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# **Estimating a Profit Function in the Presence of Inefficiency: An Application to Russian Agriculture**

**Carlos Arnade and Michael A. Trueblood**

The relationships among cost functions, distance functions, and technical inefficiency are utilized to show how technical inefficiency scores can be incorporated into the specification of a profit function and a related system of output supply and input demands. A method also is introduced for incorporating allocative efficiency scores into the same system. The theoretical and empirical approach requires fewer assumptions than those made in many studies. An illustrative example is provided for Russian agriculture for 1994–95, a period when significant technical and allocative inefficiency was known to exist. The results demonstrate inefficiency limits the supply response to prices, thus leading to lower estimates of output response compared to a traditional supply model in which efficiency is assumed.

*Key words:* distance function, profit function, Russia, supply response, technical efficiency

## **Introduction**

In the past two decades, much of the empirical literature concerning agricultural production has fallen into two major categories. One strand of the literature estimates the price response of agricultural supply and input demands assuming efficiency (e.g., Ball; Shumway, Saez, and Gottret). Another strand calculates various producer inefficiencies, particularly technical inefficiency (e.g., Battese; Seiford), and ignores price responses. However, few studies in the literature have combined these two issues. The objective of this study is to introduce a method for modeling and testing the impact of efficiency measures on output supply and input demand.

One method for dealing with both production inefficiencies and the supply response to prices requires joint estimation of profit function parameters and efficiency scores in a single step (Kumbhakar 1996, 2001). Specific estimates of inefficiency scores for each observation are derived from an estimated parameter in the profit function and a distribution function of model errors. While this technique has many advantages, such as being able to apply statistical testing procedures to estimates of inefficiency, it relies on assumptions about model error structure and can be computationally intensive. Using this technique, it is not always possible to overcome the difficult task of sorting out allocative inefficiency from technical inefficiency.

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Review coordinated by Gary D. Thompson.

In this article, a method is developed for representing inefficiency scores as variables when estimating a system of output supply and input demand equations.<sup>1</sup> Using a novel approach, this study demonstrates theoretically one way technical and allocative inefficiency can be incorporated into a system of output supply and input demand equations. Our theoretical and empirical approach requires fewer assumptions than those made in many studies, but must be implemented in two steps.

In the first step, inefficiency scores are obtained using programming techniques. The second step employs econometric methods to model the impact these scores have on output supply and input demand. To demonstrate the method, technical and allocative inefficiency scores for 73 Russian oblasts (equivalent to states or provinces) are calculated using standard nonparametric methods. Then, the inefficiency scores are specified as an explanatory variable in a profit function for Russian agriculture. A system of output supply and input demand equations is derived from this profit function. Using two years (1994 and 1995) of cross-sectional data, the parameters of the system of output supply and input demands are estimated econometrically, taking into account the effect inefficiency scores may have on parameter estimates.

To test the alternative model specifications in the Russian example, standard econometric tests are used to determine the contribution of inefficiency scores to the performance of the estimated model. Statistical tests of the contribution of technical and allocative inefficiency measures to model performance are mixed. The model shows Russian producers were sensitive to some prices, particularly input prices in the 1994–1995 period, and widespread technical and allocative inefficiencies restricted the response of output supply to price changes. While these findings provide some insight into Russian agriculture, the empirical section primarily serves the goal of demonstrating one method for estimating output supply and input demand in the presence of technical and allocative inefficiency.

### **Deriving a Profit Function in the Presence of Inefficiency**

Kumbhakar (1996) provides one of the most comprehensive examples for jointly estimating inefficiency measures and dual behavioral functions. To derive the profit function, inefficiency was specified as interacting with inputs in a production function. Kumbhakar (1991) used a parallel approach to specify and estimate cost functions in the presence of inefficiency. The production function with an inefficiency term was specified as part of a standard profit-maximization problem to derive the corresponding profit function. The profit function was specified as a function of shadow prices, and an inefficiency parameter was estimated jointly with the profit function parameters. Observation-specific inefficiency scores were then obtained from this inefficiency parameter and the distribution functions of the econometric error.

Kumbhakar's technique has the advantage of estimating inefficiency scores and econometric parameters in one step. Furthermore, the approach allows standard statistical testing procedures to establish a level of confidence in the inefficiency scores.

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<sup>1</sup> Jonasson and Apland have estimated an agricultural sector supply model that first estimates farm-level inefficiency as an input into a sector supply model. In their study, inefficiency and supply response were both calculated using linear programming methods.

However, this methodology relies on computationally intensive estimation techniques, cannot always distinguish different types of inefficiency, and imposes restrictions on the distribution of model errors. In contrast, the method introduced here requires two steps and does not subject inefficiency scores to statistical tests. Further, our approach relies on less restrictive assumptions and sorts out the effects of technical and allocative inefficiency.

