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DISCUSSION
PAPER

PROFIT EFFICIENCY ANALYSIS UNDER LIMITED INFORMATION WITH AN APPLICATION TO GERMAN FARM TYPES*

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ABSTRACT

Lack of information about technology and prices often hampers the empirical assessment of the validity of the profit maximization hypothesis. We show that the non-parametric Data Envelopment Analysis (DEA) methodology comprises natural tools for dealing with such incomplete information. In particular, we focus on the economic meaning of the DEA model that builds on assumptions of monotone and convex production possibility sets, and provide some extensions that further exploit this economic interpretation. This perspective on DEA is all the more attractive since its original use for technical efficiency analysis is sometimes questionable given its restrictive production assumptions. An application to German farm types complements our methodological discussion. By using nonparametric tools to test specific hypotheses about profit differences, we further demonstrate the potential of the non-parametric approach in deriving strong and robust statistical evidence while imposing minimal structure on the setting under study.

KEYWORDS: profit maximization hypothesis, Data Envelopment Analysis, non-parametric techniques, agriculture

JEL-CLASSIFICATION: C12; C14; D21; P32; Q12

1. INTRODUCTION

Economic theory represents production-allocation decisions as constrained optimization problems; producers optimize their objectives subject to constraints imposed by the production technology. Within the neoclassical paradigm, firms are typically assumed to maximize profits. Given its crucial role in mainstream microeconomic theory, it is interesting to test this assumption empirically, and to quantify deviations from it (or 'inefficiencies') in a meaningful way. Many valuable insights can be gained from tests that build on a functional specification of the production technology. By explicitly integrating inefficiencies in a so-called non-maximum profit function, Khumbakar (2001) shows how conventionally employed calculus tools can still contribute to economists' understanding of productive activities. Yet, with an eye towards the testing of the behavioral assumption of profit efficiency, such approaches ultimately remain restricted by the idiom of some imposed functional form. This is unfortunate because reliable empirical specification tests are not available in many cases, and more fundamentally because economic theory is completely silent on this issue: profit maximization does not imply any particular functional form.

A systematic methodology for empirical profit efficiency analysis that does not need a functional specification of the technology constraints originated from the work by Afriat (1972), Hanoch and Rothschild (1972), Diewert and Parkan (1983) and Varian (1984), building on the activity analysis approach of Koopmans (1951), the duality theory of Shephard (1953), the efficiency analysis approach of Farrell (1957), and the revealed preference theory of Samuelson (1948). This 'revealed profitability' methodology merely needs information on quantities and prices, and essentially applies the theory of convex sets to such data rather than considering them through the lens of a pre-specified function.

However, the hitherto proposed tools for non-parametric profit analysis require full price information. Already Debreu (1951) and Farrell (1957) expressed their concern about the ability to measure prices accurately enough to make good use of economic efficiency measurement. For example, accounting data can give a poor approximation for marginal opportunity costs because of debatable valuation schemes. And even when reliable price information can be retrieved, such information frequently applies only to a subset of input and output commodities.

In this paper, we show that the popular Data Envelopment Analysis (DEA) methodology can be used to remedy the problem of incomplete price information. More specifically, we forward the frequently used DEA model introduced by Banker *et al.* (1984) as the natural solution for dealing with incomplete price information when assessing the validity of the profit maximization hypothesis.

We note at the outset that the DEA model is commonly employed for *technical* efficiency analysis, i.e. the analysis of quantitative waste in production. Yet, even though technical efficiency is a necessary condition for profit efficiency, technical efficiency maximization does not figure as a primal behavioral motivation of our textbook *Homo Economicus*. Moreover, the Banker *et al.* DEA model has some shortcomings as a tool for technical efficiency analysis. The model builds on assumptions of monotone and convex production possibility sets, which are unsustainable in many settings. For example, monotonicity excludes congestion, which is frequently observed in agriculture, transportation and engineering; see e.g. Färe *et al.* (1985). In addition, convexity assumes away indivisible inputs and outputs, economies of scale, and economies of specialization, of which the economic importance was already stressed by Farrell (1959, p. 378 – 379). McFadden (1978; p. 8-9) explicitly stated that the rationale for monotonicity and convexity assumptions in production theory lies 'in their analytical convenience rather than in their economic realism'.

We cannot help but notice that, on a conceptual level, such a rationale is in fact similar to the justification of parametric testing methods.

While DEA may not always fit in very nicely with microeconomic theory as a tool for technical efficiency analysis (although it is conventionally employed for that purpose), we re-institute it here as a well-founded tool for *profit* efficiency testing and measurement. Within this perspective, we additionally provide some extensions of the original Banker *et al.* model, pertaining to the incorporation of monetary (cost or revenue) data for a limited number of commodities and the measurement of 'mix' (in)efficiency.

DEA models are frequently employed for analyzing the agricultural sector; see e.g. the recent studies by Piesse, Thurtle and Turk (1996), Thiele and Brodersen (1999) and Mathijs and Swinnen (2001). However, these studies use DEA for technical efficiency assessment. Conversely, testing the validity of the standard profit maximization hypothesis may be particularly relevant for agriculture, given the peculiar circumstances of the farming business. Hence, we believe the agricultural sector forms a prime area for demonstrating the possible use of DEA for nonparametric profit efficiency analysis, and for illustrating the extensions that we propose. In particular, we study the profit performance of 600 German farm types in the period 1995-1997, and investigate specific hypotheses about differences in revealed profitability according to region, ownership type and production type. In line with the non-parametric orientation of the efficiency analysis methodology, we hereby use non-parametric statistical testing procedures; this further demonstrates the potential of the non-parametric methodology in deriving powerful and robust results while imposing minimal structure on the (largely unobserved) setting under investigation.

The remainder of the paper is organized as follows. Section 2 discusses methodological issues. Section 3 presents our application to German farm types. Finally, section 4 summarizes and contains some concluding remarks.

2. METHODOLOGY

To study firm choices we need a convenient way to summarize the production possibilities of the firm, i.e. which inputs and outputs are technologically feasible. The set of all technologically feasible input-output combinations is called the *production possibility set*.

To formally represent that set, we denote by $z = (z^1,...,z^q) \in \Re^q$ a (non-zero) netput vector with z^j the netput quantity of commodity j.[1] As usual, positive components of z represent outputs and negative components represent inputs. Throughout we assume that the vector z captures at least one input and at least one output. The production technology is represented by the non-empty and closed production possibility set

(1) $T \equiv \left\{ z \in \Re^q \,\middle|\, \text{netput } z \text{ is technically feasible} \right\}$.

We next construct a simple algebraic gauge for profit maximization. We focus on the netput vector $z_j = (z_j^1,...,z_j^q) \in T$ and denote by (non-zero) $p_j \in \Re_+^q$ the corresponding price

[1] Throughout the text we use $\Re^q$ for a q-dimensional Euclidean space, and $\Re_+^q$ denotes the positive orthant. Slightly abusing standard notation, we further use $\left(a^1,...,a^b\right) \in \Re^b$ for $\left(a^1...a^b\right)' \in \Re^b$, and ac for $a'c$ $\left(a,c \in \Re^b\right)$.

vector. Let $q\left(z_j, p_j; T\right) \equiv \max_{z\in T}\left[p_j\left(z - z_j\right)\right]$. We say that the vector z_j is *profit efficient* if and only if it is profit maximizing over the set *T*, i.e.

(2) $$q\left(z_j, p_j; T\right) \equiv \max_{z\in T}\left[p_j\left(z - z_j\right)\right] = 0 .$$

The measure $q\left(z_j, p_j; T\right) \geq 0$ can be interpreted as a measure for profit efficiency; higher values indicate worse profit efficiency performance.

Condition (2) is readily tested if the set *T* and the price vector p_j are perfectly observed. Unfortunately, in practice only limited technology and price information is usually available.

PROFIT EFFICIENCY AND DEA

To deal with the problem of limited technology information, the non-parametric approach to production analysis starts from the set of *observed* netput vectors *S*, and merely assumes that observed vectors are technically feasible, i.e. $S \subseteq T$.[2] Now, for $z_j \in S$ we get instead of condition (2)

(3) $$q\left(z_j, p_j; S\right) = \max_{z\in S}\left[p_j\left(z - z_j\right)\right] = 0 .$$

Observe that $S \subseteq T$ implies $q\left(z_j, p_j; S\right) \leq q\left(z_j, p_j; T\right)$, i.e. (3) is a necessary condition for (2) and $q\left(z_j, p_j; S\right)$ provides a lower bound approximation for the true profit efficiency measure $q\left(z_j, p_j; T\right)$. Interestingly, since *S* is a finite and discrete set, the computation of $q\left(z_j, p_j; S\right)$ merely involves linear programming; see e.g. Varian (1984).

The standard non-parametric approach assumes that prices are perfectly observed. However, as discussed in the Introduction, reliable price information is often not available. We can show that the standard DEA model introduced by Banker *et al.* (1984) provides an intuitive test for condition (3) under incomplete price information.

To see this, we first consider the extreme case where no price information at all is available, except from the fact that prices are non-negative, i.e. we can only impose $p_j \in \Re^q_+ \setminus \{0_q\}$, with 0_q the *q*-dimensional zero vector. A necessary condition for (3) (and hence for (2)) is that there exists at least one price vector under which z_j is profit maximizing over the observed sample *S*, i.e.

