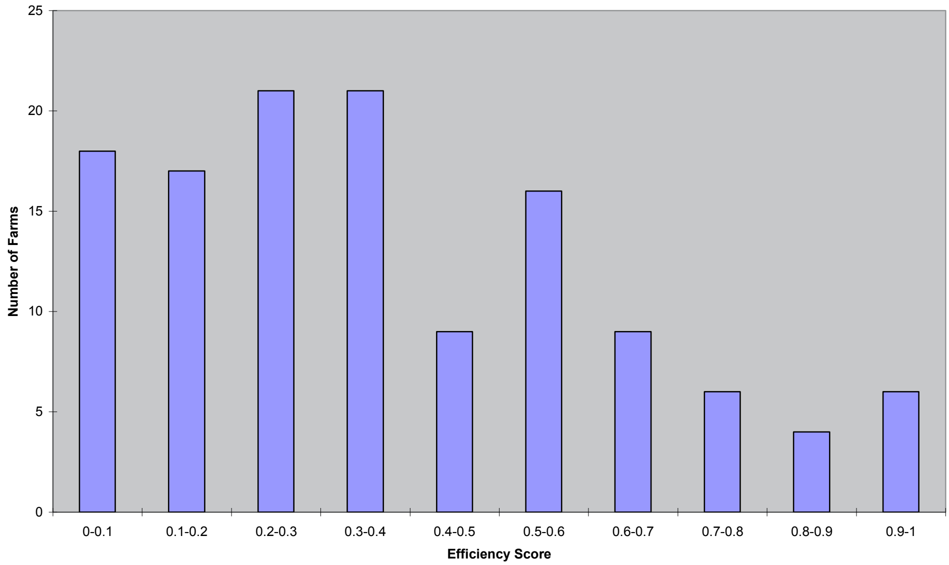

Figure 2 presents the frequency distribution of efficiency scores and indicates a high level of heterogeneity within the sample. The distribution is very flat, as reflected by a standard error of 0.26, and is spread over the whole possible range, from a minimum of zero to a maximum of 0.97. We now turn to the direct analysis of the IR by investigating whether these large variations in technical efficiency scores are related to farm size. The likelihood ratio tests already demonstrated the existence of a significant relationship between farm size and efficiency, which is confirmed in Table 4 by the large t-ratio of parameter δ_a. Furthermore, note that this parameter takes a strictly positive sign, indicating that larger farms in our sample are less efficient than smaller ones. Hence, we conclude to the existence of a statistically significant IR in Philippine brackishwater aquaculture. We would like, however, to go further in identifying the strength of this relationship, which cannot be established directly from the parameter estimates and we now implement for that purpose the two approaches discussed in the methodological section.

Our first suggestion was to compare the full model to a restricted version where farm size is dropped as an inefficiency effect. We find that for the full specification, inefficien-

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[25] An analogy with agriculture might be useful here. Extensive aquaculture, like organic farming, seems to be management intensive while intensive aquaculture, like conventional farming, tends to rely on the application of standard technological packages that leave little initiative to the farmer.

cies account for 86% of the total variance term, implying that the bulk of the variation in production not accounted for by physical factors is attributed to inefficiencies rather than random shocks (i.e., what Pascoe and Coglan, 2002, refer to as luck). For the restricted model, where farm size is dropped from the z vector, inefficiencies account for only 73% of the total variance term. We therefore conclude that variations in production not accounted for by inputs are attributable to random shocks for 14%; farm size for 13%; and unexplained inefficiencies for 73%. This implies that the IR, although statistically significant, appears to be of only limited quantitative importance.

Next, we compute the efficiency elasticity of farm size corresponding to equation (13) and obtain a value of -0.137 at the sample mean. This indicates that a 10% increase in farm size decreases the level of farm-level efficiency by a modest 1.4% for the average farm and confirms the previous result of an IR of only limited strength. When farm-level efficiency is predicted by the mode of the distribution of u given e, the efficiency elasticity at the sample mean takes the same value at the three-digit level. The results are therefore robust to the choice of predictor used to infer farm-level efficiency scores.