(4) $$\begin{gathered}\exists p_j \in \Re^q_+ \setminus \{0_q\} : q\left(z_j, p_j; S\right) = \max_{z\in S}\left[p_j\left(z - z_j\right)\right] = 0 \\ \Updownarrow \\ q^I\left(z_j, \Re^q_+; S\right) \equiv \min_{p_j \in \Re^q_+ \setminus \{0_q\}} \max_{z\in S}\left[p_j\left(z - z_j\right)\right] = 0.\end{gathered}$$

Obviously, given that $z_j \in S$ we have $0 \leq q^I\left(z_j, \Re^q_+; S\right) \leq q\left(z_j, p_j; S\right)$ for any $p_j \in \Re^q_+$. Unfortunately, unlike the preceding measures $q^I\left(z_j, \Re^q_+; S\right)$ cannot be considered as an

[2] This assumption makes abstraction of measurement errors in the input and output data. Tools for extending the non-parametric approach to deal with measurement errors have been proposed; see e.g. Grosskopf (1996). We return to the issue of measurement errors in our application in Section 3.

adequate efficiency gauge since no real meaning attaches to a strictly positive value. This is essentially due to the fact that the (positive) price vector is now endogenously selected for each $z_j \in S$; if there does not exist a price vector under which z_j is profit maximizing over the sample S, we have $q^I\left(z_j, \Re^q_+; S\right) > 0$, but the value will be infinitesimally small.

To remedy that problem, we normalize the prices. We focus on prices that imply an input cost level of unity for the evaluated vector. We accordingly make the explicit distinction between input and output vectors, i.e. we use $z = (-x, y)$ with $x \in \Re^l_+$ the input vector and $y \in \Re^{q-l}_+$ the output vector. Similarly, we decompose $p_j = \left(p^I_j, p^O_j\right)$ with $p^I_j \in \Re^l_+$ the input price vector and $p^O_j \in \Re^{q-l}_+$ the output price vector. Incorporating the price normalization constraint, condition (4) changes to

$$(5) \qquad q^{IN}\left(z_j, \Re^q_+; S\right) \equiv \min_{p_j \in \Re^q_+} \max_{z \in S} \left[p_j \left(z - z_j\right) \middle| p^I_j x_j = 1 \right] = 0, \text{ or}$$

$$(6) \qquad q^{IN}\left(z_j, \Re^q_+; S\right) = \min_{p^I_j \in \Re^l_+,\, p^O_j \in \Re^{q-l}_+} \ \max_{(-x,y) \in S} \left[p^O_j \left(y - y_j\right) - p^I_j \left(x - x_j\right) \middle| p^I_j x_j = 1 \right] = 0.$$

Normalizing the prices does not affect the test for profit efficiency: we still have $q\left(z_j, p_j; S\right) = 0$ for any $p_j \in \Re^q_+$ (with $p^I_j x_j = 1$) only if $q^{IN}\left(z_j, \Re^q_+; S\right) = 0$.[3] Imposing that $p^I_j x_j = 1$, we can re-express (6) as

$$(7) \qquad \begin{aligned} & q^{IN}\left(z_j, \Re^q_+; S\right) = \\ & 1 - \max_{p^I_j \in \Re^l_+,\, p^O_j \in \Re^{q-l}_+,\, u \in \Re} \left[p^O_j y_j - u \middle| p^I_j x_j = 1; u \geq p^o_j y - p^I_j x \quad \forall (-x, y) \in S \right] = 0, \end{aligned}$$

where u is the maximum profit level over the sample S under the endogenously selected price vector $p_j = \left(p^I_j, p^O_j\right)$. Again, checking (7) only requires linear programming.

The measure $q^{IN}\left(z_j, \Re^q_+; S\right)$ can be interpreted as the actual cost level (equaling unity) minus the required cost level for z_j to be profit maximizing over the sample S. This reveals the focus on input performance when evaluating a firm's profit efficiency for given output (revenue). This is often a good model to evaluate production performance; many firms pursue profit maximization where the controllable variables are the cost-generating inputs while the revenue-generating outputs should be taken as given, and it seems intuitive to measure firm performance only in terms of controllable dimensions. In addition, condition (7) clearly reveals that most favorable prices are implicitly selected for the evaluated netput vector, i.e. we apply 'benefit-of-the-doubt pricing' in the absence of full price information.[4]

The focus on input performance is also apparent from the dual formulation of (7), i.e.

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[3] Only relative prices matter in the profit efficiency test; if $q\left(z_j, p_j; S\right) = 0$ for some $p_j \in \Re^q_+$ then $q\left(z_j, t\, p_j; S\right) = 0$ for all $t > 0$.

[4] The reader may notice some analogy between the approach advocated here and the 'shadow price' approach discussed in Färe *et al.* (1990). Still, the approaches differ substantially. First, Färe *et al.* concentrate on cost efficiency while our focus is on profit efficiency. More importantly, Färe *et al.* start from a continuous (piecewise linear) empirical representation of technology, and determine 'shadow' prices in a second step as the marginal rates of input substitution/output transformation derived from the boundary of that empirical production set. By contrast, the approach discussed in this paper starts directly from the observed set of netput vectors and does not use further production assumptions.

(8) $$q^{IN}\left(z_j, \Re^q_+; S\right) = 1 - \min_{l_z \in \Re_+ \; \forall z=(-x,y)\in S} \left[q \,\middle|\, y_j \le \sum_{z\in S} l_z y; q x_j \ge \sum_{z\in S} l_z x, \sum_{z\in S} l_z = 1 \right] = 0 .$$

In words, we look for (one minus) the maximal equiproportional input contraction (for given output) within the set

(9) $$CMH(S) \equiv \left\{ (-x', y') \,\middle|\, y' \le \sum_{z\in S} l_z y; x' \ge \sum_{z\in S} l_z x, \sum_{z\in S} l_z = 1, l_z \in \Re_+ \;\; \forall z = (-x, y) \in S \right\},$$

i.e. the *convex monotone hull* of the observed sample *S*. Recall from our discussion in the Introduction that convexity and monotonicity of a production possibility set is unrealistic to assume in many practical situations. However, convexity and monotonicity naturally ensue from the profit efficiency test: the optimal profit level for some price vector $p_j \in \Re^q_+$ over the set *S* equals that over the set *CMH*(*S*); see also Varian (1984). Hence, in contrast to the case of technical efficiency analysis, convexity and monotonicity are harmless assumptions when analyzing the standard profit maximization model.

We illustrate these points in figure 1, which presents a one input-one output situation. To keep the exposition simple, the set *S* contains only three netput vectors, i.e. $S = \{z_1, z_2, z_3\}$ with $z_j = (-x_j, y_j)$ (*j* = 1, 2,3).

We first consider profit efficiency when relative prices are known. Suppose that all three firms are to be evaluated at prices that determine the slope of the iso-profit line *aa'*. Given these prices, the vector z_1 is profit maximizing over *S* and z_2 and z_3 are obviously profit inefficient. This conclusion does not change when imposing convexity and monotonicity on the production possibility set, i.e. z_1 remains profit maximizing over the set *CMH*(*S*) and z_2 and z_3 remain profit inefficient.

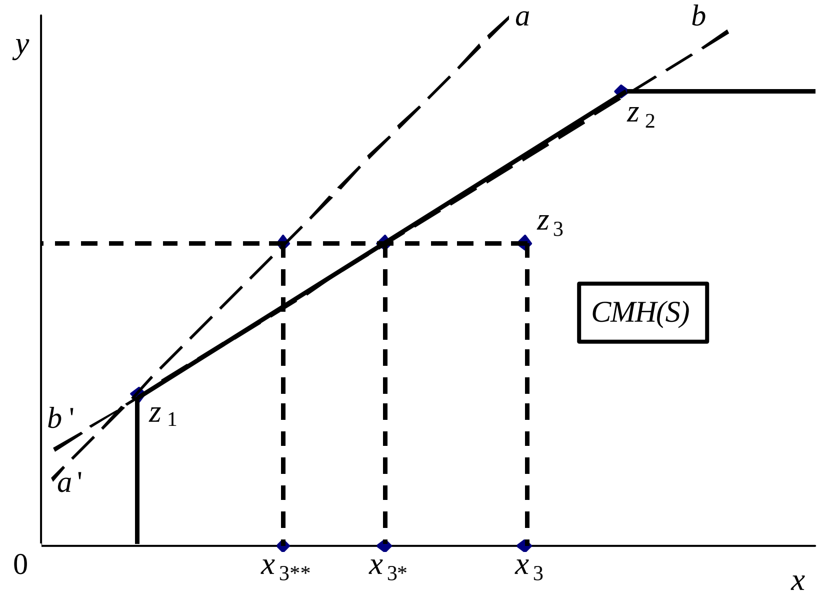
Next, we turn to the situation of incomplete price information. We have that z_2 can no longer be diagnosed as profit inefficient; there exists at least one price vector under which it becomes profit maximizing over *S* (e.g. the vector corresponding to the iso-profit line *bb'*). The vector z_3, on the other hand, is still identified as profit inefficient; there does not exist a price vector such that it meets the necessary profit efficiency condition. More generally, for all netput vectors on the boundary of the set *CMH*(*S*) (like z_1 and z_2) we can construct a price vector that makes these netput vectors profit maximizing over *S*, while the opposite holds for points in the interior of that set (like z_3).

Finally, we can evaluate the degree of profit efficiency of an inefficient vector like z_3 by using the measure $q^{IN}\left(z_3, \Re^q_+; S\right) = \left(1 - 0x_{3*}/0x_3\right) > 0$; the netput vector z_3 meets the necessary profit efficiency condition (8) when it reduces its input with a factor $0x_{3*}/0x_3$. Profit efficiency can no longer be rejected for the resulting vector $(-x_{3*}, y_3)$; this vector is profit maximizing over the sample *S* for relative prices determining the slope of the iso-profit line *bb'*. The factor $0x_{3*}/0x_3$ can also be interpreted as the minimally needed relative cost decrease for z_3 to become profit maximizing over *S* when keeping the revenue level fixed. Clearly, the relative prices corresponding to the slope of the iso-profit line *bb'* are more favorable for evaluating profit efficiency of z_3 than e.g. those corresponding to *aa'* (i.e.

$\left(1-0x_{3**}/0x_3\right)>\left(1-0x_{3*}/0x_3\right)$), which demonstrates the 'benefit-of-the-doubt pricing' principle that underlies $q^{IN}\left(z_j,\Re_+^q;S\right)$ in (7).

The figure further demonstrates why *CMH*(*S*) is naturally associated with profit maximization. When checking profit efficiency one refers to iso-profit hyperplanes, and it are these which constitute *CMH(S).* By contrast, one does not refer to iso-profit hyperplanes when strictly focusing on the properties of the (technical) production possibilities set, implying that convexity and monotonicity are to be 'imposed', sometimes erroneously, in the case of technical efficiency analysis.

Figure 1: Profit efficiency measurement under limited information



We are now in a position to institute the profit efficiency interpretation of the DEA model that Banker *et al.* (1984) originally proposed for *technical* efficiency assessment. The second term in (8) gives the Debreu (1951)-Farrell (1957) (*DF*) input efficiency measure computed with respect to *CMH*(*S*). For expositional convenience, we will further denote that measure as

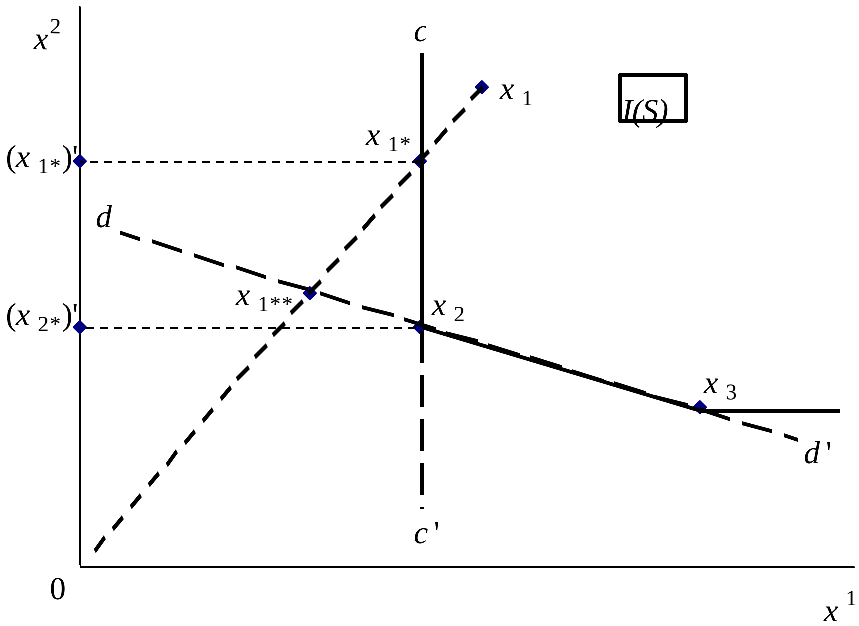
(10) $$q^{DF}\left(z_j,CMH(S)\right)\equiv\min_{l_z\in\Re_+\forall z=(-x,y)\in S}\left[q\left|y_j\leq\sum_{z\in S}l_z y;q\,x_j\geq\sum_{z\in S}l_z x,\sum_{z\in S}l_z=1\right.\right].$$

We have that $q^{DF}\left(z_j,CMH(S)\right)\in[0,1]$ and $q^{IN}\left(z_j,\Re_+^q;S\right)=1-q^{DF}\left(z_j,CMH(S)\right)$. Hence, $q^{IN}\left(z_j,\Re_+^q;S\right)=0$ if and only if $q^{DF}\left(z_j,CMH(S)\right)=1$. This unveils the *profit* efficiency interpretation of $q^{DF}\left(z_j,CMH(S)\right)$, which is precisely the efficiency measure that Banker *et al.* (1984) proposed. In view of the foregoing discussion, we believe that interpreting $q^{DF}\left(z_j,CMH(S)\right)$ in profit terms is better justified than interpreting it in the pure technical (quantity) terms for which it was originally intended.

We provide an illustration of the *DF* measure for a two-input situation in figure 2. For simplicity, we again consider a sample of only three observations, which now all produce the same output y, i.e. $S=\{z_1,z_2,z_3\}$ with $z_j=(-x_j,y)$ (j = 1,2,3). Under these conditions, $q^{DF}(z_j,CMH(S))$ (j = 1, 2,3) is computed as the maximal equiproportional input contraction within the input set bounded by the convex monotone hull of the three observed input vectors, i.e. within $I(S)=\{x|(x,y)\in CMH(S)\}$ in figure 2. For example, for the netput vector z_1 we have $q^{DF}(z_1,CMH(S))=0x_{1*}/0x_1$ (and thus $q^{IN}(z_1,\Re^q_+;S)=(1-0x_{1*}/0x_1)$). Because $q^{DF}(z_1,CMH(S))<1$, we conclude that z_1 does not pass the necessary profit efficiency test. Similarly, z_2 and z_3 do satisfy the profit efficiency condition.

We again stress the attractive price interpretation of the *DF* measure. For the netput vector z_1 the (relative) implicit input prices used for estimating the profit efficiency measure correspond to the slope of the iso-cost line *cc'*; under these prices both x_{1*} and x_2 are cost minimizing over *S*. These are most favorable prices for evaluating the profit efficiency of z_1; for example, under the relative input prices that make both x_2 and x_3 cost minimizing over *S* (see the iso-cost line *dd'*) the resulting profit efficiency measure is $(1\text{-}0x_{1**}/0x_1)$, and obviously $(1\text{-}0x_{1**}/0x_1)>(1\text{-}0x_{1*}/0x_1)$.

Figure 2: Profit efficiency, *DF* input efficiency and mix efficiency



The efficiency condition in (10) merely uses quantity information. However, in much applied work (even on 'technical' efficiency analysis) only cost and revenue data rather than pure quantity data are available for individual input and output dimensions. Such revenue or cost information for a subset of input and output commodities can also be integrated in the above framework: we construct an input subvector $x^*\in\Re^{\bar{l}}_+$ $(1\le\bar{l}\le l)$ and an output subvector $y^*\in\Re^{\overline{q-l}}_+$ $(1\le\overline{q-l}\le q-l)$, with one input (output) the monetary sum value of all inputs (outputs) for which cost (revenue) data are available while the remaining inputs (outputs) contain only quantity information.

It is easy to verify that such use of cost (or revenue) data for particular inputs (or outputs) is consistent with our ultimate goal to test necessary conditions for (3) if the following two conditions are satisfied for the inputs and outputs contained in the monetary subvectors.[5] First, the observed monetary values should reliably reflect the true cost/revenue values faced by firms. Second, all firms should face the same prices for the input and output commodities.[6]

Using vectors x^* and y^* instead of the original (quantity) vectors x and y in (7) (or (8)) actually implies a hybrid form of the 'full price information' condition (3) and the 'no price information' condition (5): actual prices are used for determining the relative value within the subvectors of inputs and outputs for which reliable price information is available, while implicit, most favorable prices are used for determining relative values within the subvectors for which no reliable price information is available. Evidently, most favorable prices must also be used for comparisons *between* the different subvectors. We illustrate this approach in Section 3.

ZERO PRICES AND MIX EFFICIENCY

From our above discussion, we know that using $q^{DF}\left(z_j, CMH(S)\right)$ implies testing for profit maximization under 'benefit-of-the-doubt pricing'. Inconveniently though, the selection of most favorable prices does not exclude *zero prices*; see the single price restriction $p_j^I \in \Re_+^l$, $p_j^O \in \Re_+^{q-l}$ in (7). Intuitively however, we are inclined to label a netput vector as profit efficient if and only if it is profit maximizing over the production possibility set under a *strictly positive* price vector; this notion of profit efficiency is consistent with the fundamental theorems of welfare economics.

The possibility of zero implicit prices has a direct interpretation in quantity terms; the *DF* measure may label a netput vector as efficient when it is actually still characterized by 'wasteful production' as compared to other vectors in the reference input set. Specifically, after maximum *equiproportional* input adjustment it may still be possible to further reduce some *individual* inputs.

As an illustration, we take again our example of figure 2. In that example, the input vector x_{1*} (the *DF* reference vector of x_1) is efficient according to the equiproportional *DF* measure while it exhibits waste in the second input dimension. In price terms, x_{1*} is cost minimizing over the sample only if a zero implicit price is accorded to the second input; x_{1*} produces y at a higher cost level than x_2 for any positive price accorded to that input.

Cherchye and Van Puyenbroeck (2000) developed a general shadow price framework for technical efficiency assessment that solves this problem associated with the *DF* efficiency measure. Specifically, as residual inefficiency not captured by *DF* measures typically pertains to the adopted input and output mixes (see e.g. figure 2), they make the distinction between *DF* and 'mix efficiency'. We will here summarize the main ideas pertaining to the proposed treatment of zero implicit prices and mix inefficiency, and refer to the aforementioned paper for a more rigorous analysis.

Intuitively, the zero shadow price problem can be overcome by searching for an alternative reference vector. Inspection of figure 2 strongly suggests to take the vertex point x_2, since x_2 is not only supported by the same iso-cost line (*cc'*) as x_{1*}, but can additionally be supported

[5] Färe *et al.* (1994) forward similar conditions in their discussion on efficiency assessment when cost and revenue data rather than pure quantity data are available.