From a methodological point of view, it is also interesting to compare our results to those obtained by application of the procedure suggested by Pascoe and Coglan (2002) to quantify the explanatory power of the inefficiency effect variables. When regressing by OLS the predicted efficiency scores against the logarithm of farm size, we obtain results that are simply inconsistent with the first-stage maximum-likelihood estimation. The estimated efficiency elasticity of farm size at the sample mean is 0.24, with a t-ratio of 3.52, and the R-squared for this regression is only 9%. Clearly, the sign of the elasticity is inconsistent with that of parameter δ_a in Table 4. Furthermore, these results suggest that farm size explains only 7.7% (=0.09*0.86) of the variation in outputs not accounted for by physical inputs, while we find a value almost twice as large. Hence, we conclude that this procedure, which is not consistent with the underlying model of efficiency measurement, can lead to erroneous conclusions regarding both the direction and the strength of the relationship between inefficiency effect variables and efficiency scores. We therefore believe that our methodological contribution is important in deriving the policy implications of the popular Battese and Coelli (1995) model.

Finally, we simulate the production effect of applying the Comprehensive Agrarian Reform Law, with its five hectare retention limit, to fish ponds. This is done by considering that large farms are broken done into units of five hectares, while farms smaller than the limit are not affected. We compute the adjustment in efficiency for each farm via equations (8-10), and the production effect is found by multiplying the change in efficiency by observed production. In accordance with the previous results, we find that this hypothetical land reform would increase production of the sample farms only marginally (3.5% for prawns, 2.5% for milkfish, 2.3% for crabs and 3.4% for tilapia).

5. Discussion and conclusion

This paper uses a stochastic ray production function in order to investigate a potential inverse relationship in Philippine brackishwater aquaculture, based on a cross-section of 127 farms. The estimated multi-product technology is not separable in inputs and outputs, implying that our approach is superior to the estimation of a stochastic production function, which requires the aggregation of outputs into a single index. Returns to scale are slightly decreasing at the sample mean but the CRS hypothesis cannot be rejected. The distribution of efficiency scores is spread out over the whole possible range with an average value of 0.37, which is extremely low. Large potential productivity gains are therefore achievable in the study area, without any change in the technology, output mix or input combination. Is land redistribution or an improvement in the functioning of the land market a key to achieving these efficiency gains? Our analysis reveals that it is probably not the case. We find that there clearly exists a significant inverse relationship between farm size and productivity, but that the strength of this relationship is limited. Farm size explains only 13% of the variability in outputs not accounted for by physical inputs, against 73% for unidentified factors, and 14% for random shocks. The elasticities that we derive indicate that when farm size doubles, efficiency decreases by 14%. While substantial, that percentage is small in view of the very low average level of efficiency in the sample. It is therefore likely that application of the land reform laws to brackishwater fish ponds, which so far have secured exemptions via intense political lobbying by the pond owners and lease holders, does not constitute a panacea to unlock the productive potential of these areas. There might be legitimate reasons, on equity grounds, to call for the removal of these exemptions, but the efficiency case for this policy carries only limited weight. We know that the cost of implementing land redistribution programs is always high, and that is likely to be particularly true in the Philippines where issues of corruption, weak law enforcement and slow-moving bureaucracy in coastal areas are well documented (Primavera, 2000).

Although this is an important result for policy formulation, it is unfortunately a negative one as we are left with the conclusion that variations in efficiency relate to unexplained factors. The best we can do at this level is therefore to speculate on the underlying reasons leading to the poor average technical performance of the farms. Here, we believe that the lack of R&D investment in brackishwater aquaculture is a key constraint to the production and productivity growth of the sector. Even aquaculture specialists recognize the difficulty of managing these systems, and it therefore seems that there is a need to generate knowledge before even considering investment in extension services. It remains to be shown that such investments are economically desirable, but our results suggest that the potential gains from improved farm management are very large.