[6] Price variation is possible only if it corrects for quality difference, i.e. differences in prices should make the goods 'homogenous'.

by many other iso-cost lines (one of which is *dd'*) with strictly positive prices. Consequently, a complementary measure of mix efficiency has to provide information on the (appropriately defined) distance between x_{1*} and x_2. Since $x_{1*} \geq x_2$ a natural measure for evaluating this distance is given by the normalized metric $\|x_2\|/\|x_{1*}\| = \sqrt{\sum_{i=1,2}\left(x_2^i\right)^2 / \sum_{i=1,2}\left(x_{1*}^i\right)^2}$. In general, a mix efficiency measure can thus be defined as

$$(11)\ q^{MIX}\left(z_j, CMH(S)\right) \equiv \left[\min_{l_z \in \Re_+ \forall z=(-x,y) \in S}\left(\sqrt{\frac{\sum_{i\in\{1,\dots,l\}}\left(\sum_{z\in S} l_z x^i\right)^2}{\sum_{i\in\{1,\dots,l\}}\left(x_{jR}^i\right)^2}}\ \middle|\ \begin{array}{l} y_j \leq \sum_{z\in S} l_z y; x_{jR} \geq \sum_{z\in S} l_z x; \\ \sum_{z\in S} l_z = 1 \end{array}\right)\right],$$

with $x_{jR} = q^{DF}\left(z_j, CMH(S)\right) \times x_j$ the reference input vector used to compute the *DF* input measure for the evaluated vector z_j (i.e. x_{1*} in our example).

The only caveat is that proceeding as such would imply that mix efficiency measurement is sensitive to the units in which each input dimension is measured. In our example, if the second input (say labor) is no longer measured in hours but in days, we would end up with a smaller fraction $\|x_2\|/\|x_{1*}\|$.

Dividing each original input quantity by a value expressed in the same measurement unit can solve this problem. Extending this line of reasoning to the multidimensional case, Cherchye and Van Puyenbroeck showed that one such 'units invariant' alternative for (11) is

$$(12)\ q^{M}\left(z_j, CMH(S)\right) \equiv \left[\min_{l_z \in \Re_+ \forall z=(-x,y) \in S}\left(\sqrt{\frac{\sum_{i\in\{1,\dots,l\}} q^i}{l}}\ \middle|\ \begin{array}{l} y_j \leq \sum_{z\in S} l_z y; q^i x_{jR}^i \geq \sum_{z\in S} l_z x^i\ i \in \{1,\dots,l\}, \\ \sum_{z\in S} l_z = 1; 1 \geq q^i \geq 0\ i \in \{1,\dots,l\} \end{array}\right)\right].$$

Thus, $q^M\left(z_j, CMH(S)\right) \in [0,1]$ minimizes the arithmetic mean of the (uni-dimensional) input contraction factors for the *DF* reference vector.[7] Given the economic perspective we are upholding in this paper, we additionally note that this mix efficiency measure also bears an economic (price) interpretation, viz. as a dominance measure in price space. Loosely stated, and looking again at the example, the fact that x_2 demonstrably has a more efficient input mix than x_{1*} can be translated into dual (price) terms by the claim that, given the same cost-level (of unity), x_2 can always 'afford' higher unit prices than x_{1*}.

It is easy to verify that the computation of $q^M\left(z_j, CMH(S)\right)$ once more only involves linear programming since we can first compute the minimum value under the square root operator in (12), and apply the simple positive monotone transformation of the thus obtained solution afterwards.

Finally note that the two components of profit performance (*DF* input efficiency, captured in $q^{DF}\left(z_j, CMH(S)\right)$, and input mix efficiency, captured in $q^M\left(z_j, CMH(S)\right)$) can be combined in a single, aggregated efficiency measure

[7] Sahoo and Sengupta (2001) provide an empirical assessment of this particular mix efficiency measure.

(13) $q^{A}\left(z_j, CMH(S)\right) \equiv q^{DF}\left(z_j, CMH(S)\right) \times q^{M}\left(z_j, CMH(S)\right)$,

with $q^{A}\left(z_j, CMH(S)\right) \in [0,1]$ and higher values indicating better profit efficiency performance. It follows that z_j is profit maximizing under *strictly positive* prices only if $q^{DF}\left(z_j, CMH(S)\right) = q^{M}\left(z_j, CMH(S)\right) = q^{A}\left(z_j, CMH(S)\right) = 1$.[8]

It is worth pointing out that the measure $q^{A}\left(z_j, CMH(S)\right)$ closely resembles the Zieschang (1984) (technical) efficiency measure. The mere difference is the square root in the definition of $q^{M}\left(z_j, CMH(S)\right)$. Interestingly, the Zieschang measure has attractive axiomatic ('well-behavedness') properties for the *CMH*(*S*) reference set (see e.g. Ferrier *et al.*, 1994), which carry over to the (economic) efficiency measure $q^{A}\left(z_j, CMH(S)\right)$.

Using the comprehensive measure (13), we can quickly check whether a certain z_j can be considered as consistent with profit maximization under strictly positive prices, as this amounts to $q^{A}\left(z_j, CMH(S)\right) = 1$. But, as our above discussion makes clear, the two components of $q^{A}\left(z_j, CMH(S)\right)$ provide information about basically two distinct dimensions of efficiency performance. Therefore, in our application in the next section we pay special attention to the individual *DF* and mix efficiency components.

We conclude this section by recapturing our earlier example. In figure 2, input vectors x_2 and x_3 are both mix and *DF* efficient. We know that x_1 is *DF* inefficient and mix inefficient. The mix efficiency measure $q^{M}\left(z_1, CMH(S)\right) = \left[(1 + 0(x_2)'/0(x_{1*})')/2\right]$ compares x_{1*} to x_2, and the comprehensive measure $q^{A}\left(z_1, CMH(S)\right)$ compares x_1 (or z_1) to x_2 (or z_2). Observe that, if the input vector x_{1*} were actually observed, it would be *DF* efficient but not mix efficient: it does not meet the necessary profit efficiency condition outlined above. Notice that the reverse situation is also possible: netput vectors can be mix efficient but *DF* inefficient.

3. APPLICATION

We apply the proposed methodology to a sample of German farms over the two seasons 1995-1996 and 1996-1997. Thiele and Brodersen (1999) analyzed the technical efficiency of this sample. We complement their analysis with results for profit efficiency.[9] We first describe the application setting, and motivate why this setting is well suited for applying the non-parametric methodology presented in the previous section. Subsequently, we review the most interesting results of our exercises. For ease of notation, we use q^k for $q^{k}\left(\cdot, CMH(S)\right)\ (k = DF, M, A)$ in this section.

[8] Imposing an additional output mix efficiency requirement can further strengthen this necessary condition for profit maximization; the treatment of output mix efficiency is readily analogous to that of input mix efficiency. However, since we focus on inputs as the controllable performance dimensions, we do not discuss output mix efficiency in this paper. In addition, in our application discussed in the next section there is only one output, and so the possibility of output mix inefficiency is excluded.

[9] We thank Holger Thiele for generously providing the data.

SETTING

The original data set contains 8773 farms per season (i.e. approximately 1.5 percent of the total population of German farms), and is grouped in 600 farm types, where each 'farm-type observation' is an average of (at least 3) farms with a similar total gross margin potential. The fact that groups of similar farms are used as observational units is interesting because the non-parametric approach builds directly on the observed data and therefore is very sensitive to measurement errors; evidently, using group data averages out -at least to some extent- measurement errors in individual observations. In addition, the fact that the non-parametric orientation builds on a convex monotone hull of the observed input-output vectors makes it sensitive to sampling error, i.e. efficiency tests may lack discriminatory power in small samples (see e.g. Simar and Wilson, 2000, for a more elaborate discussion of this sampling error problem). From that perspective, the fact that the sample consists of as much as 600 observations is attractive in that it makes the application of the non-parametric methodology meaningful; we can argue that the observed sample provides a good representation of the true production technology. Furthermore, consistency results that have been established for the non-parametric DEA-model that we apply here suggest that the interdependency problem -i.e. the fact that any obtained efficiency value is found upon comparison with *CMH*(*S*), and in that sense depends on the exact location of all observed netput vectors- diminishes for large samples. Hence, these asymptotic results *inter alia* imply that we can have reasonable confidence in test results aimed at comparing different 'independent' subgroups of our sample (see e.g. Banker et al., 1999, and Simar and Wilson, 2000).

The original data set consists of five inputs (labor units per farm (I1), hectares managed by the farm (I2), capital in Euro (I3), variable inputs (seeds, fertilizer, etc.) in Euro (I4) and miscellaneous inputs (electricity, water, etc.) in Euro (I5)) and three outputs (crop returns in Euro (O1), livestock returns in Euro (O2) and miscellaneous returns in Euro (O3)); see Thiele and Brodersen (1999) for more details. Thus, for three inputs (I3, I4 and I5) and all three outputs monetary data (i.e. cost and revenue data) are available. Following the method outlined in Section 2, we use this monetary information to end up with three inputs (I1, I2, and I3+I4+I5) and a single, aggregated output variable (01+02+03).[10] Further, it is reasonable to assume that only the inputs are the controllable variables for the farm managers, while the output (revenue) should be treated as exogenously given. Hence, we will adopt the input orientation discussed in Section 2.

The sample can be decomposed along three dimensions. First, we can distinguish between *regions*: data are available for seven federal länder of former West Germany ((a) Schleswig Holstein, (b) Lower Saxony, (c) North Rhine-Westphalia, (d) Hesse, (e) Rhineland-Platinate, (f) Baden-Württemberg and (g) Bavaria) and for five federal länder of former East Germany ((a) Brandenburg-Berlin, (b) Saxony-Anhalt, (c) Mecklenburg-Western Pomerania, (d) Thuringia and (e) Saxony). Second, we can group farms according to *ownership type*: (a) individual farms, (b) partnerships, and (c) companies and co-operatives. The latter farm category is only found in the East German länder since it consists of 'large–scale successor organizations' (LSOs) of former collective and state farms. Finally, we have data for different *production types*: (a) crop farms, (b) livestock farms, (c) pig and poultry farms, and (d) mixed farms. Table 1 shows the composition of the sample.

[10] Recall that we thus assume that all German farm types face the same (quality-corrected) prices for I3, I4 and I5 and O1, O2 and O3. In the absence of more price information, it seems indeed plausible that price differences (over regions, ownership types and production types) for the respective commodities are essentially due to quality differences.

Table 1: Number of observed farms per category

	Private farms	Partnerships	LSOs	*Row totals*
Pig and Poultry farms	3 + 42	4 + 11	7 + 0	*14 + 53*
Crop farms	72 + 136	10 + 30	13 + 0	*95 +156*
Livestock farms	67 + 111	10 + 14	12 + 0	*89 + 125*
Mixed Production	4 + 41	2 + 11	10 + 0	*16 + 52*
Column totals	*146 + 330*	*26 + 56*	*42 + 0*	***214 + 386***

Note: the first number refers to East German farms, the second number to West German farms.

We investigate whether there are statistically significant differences in profit efficiency according to production structure, region, or ownership structure. Similar research questions have appeared elsewhere; see Sarris *et al.* (1999) for a discussion and survey of empirical results pertaining to eastern European agriculture. Many DEA studies address hypothesis testing through superficial (graphical) interpretation of individual efficiency results, and do not use well-established testing techniques. Alternatively, parametric methods are used to explain DEA efficiency values, e.g. Tobit regression techniques as in Mathijs and Swinnen (2001). This seems at odds with a general non-parametric orientation, as it implies imposing parametric structure on the unknown distribution of the inefficiencies.

The alternative that we employ rests on simple non-parametric statistical testing procedures. Most of the tests below can be found in classical textbooks on non-parametric statistics (e.g. Marascuilo and McSweeney, 1977; or Hollander and Wolfe, 1999). A prime reason for adhering to distribution-free methods relates to the distribution of efficiency values, which cannot be thought of as Gaussian. For example, using the Shapiro-Wilk test, we obtain a probability value of less than 0.0001 for the q^{DF}-values. The normal distribution fits even less for the q^{M}-values. Recalling how the q^{A}-values are constructed, it is rather unsurprising that also in that case the working hypothesis of normality is highly questionable.

One way to proceed would be to look for other 'underlying' parametric distributions (e.g. exponential, half-normal or beta distributions). We deliberately do not opt for this route in this paper, but instead apply non-parametric testing tools to investigate hypotheses about profit efficiency differences.

Specifically, we employ non-parametric techniques to compare subsamples of production units. Some authors (e.g. Brockett and Golany, 1996; Thiele and Brodersen, 1999; Talluri *et al.*, 2000) have applied similar techniques in combination with DEA, albeit that such research does not focus on profit efficiency. One aim of this section is to present a more comprehensive toolkit of (still fairly standard) testing techniques and thus to further underscore the particular attractiveness of non-parametric statistics in conjunction with non-parametric (profit) efficiency analysis. In addition, our methodology allows for distinguishing between *DF* efficiency and 'mix efficiency'. Particularly, many of the tests below address the question whether there are significant differences in the frequency distribution (or the median) of the efficiency measures q^{DF}, q^{M}, q^{A} associated with different groups (in terms of region, ownership type and production type). In checking the validity of the conventional profit maximization model for German farm types, we thus follow the original suggestion of Farrell (1957) that "it is to such frequency distributions that we must look for a measure of the success of the analysis, corresponding to the multiple correlation coefficient in regression analysis" (p. 270). Varian (1990) expressed the same idea of looking at frequency distributions of economically meaningful measures of profit maximization, stating that "the pattern of violation can tell us a lot about what is going on in the data" (p. 130). It are precisely such patterns of violation that we try to discern in our empirical analysis.

FARMS AS FACTORIES?

The dataset compiled by Thiele en Brodersen (1999) considers farms with different kinds of output specialization. We here use this decomposition to examine whether there are systematic differences between the profit efficiency values of crop farms, livestock farms, pig and poultry farms and mixed farms.

Given that our purpose is to test the empirical validity of the profit maximization hypothesis, such differences may be expected *a priori*. It suffices to recall that the basic assumption, as tested on the basis of condition (2), explicitly considers a non-random relation between individual input decisions and realized profits. Yet if profit uncertainty enters the picture, e.g. because outputs vulnerable to weather conditions are not sold in futures markets, this behavioral assumption obviously has some drawbacks. Theoretically, it neglects any impact of the producer's degree of risk aversion and (subjective) beliefs on his productive decisions. Furthermore, to the extent that farms are hit by idiosyncratic shocks, this may bear on their empirical relative profit efficiency performance. This observation becomes a key concern if one's focus would shift (similar to many research in this area) from 'testing the empirical validity of the yardstick' to the far more normative exercise of 'assessing individual performance in terms of the yardstick'.

Figure 3 confirms that the yardstick of profit maximization is indeed more applicable to some farm types than to others. It is moreover in line with the foregoing comments that this is manifestly the case for pig and poultry farms, the subcategory that is least prone to natural risks during the productive process.

Figure 3: Cumulative frequency polygons of q^A-values for different production types

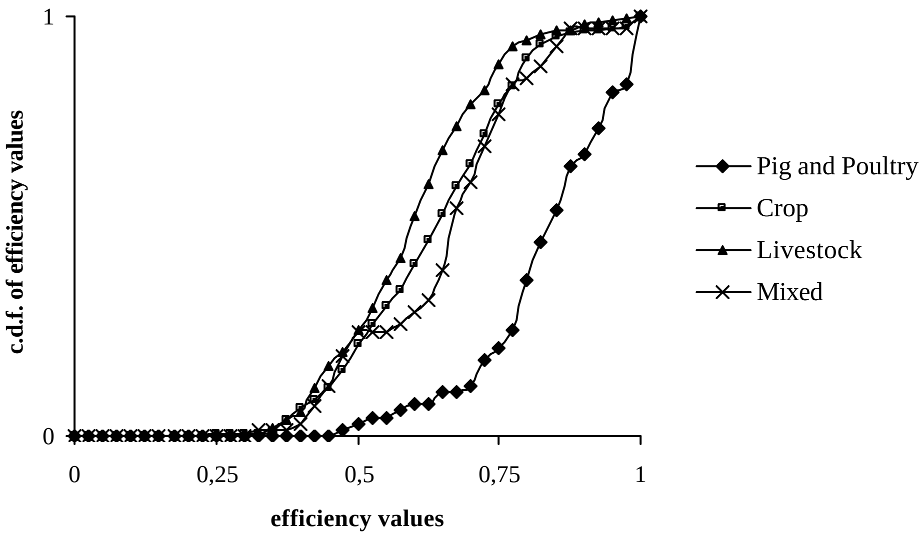


Table 2 provides further clarification of the differences in these frequency distributions; Kolmogorov-Smirnov results confirm that there is no statistical support for the hypothesis that the profit efficiency values for pig and poultry farms have a similar distribution as each of the other three farm types. This result holds for the aggregate measure, for its *DF* component, and in two of the three cases also for its mix component. Mutual comparisons between the other farm types reveal a less clear picture: crop farms are not significantly different from livestock or mixed farms on account of the q^A-values (see also figure 3), although there is a clear difference if we concentrate on mix inefficiency.[11] The reverse picture appears when comparing livestock farms to mixed farms.

The numbers displayed in table 2 refer to non-directional hypotheses. An alternative thesis, viz. that the efficiency values of pig and poultry farms are stochastically larger than those of the other three types, is confirmed at least as firmly as the general test for merely ‘different’ distributions.[12]

Table 2: Differences between production types

	Mixed	Livestock	Crop
Pig and Poultry			
q^{DF}	< 0.001	< 0.001	< 0.001
q^{M}	—	< 0.001	< 0.001
q^{A}	< 0.001	< 0.001	< 0.001
Crop			
q^{DF}	—	—	
q^{M}	< 0.001	< 0.005	
q^{A}	—	—	
Livestock			
q^{DF}	< 0.05		
q^{M}	—		
q^{A}	< 0.01		

Note: entries show the probability when the null hypothesis of equal distributions is true, as computed on the basis of a two-tailed Kolmogorov-Smirnov test; ‘—’ indicates that this probability is at least 0.1.

A supplementary way to approach the uncertainty issue is to investigate whether there are any significant differences in the dispersion of the profit efficiency values of pig and poultry farms *vis à vis* the other farm types. With the population medians unknown, but in all likelihood different, a Moses test was used to examine whether the variance of profit efficiency values of pig and poultry farms is generally lower than that associated with other farm types. We find weak statistical support for this thesis in the case of q^{DF}- and q^{A}-values (the probability values associated with the test statistics being approximately 0.12 and 0.13 respectively). Equal dispersion of q^{M}-values can however be rejected (given that the corresponding test statistic has a probability value of less than 0.0001).[13]

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[11] A figure similar to figure 5 reveals that the cumulative frequency polygon of crop farms is consistently ‘on top’ of the other three, indicating that the corresponding mix efficiency values are consistently lower. The reverse holds for pig and poultry farms.

[12] Probability values computed on the basis of the chi-square approximation for such one-tailed tests are nowhere higher than 5×10^{-5}, except for the comparison of the $?^{M}$-values with mixed farms, for which the probability value equals 0.067.