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Appendix 1. Dual properties of the ray production function

The revenue maximisation problem can be written in terms of the ray function as:

$$R(p,x) = \underset{y}{Max}(py) : f(x,\theta(y)) \geq \|y\| \tag{A.1}$$

Denoting by λ the Lagrange multiplier, the first order conditions are:

$$\frac{\partial L}{\partial y_j} = p_j + \lambda[(\sum_{m=1}^{M-1} \frac{\partial f}{\partial \theta_m} \frac{\partial \theta_m}{\partial y_j}) - \frac{y_j}{f}] = 0 \tag{A.2}$$

$$\frac{\partial L}{\partial \lambda} = f(x,\theta(y)) - \|y\| = 0 \tag{A.3}$$

Re-arranging (A.2), multiplying by y_j and summing over all outputs gives:

$$\sum_{j=1}^{M} p_j y_j = -\lambda[\sum_{j=1}^{M} \sum_{m=1}^{M-1} \frac{\partial f}{\partial \theta_m} \frac{\partial \theta_m}{\partial y_j} y_j - \frac{\sum_{j=1}^{M} y_j^2}{f}] \tag{A.4}$$

The first term of this sum can be re-written as $\sum_{m=1}^{M-1}\frac{\partial f}{\partial\theta_m}\sum_{j=1}^{M}\frac{\partial\theta_m}{\partial y_j}y_j$, but since the

function θ_m is homogenous of degree zero in y, $\sum_{j=1}^{M}\frac{\partial\theta_m}{\partial y_j}y_j=0$ Further, using (A.3), equation (A.4) reduces to:

$$R(p,x)=\sum_{j=1}^{M}p_jy_j=\lambda.f\Rightarrow\lambda=R(p,x)/f \tag{A.5}$$

This expression means that the Lagrange multiplier is simply the unit value of the norm. Applying the envelop theorem to the original problem (A.1) therefore gives us:

$$\frac{\partial R}{\partial x_k}=\lambda\frac{\partial f}{\partial x_x}=\frac{R}{f}\frac{\partial f}{\partial x_x}\Rightarrow\frac{\partial\ln R}{\partial\ln x_k}=\frac{\partial\ln f}{\partial\ln x_k} \tag{A.6}$$

Hence, the elastictities of the revenue function and output ray function with respect to any input k are equal and are expected to be positive. We also use (A.5) to rewrite (A.2), from which it follows that the marginal rate of transformation between two outputs is:

$$\frac{p_j}{p_i}=\frac{y_j(\sum_{m=1}^{M-1}\frac{\partial\ln f}{\partial\ln\theta_m}\frac{\partial\ln\theta_m}{\partial\ln y_j}-1)}{y_i(\sum_{m=1}^{M-1}\frac{\partial\ln f}{\partial\ln\theta_m}\frac{\partial\ln\theta_m}{\partial\ln y_i}-1)} \tag{A.7}$$

Suppose all the derivatives of the ray function with respect to the angles are equal to 0. This implies that the previous ratio p_j/p_i is simply equal to y_j/y_i, which can only be the case if the PPF is perfectly approximated in the plane $(y_i;y_j)$ by a circle. Hence, the restriction that all derivatives of the ray production function with respect to the *(M-1)* angles are equal to zero means that the PPF is a perfect sphere of dimension M.

The ray function also shares some dual properties with the minimum cost function. We proceed as before to rewrite the Lagrangian of the cost minimisation problem:

$$C(y,w)=\underset{x}{Min}(wx):f(x,\theta(y))\geq\|y\| \tag{A.8}$$

The FOCs are:

$$\frac{\partial L}{\partial x_k}=-w_k+\lambda\frac{\partial f}{\partial x_k}=0 \tag{A.9}$$

$$\frac{\partial L}{\partial \lambda} = f(x, \theta(y)) - \|y\| = 0 \tag{A.10}$$

Proceeding as before it follows that , implying that:

$$\frac{w_k x_k}{C} = S_k = \frac{\partial \ln f}{\partial \ln x_k} \frac{1}{\varepsilon_{scale}} \tag{A.11}$$

The elasticity of the ray function with respect to any input x_k is therefore interpreted as the scale-adjusted (optimal) cost share of that input.