[13] For each efficiency measure, the results were obtained by considering random subsets of size 5; 13 subsets in the case of pig and poultry farms and 106 subsets for all other types. Given the random nature of the Moses test,

These first tests support the thesis that some farming subcategories –not surprisingly those dubbed pig and poultry 'factories'– conform better to the neoclassical definition of the firm than others. More generally, we think these tests demonstrate that there is often a need to consciously deal with uncertainty when discussing profit efficiency.

OWNERSHIP, PRINCIPAL-AGENT PROBLEMS AND PROFIT EFFICIENCY

We next look at the possible effect of organizational form on profit efficiency. Such an effect may exist, following the line of research which states that moral hazard is less of a problem in private farms than in partnerships and –to an even greater extent- in LSOs. Private ownership implies that the farmer is residual claimant and that the incentive to free ride is largely mitigated. Also, effort monitoring is easiest in private farms, which should be revealed by relatively favorable results in an empirical test of profit efficiency. Conversely, principal-agent problems will become more of an issue in partnerships, and even more in LSOs (see e.g. Schmitt, 1991; and Allen and Lueck, 1998).

Using regression analysis, Mathijs and Swinnen (2001) indeed found that ownership matters for efficiency, but that this result depends on the output specialization of the farm: the agricultural activity in itself can affect moral hazard and effort monitoring (see their example of livestock production versus easier-to-monitor and less labor intensive crop production). As we maintain the idea of non-parametric testing, we used ranks as the dependent variable in a two-way ANOVA to get some information on this issue. In order to account for differences in production type, we first used an 'aligned ranks' method (see e.g. the Hodges-Lehman tests as described in Marascuilo and McSweeney, 1977), which boils down to an approach whereby, prior to ranking, mean production type effects are neutralized by subtracting a correction factor from the original efficiency values. For instance, the average q^A-value of pig and poultry farms is 0.829, which is higher than the sample average of 0.676. This positive block effect (0.153) is then subtracted from the efficiency value of each pig and poultry farm. A similar procedure is followed for the other production types.[14] The upper part of table 3 summarizes our findings. The first row shows the sum of aligned ranks per column, divided by the total number of observations per column to account for the unbalanced nature of the original two-way layout. Low values thus reveal a high average overall ranking. Hence, taking into account the mean production type effect we observe that private farms (the first column) perform significantly better .

Aligned rankings make good use of 'between block' information and allow for a rather clear summary representation, but the associated test statistics do not depend on the ranks of the original observations. Alternative, completely distribution-free two-way ANOVA procedures are fundamentally based on 'within block' rankings rather than aligned rankings over the entire sample. The lower part of table 3 presents such distribution-free test statistics, obtained by using the Mack and Skillings (1980) procedure. The first row displays weighted sums of cell ranks for the different ownership types.[15] These values are to be compared with the expected mean value if ownership has no effect on the rankings. The difference between

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the values reported in the main text are based on the biweighted mean of (3 ×) 20 test runs. Alternative statistics, such as trimmed means, yield qualitatively similar results.

[14] The block effects for these other types are all negative (meaning that the associated average efficiency value is below the average for the entire sample). Specifically, we have a correction factor of –0.05 for crop farms, -0.08 for livestock farms, and –0.03 for mixed production farms. These numbers are consistent with the results displayed in figure 3.

[15] The weights are equal to the inverse of the number of observations per production type. Furthermore the ranks in each cell are only based on the relative performance vis-à-vis farms of the same production type, i.e. 'within a block' as indicated in the main text.

the actually observed sum of ranks and the expected mean is displayed in the second row. We again find that private farms have a lower ranking than expected under the null hypothesis, while the opposite holds for the two other types.

Similar exercises can be carried out when reversing the roles of production types and ownership types, so checking for main effects of production types on profit efficiency. These and related issues are discussed more elaborately in Appendix A.

Table 3: Ownership and profit efficiency with corrections for production type

	Private farms	Partnerships	LSOs
Sum of aligned interblock ranks	275.86	355.18	475.95
Difference with			
Partnerships	-79.32 *(a)*		
LSOs	-200.09 *(a)*	-120.77 *(a)*	
Weighted sum of intrablock ranks (observed)	220.29	48.90	32.81
Difference with expected *(b)*	-19.20	7.57	11.63

Note: *(a)* indicates that the differences in mean rankings for different ownership types are significant at the 0.05 level, following the comparison procedure outlined in Marascuilo and McSweeney (1977, p. 410-414); *(b)* indicates that the associated value of the Mack-Skillings test statistic (57.51) implies a rejection of the null hypothesis that ownership has no effect on the rankings.

The previously proposed framework further allows us to check whether there are systematic differences between ownership types as regards the occurrence of implicit zero prices. Here, this is particularly interesting as the moral hazard problem primarily relates to one specific input. Indeed, if principal-agent problems exist, one expects that labor will more frequently be 'wasteful' for LSOs and –to a somewhat lesser extent- partnerships. This hypothesized link between farm ownership and moral hazard problems is corroborated for our data as the 'labor'-column in table 4 shows.

Table 4: Farm ownership and implicit zero factor prices

	Labor	Land	Miscellaneous
Private farms	0.6	49.8	50.2
Partnerships	11.0	56.1	22.0
LSOs	85.7	90.5	0

Note: entries should be interpreted as follows: the 'most favorable farm-specific shadow price' associated with labor is zero for 0.6 percent of all private farms in the sample, for 11 percent of all partnerships in the sample, etc.

Table 4 provides some additional insights. The pattern in the last column indicates that partnerships are more successful than private farms in passing the minimal optimal allocation test for miscellaneous inputs. One possible explanation could be that partnerships allow for gains of task specialization, which may be particularly large for tasks such as general management decisions, pesticide application, etc. (see Allen and Lueck, 1998). Unfortunately, the dataset provides no information on task specialization within farms, and a direct test of this hypothesis is therefore impossible.[16] The result that land is 'wasted' so often

[16] Extending this line of reasoning, gains from specialization seem even more persistent in LSOs. The positive impact of (even more) specialized managers on allocative decisions would then show up by a very low number in the third column of the last row in table 3. We stress however that one must be cautious with the

(see the second column) may be due to its fixed nature and the existence of random production shocks.[17] An alternative explanation for the results of the land factor starts from the recognition that we ignore any possible regional (in casu East-West) variation in table 4. Upon decomposing each entry in the table, we indeed find some indications for such differences. To take the most striking example, the land/partnerships entry in table 4 (56.1%) actually conceals a figure of 92.3% for eastern partnerships and of 39.3% for their western counterparts. We will return to this issue shortly. However, to conclude our discussion of moral hazard we emphasize that regionally decomposed implicit factor price figures are far more stable for labor (the highest East-West difference –for partnerships– amounts to merely 4.8%), and the gist of our argument as displayed in the labor column of table 4 therefore remains unaffected.

INTER-REGIONAL DIFFERENCES

Interesting patterns of violation may also ensue from a regional breakdown of the profit efficiency measure. Results of the Kruskal-Wallis test directly confirm that it is extremely unlikely that the länder-specific efficiency values are samples which are all drawn from the same population: for q^{DF}, q^{M} and q^{A} the corresponding values of the Kruskal-Wallis test statistics have probability values of 4.42×10^{-40}, 1.02×10^{-26} and 6.25×10^{-46}, respectively.

Such overwhelming evidence of overall inter-regional differences leads to the more specific question which länder are actually different. Table 5 provides a succinct overview of pair-wise comparisons between länder, with the upper triangular part displaying results on the basis of the rankings of the comprehensive efficiency measure (13) and the lower triangular part focusing on comparisons of the mix-efficiency measure (12). While there is no evidence for an impact due to differing geographical characteristics (e.g. between the northerly lowlands and more mountainous areas), there is an apparent distinction between two blocks in the table, to wit, (former) West German länder and East German länder. This partition is significant for the aggregate efficiency measure as well as for the mix efficiency measure. (Results for the *DF* values, which are not displayed, are similar to those for the aggregate efficiency measure.) These results substantiate the frequent practice in applied work to consider farms in transition economies *a priori* different from farms in market economies. Consistent with such approaches, and backed up by the results in table 5, we treat former West German and East German farms as two different groups in our remaining analysis.

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interpretation of the zero value in that table. There is an additional factor at play, to wit, the fact that there are already many zero shadow prices for the other two inputs in the LSO case. As figure 3 clearly reveals, one cannot have relative zero prices in all input dimensions simultaneously after radial projection on a facet of *CMH(S)*.

[17] While the difference between LSOs and the other two ownership types for 'land' seems quite startling, we think this feature can largely be explained by land *quality* differences. As noted by Thiele and Brodersen (1999, p. 338-339), "companies and co-operatives produce to a greater extent in areas with lower yield potential". Since the original data are silent on such quality differences, we can evidently expect the result that LSOs perform relatively worse in terms of this particular input.

Table 5: Pairwise comparisons of inter-länder rank differences

	SH	NI	NW	HE	RP	BW	BY	BB	ST	MV	SN	TH
SH		—	—	—	—	—	—	+++	+++	+++	+++	+++
NI	—		—	—	+	+	—	+++	+++	+++	+++	+++
NW	—	—		++	++	++	—	+++	+++	+++	+++	+++
HE	—	—	—		—	—	—	+++	+	+++	+++	+++
RP	—	—	—	—		—	—	+++	++	+++	+++	+++
BW	—	—	—	—	—			+++	++	+++	+++	+++
BY	—	—	—	—	—	—		+++	+++	+++	+++	+++
BB	***	***	***	***	***	***	***		—	—	—	—
ST	***	***	***	***	***	***	**	—		—	—	—
MV	***	***	***	***	***	***	***	—	—		—	—
SN	***	***	***	**	***	***	*	—	—	—		—
TH	***	***	***	***	***	***	***	—	—	—	—	

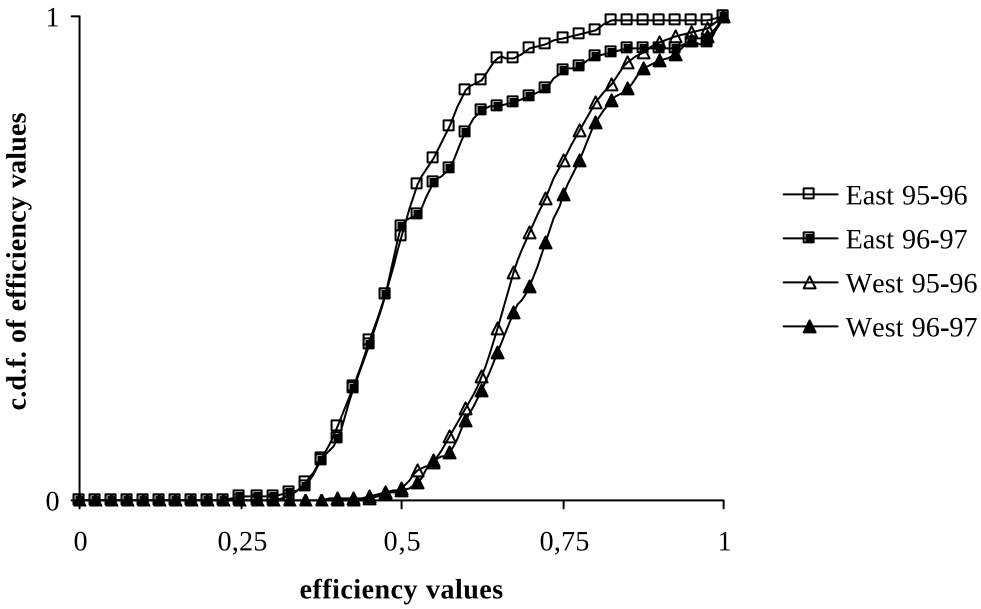
Note: in the upper (lower) triangular part, '+++', '++' and '+' ('***' '**' and '*') indicate that the difference of the mean ranks of the q^A-values (q^M-values) between two regions is larger than a threshold value consistent with an overall significance level of 0.001, 0.01 and 0.05, respectively; SH: Schleswig Holstein; NI: Lower Saxony; NW: North Rhine-Westphalia, HE: Hessen; RP: Rhineland-Platinate; BW: Baden-Württemberg, BY: Bavaria; BB: Brandenburg-Berlin; ST: Saxony-Anhalt, MV: Mecklenburg-Western Pomerania; SN: Saxony; TH: Thuringia.

PERSISTENT DIFFERENCES BETWEEN EAST AND WEST?

Figure 4 shows the cumulative frequency distributions of the q^A-measure for West German and East German farms. For each of the two seasons covered in the dataset, violations of the profit maximization model were stochastically larger in former East Germany. In this very short time span we find no evidence of catching up: the median of all possible west-east differences in q^A-scores is 0.193 in 1995-1996 and this robust location-shift estimator actually increases slightly to 0.200 in the next season. Indeed, the figure reveals that both subsamples experienced a slight profit efficiency improvement in the second season. Still, we reckon the overall period covered by our dataset to be too short to meaningfully talk about technological progress, and therefore confine ourselves to a static analysis . Evidently, also in the static case the assumption of equally distributed efficiency values is highly improbable, as can quickly be confirmed by e.g. a one-tailed Kolmogorov-Smirnov test (the probability value associated with the obtained test statistic is 8×10^{-48}).[18]

[18] The same observation holds for the two components of q^A: the p-value for q^{DF}-values is 8.84×10^{-42}, and 9.68×10^{-37} for the q^M-values.

Figure 4: Profit efficiency values: East versus West



This general picture remains unaltered on a more disaggregate level: table 6 reveals that the persistent difference between the distribution of the efficiency values remains, whether we focus on certain farm subcategories or on different ownership types; the sole exception relates to the pig and poultry 'factories' discussed earlier.[19]

Table 6: Efficiency values and East-West rank differences for production and ownership types

	Average ?^{DF}-values		Average ?^{M}-values *(a)*		*Rank differences (b)*	
	West	East	West	East	q^{DF}	q^{M}
Production types						
Crop farms	0.71	0.57	0.97	0.92	*0.00*	*0.00*
Livestock farms	0.69	0.52	0.97	0.94	*0.00*	*0.00*
Pig and poultry farms	0.86	0.81	0.98	0.93	*0.47*	*0.12*
Mixed production	0.72	0.53	0.98	0.91	*0.00*	*0.00*
Ownership types						
Individual farms	0.73	0.57	0.97	0.94	*0.00*	*0.00*
Partnerships	0.70	0.49	0.98	0.93	*0.00*	*0.00*
Companies		0.64		0.90		
Co-operatives		0.54		0.90		

Notes: *(a)* given the different construction of the ?^{DF}-measure and the ?^{M} -measure, the values in column 1 (2) cannot readily be compared with the corresponding values in column 3 (4), i.e. one should not promptly conclude that *DF*-efficiency is 'consistently lower than' mix-efficiency; *(b)* results of Mann-Whitney tests; entries show the one-tailed normal probabilities associated with the hypothesis that the median efficiency values of East German and West German farm types are equal.

[19] It is not a coincidence that our values for the ?^{DF}-values are lower than those reported in Thiele and Brodersen's table 5, as tests based on profit efficiency have more discriminatory power than tests based on technical efficiency. (Recall that we use a hybrid model to assess profit efficiency, which exploits the available price information.)

Due to the highly unbalanced nature of the dataset (recall table 1), a satisfactorily overall statistical examination (e.g. via log-linear analysis) of *ceteris paribus* differences between East- and West Germany is not feasible. Yet, for some combinations of production and ownership types there are enough data for at least an exploratory comparison. For instance, focusing on individual livestock farms, we find that the average $?^{DF}$ –value in East Germany amounts to only 0.54, versus 0.70 in West Germany. Of course, this can be complemented with a comparison of the $?^{M}$-values. We here briefly bring up a particularly appealing variant of the latter exercise, viz. to look at East-West differences on the basis of the uni-dimensional shrinkage factors that underlie $?^{M}$ (see (12)). Such a detailed analysis reveals an outspoken difference between East German farms and West German farms for the input factor land; see table 7.

Table 7: Some detailed comparisons between East and West

	Average $?^{DF}$ – value (East/West)	Average shrinkage factor per input (East / West)		
Farm type		Labor	Land	Miscellaneous
Individual livestock	0.54 / 0.70	0.99 / 1	0.77 / 0.93	0.87 / 0.82
Individual crop	0.60 / 0.71	1.00 / 0.99	0.57 / 0.85	0.88 / 0.92
Livestock partnerships	0.40 / 0.58	1.00 / 0.99	0.63 / 0.97	0.99 / 0.93
Crop partnerships	0.47 / 0.66	0.99 / 0.94	0.25 / 0.86	1.00/ 0.94

Putting things into the right perspective, we emphasize that the results in tables 6 and 7 merely indicate that the profit maximization model, even when applying benefit-of-the-doubt pricing, seems less pertinent for the subsample of East German farms. This is obviously not tantamount to saying that profit maximization is a less pertinent *behavioral assumption* for East German farmers; it could be that there are other factors at play. By revealing important differences in slacks related to land use, table 7 actually provides a first indication for this, notably if we take into account existing imperfections in agricultural land markets, the unwillingness of land owners to make long-term investments in land improvement, the fact that land leasing occurs far more often in former East Germany, etc. (see e.g. Sarris *et al.* (1999) for a more elaborate discussion).[20] More generally, our empirical results on mix-inefficiency lend some support to the concluding statement of Thiele and Brodersen (1999) that, given delayed adjustment, incomplete factor markets, and government intervention during transition, "the inefficiencies of East German farms are not so much a matter of differences in ownership and production types, but rather the result of *sub-optimal input allocation*" (p. 345, our emphasis). Indeed, the mix efficiency measure $?^{M}$ provides the moderate consistency check whether benefit-of-the-doubt input price vectors –appealing to use whenever there are doubts about using 'market' prices– contain zero entries, which may exactly be regarded as a necessary condition for optimal input allocation. We refer to appendix B for additional tests of the relative influence of the two components $?^{DF}$ and $?^{M}$ on the overall profit efficiency measure $?^{A}$ for East and West German farms.

[20] Although Thiele and Brodersen (1999) make some critical comments on the lack of quality adjusted land data in the dataset, they refer to other sources to state that land-quality differences between East and West are on average very small. Note that this is not consistent with our earlier remark in footnote 17, where we only focused on LSOs.

4. SUMMARY AND CONCLUDING REMARKS

Standard non-parametric tests for profit efficiency conveniently do not require a parametric specification of the technology. But they do require full price information, which is often problematic in practical applications. Starting from this observation, we have forwarded the DEA model proposed by Banker *et al.* (1984) as the natural alternative for assessing profit efficiency in a non-parametric way when reliable information about the true prices is lacking. In particular, that model most intuitively applies an endogenous ‘benefit-of-the-doubt pricing’ in the absence of full price information. Further, we have discussed two extensions of the Banker *et al.* model. First, we have shown how to proceed when reliable prices can be observed for subvectors of commodities, or when only cost or revenue data rather than pure quantity data are available for individual input or output dimensions. In addition, we have presented an economically consistent procedure for measuring ‘mix’ efficiency, which deals with the problem of zero implicit prices associated with the basic efficiency assessment model.

It is worthwhile to stress once more that interpreting the results generated by the Banker *et al.* model in terms of technical efficiency can be tricky, since it builds on production assumptions (monotonicity and convexity) that are not generally tenable. In addition, this risk of specification error conflicts with the very nature of the non-parametric approach, which is often credited for imposing minimal (non-verifiable) structure on the production setting at hand. Therefore, we advocate the interpretation of the same results in terms of profit efficiency. In fact, that interpretation is all the more attractive since profit maximization and not technical efficiency maximization is conventionally used as a primal behavioral assumption.

For completeness, we note that many practical applications consider scale efficiency as an integral component of technical efficiency. Scale efficiency assessment boils down to comparing efficiency values as obtained relative to the convex monotone hull of the sample with those obtained with respect to a conical hull of the data, i.e. the technology representation obtained after adding constant returns to scale to the assumptions of convexity and monotonicity. We have abstracted from scale efficiency measurement. From the perspective upheld in this paper, constant returns to scale is an even more stringent technology assumption than convexity and monotonicity. In terms of profit maximization, using the conical hull of the data as the reference production set essentially implies benchmarking on a (long run) optimal profit level of zero under the endogenously selected prices. We did not use this reference set since the assumption of zero maximum profit does not seem generally tenable for the agricultural setting that we study. Moreover, we emphasize that our modeling assumptions do not *a priori* exclude maximum profit levels of zero; zero profit will be the benchmark if such is revealed from the data, i.e. *a posteriori*. In fact, we believe that letting the data speak for themselves in this way falls more in line with the non-parametric philosophy. Still, it is worth to indicate that our general insights are readily extended towards the case where one chooses to impose the benchmark of a zero maximum profit level.

Our application to German agriculture illustrates the usefulness of the concomitant profit efficiency values for addressing specific research questions. Two possible critiques on the presented portfolio of statistical tools can be that (i) most test-statistics we used are originally designed to compare independent (sub)samples, whereas any efficiency value is *de facto* derived upon comparison with 'all other' netput vectors, and (ii) that we only tests necessary conditions, thus providing at best only lower bound estimates for the true profit efficiency measures. Yet, as regards the first critique, we repeat that interdependency can be mitigated via large samples such as ours, or, alternatively, via resampling techniques such as proposed in Simar and Wilson (1998). Turning to the second critique, one can evidently disapprove of our statistical inferences by claiming that we have eventually little to say about the *true* profit efficiency of firms. Our equally evident answer is that such information is simply not available. We opt for a second-best route, accepting the position that full information is not always obtainable in practice. In fact, for the reasons listed above, we strongly believe that the non-parametric (asymptotic) tests bear clear indicative value. It simply is the best we can do with the given data; we exploit the (limited) information that is available to the fullest extent.

At least, our results can give robust evidence for or against certain hypotheses. Inspection of the pattern of efficiency measures gives us insight in (a) the possible impact of product specialization, (b) the relationship between the assumption of profit maximization and ownership/incentive structures, and (c) the transition issue. Our main findings in these three respects can be summarized as follows:

(a) We find that the profit maximization hypothesis is violated much less systematically for pig and poultry farms than for other farm types. We think this feature arises because these latter farm types are much more prone to profit uncertainty, which is normally not taken up in the standard modeling of firm decision making.[21]

(b) The basic neoclassical model of producer behavior abstracts from ownership structure. Yet, it is well known that principal-agent problems may bear on profit maximization. Our aggregate results are similar to those obtained by other authors: private farms fare best in this respect, followed by partnerships and corporate-style farms respectively. We find supplementary corroboration for the impact of farm organization on effort monitoring via the minimal consistency check on the shadow price of labor; as a rule this price is positive for privately owned farms, whereas it is zero for the overwhelming majority of corporate-style farms in our sample.

(c) Violations of the profit maximization hypothesis were stochastically larger in former East Germany. Obviously, this overall difference can partially be attributed to differences in ownership type, as large corporations and co-operatives are typically found in former East Germany. Yet, there is persistent evidence for making a *ceteris paribus* distinction between East German and West German farms for the period that we considered. The difference between the two regions emerges when looking at the traditional *DF* efficiency measure but also if we compare mix efficiency results, thus suggesting that 'wrong' input mixes are an important source of inefficiency for East German farms. The limitations of these last assertions must be noted: we have mainly been concerned with a static analysis of differences between East and West since the short period covered by our sample prevents us to draw important conclusions regarding dynamic aspects. Using panel East German data, Mathijs and Swinnen (2001) report that the (technical) efficiency gap between LSOs and privately owned farms has decreased during transition. It seems an interesting avenue for further research to combine both their and our framework, i.e. to conduct a dynamic analysis of profit efficiency with West German farms included.

[21] The analysis of effects of uncertainty on production decisions, and the study of underlying attitudes towards risk, has received some attention in the literature; see e.g. the recent studies by Appelbaum and Ullah (1997) and Kuosmanen and Post (2002).

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APPENDIX A: PRODUCT SPECIALIZATION, OWNERSHIP AND PROFIT EFFICIENCY

Table A1 is the counterpart of table 3. It provides summary information on the main effect of production types on rank transformations of $?^A$ –values on the basis of two-way ANOVA analyses; see the main text for a discussion on how this table is constructed. We find that production types have a clear impact on profit efficiency. The results are in agreement with figure 3, which broadly seems to suggest the ordering pig and poultry '>' mixed production '>' crop '>' livestock.

Table A1: Production type and profit efficiency with corrections for ownership type

	Pig and poultry farms	Crop farms	Livestock farms	Mixed Production
sum of aligned interblock ranks				
	102.15	**310.95**	**361.17**	**266.41**
Difference with				
Crop farms	*-208.80 (a)*			
Livestock farms	*-259.02 (a)*	*50.22 (a)*		
Mixed Production	*-164.26 (a)*	*-44.54*	*94.76 (a)*	
Weighted sum of intrablock ranks				
(observed)	**10.86**	**133.00**	**128.06**	**29.58**
Difference with expected (b)	*-22.86*	*6.94*	*20.59*	*-4.67*

Notes: *(a)* and *(b)* have a similar meaning as in table 3.

We conclude our discussion of the influence of production specialization and farm ownership on profit efficiency by reporting some empirical results on the relation between the two former categories. Interdependency could be present if the productive process has an influence on the choice of organizational form, as thoroughly demonstrated by Allen and Lueck (1998). While our data are not optimal to check the rich microeconomic model used by these authors in a satisfying way, checking whether our explanatory variables are mutually independent is of course of interest in its own right.

Table 1 in the main text shows the various combinations of ownership type and production type for our complete sample of 600 farms. A chi-square test on these data does not allow us to reject the null hypothesis of independence. The Cramér coefficient amounts to merely 0.002 so that we can safely assume that there is no association between organizational form and output specialization in our sample.

APPENDIX B: THE RELATIVE IMPACT OF q^{DF} AND q^{M} ON THE OVERALL PROFIT EFFICIENCY MEASURE q^{A}; A FURTHER COMPARISON OF EAST GERMAN AND WEST GERMAN FARMS

We claim that differences in input mix efficiency may be especially important to explain why East German farms are less successful in terms of the yardstick of profit maximization. To further verify this claim, we conduct two simple tests, which are admittedly parametric, and hence somewhat tentative.

From (13), it holds by definition that

(B1) $\ln q^{A} \equiv \ln q^{DF} + \ln q^{M}$.

To assess the impact of the mix-component on the overall profit efficiency value, we ran the *wrong* regression $\ln q^{A} = b_0 + b_1 \ln q^{DF}$, both for the East German and West German samples. In combination with our knowledge of the true coefficients in (B1), the mean squared error (MSE) can then be used to evaluate the relative importance of the omitted mix efficiency component.

One drawback of starting from (B1) is that it is conceptually difficult to directly compare numerical values of the *DF* and mix efficiency components. While both (10) and (11) are relative distance measures, the first pertains to the (normalized) Euclidean distance between two points, whereas the second may be regarded as an angular distance measure between two vectors. As an illustration, note that the seemingly high average mix efficiency value of 0.93 for all East German Farms would imply an angle of more than 20 degrees between vectors ox_1 and ox_2 in figure 3, i.e. *about twice* the angle for West German farms (with an average mix efficiency -value of 0.97). To facilitate comparisons, we therefore examine the regression coefficients $ß_1$ and $ß_2$ in the standardized multiple regression $z(\ln ?^{A}) = ß_1\, z(\ln ?^{DF}) + ß_2\, z(\ln ?^{M})$ where $z(\ln (\bullet))$ is the standard normal transformation of logged efficiency values.

Table B1 shows the results for both methods when respectively applied to East German and West German farms. The values obtained via method A are admittedly small, which reflects the residual nature of the mix-efficiency component in calculating the overall profit efficiency values, the different structure of the two distance measures, and the fact that equation B1 is expressed in logarithmic terms. Nevertheless, the bias (and MSE) introduced by omitting the mix-efficiency component is considerably higher for East German farms, which seems to validate our claim. The entries for method B indicate that a one-standard deviation increase in the logged q^{M}-value ceteris paribus entails an increase of 0.127 standard deviation units of the overall gauge in the case of West German farms. This effect is larger for East German farms, while the opposite holds for the other component, again indicating the greater impact of the mix-efficiency component on the overall profit efficiency value.

Table B1: Relative impact of the two components on overall profit efficiency

	West German farms	East German farms
Method A (omitted regressor)		
Bias	3.928×10^{-3}	3.190×10^{-2}
Mean squared error	1.543×10^{-5}	1.018×10^{-3}
Method B (standardized regression coefficients)		
$z(\ln ?^{DF})$	0.988	0.957
$z(\ln ?^{M})$	0.127	0.163

Note: the standard errors associated with the regression coefficients are approximately zero and the R^2 associated with the two regressions in method B equal approximately unity, as can be expected from the construction of the aggregate efficiency measure.