### *Technical Inefficiency*

Economists may be less interested in using statistical procedures to test inefficiency score estimates than in using statistical procedures to test the impact inefficiency has on output supply or input demand. There are several possible ways to model and test the effect of technical inefficiency on producer behavior. The approach developed below exploits the established dual relationship between cost and distance functions, and the established relationship between distance functions and technical inefficiency. These two previously established relationships are joined to show there already exists a relationship connecting the primal concept of technical inefficiency to the specification of a profit function, and by extension, the supply function.

To observe this, consider a production technology that is homogeneous of degree  $k$  in inputs and outputs, and in which outputs are separable from inputs. One of the numerous options used for characterizing the technology is the input distance function (Färe and Primont, p. 152). By definition, the input measure of technical inefficiency, which represents the amount by which inputs can be reduced to produce the same level of output, is equal to the reciprocal of the input distance function (e.g., Färe, Grosskopf, and Lovell). The input distance function is homogeneous of degree  $-1/k$  in outputs if the technology is homogeneous of degree  $k$  (Färe and Primont), i.e.,

$$(1) \quad \gamma^{-1/k} D_I(\mathbf{y}, \mathbf{x}) = D_I(\gamma \mathbf{y}, \mathbf{x}),$$

where  $D_I(\cdot)$  is the input distance function,  $\mathbf{y}$  is an  $n$ -vector of outputs,  $\mathbf{x}$  is an  $m$ -vector of inputs, and  $\gamma$  is a parameter.

There is a duality between the cost function and any function representing the frontier of the technology. The duality between the input distance function and cost function when there is no inefficiency present is specified as:<sup>2</sup>

$$(2) \quad C(\mathbf{y}, \mathbf{w}) = \min_{\mathbf{x}} \mathbf{w}'\mathbf{x}, \quad \text{s.t.: } D_I(\mathbf{y}, \mathbf{w}) = 1,$$

where  $\mathbf{w}$  is a vector of input prices, and the other terms are as previously defined.

Suppose there exists a firm which is technically inefficient, and the measure of inefficiency is  $\theta$ . As established by Färe et al., the distance function is equal to the reciprocal of programming-based measures of the firm's technical inefficiency. This relationship indicates that if technical inefficiency is present, the behavior of the firm is influenced by this inefficiency. To represent this, the cost-minimization problem may be written as follows:

<sup>2</sup> See Shepard or Deaton for an analogous discussion of the expenditure function.

$$\begin{aligned}
 (3) \quad & \min_{\mathbf{x}} \mathbf{w}'\mathbf{x}, \quad \text{s.t.: } D_I(\mathbf{y}, \mathbf{x}) = \frac{1}{\theta} \\
 & = \min \mathbf{w}'\mathbf{x}, \quad \text{s.t.: } \theta D_I(\mathbf{y}, \mathbf{x}) = 1 \\
 & = \min \mathbf{w}'\mathbf{x}, \quad \text{s.t.: } D_I(\theta^{-k}\mathbf{y}, \mathbf{x}) = 1 \\
 & = C(\theta^{-k}\mathbf{y}, \mathbf{w}) = \theta^{-1}C(\mathbf{y}, \mathbf{w}).
 \end{aligned}$$

The transition between the second and third lines of (3) comes from the degree of homogeneity of the distance function. The last line results from the properties of cost functions under output homogeneous technology (Chambers; Färe and Primont).

The corresponding profit-maximization problem can be denoted by:

$$(4) \quad \max_{\mathbf{y}} \mathbf{p}'\mathbf{y} - \theta^{-1}C(\mathbf{y}, \mathbf{w}),$$

where  $\mathbf{p}$  is a conformable vector of output prices.

The first-order condition for each  $y_i$  is:

$$(5) \quad \theta p_i = \frac{\partial C}{\partial y_i}, \quad i = 1, \dots, N.$$

The resulting profit function can be written as:

$$(6) \quad \Pi^*(\theta \mathbf{p}, \mathbf{w}) = \max \mathbf{p}'\mathbf{y}^* - \theta^{-1}C(\mathbf{y}^*, \mathbf{w}),$$

where  $\mathbf{y}^*$  denotes the optimal output levels. Taking the derivative of (6) with respect to prices, it can be shown Hotelling's lemma still holds so that:

$$\begin{aligned}
 (7) \quad & \frac{\partial \Pi^*}{\partial p_i} = y_i^*(\theta \mathbf{p}, \mathbf{w}), \quad i = 1, \dots, N, \\
 & -\frac{\partial \Pi^*}{\partial w_j} = x_j^*(\theta \mathbf{p}, \mathbf{w})/\theta, \quad j = 1, \dots, M,
 \end{aligned}$$

where  $y_i^*$  is output of good  $i$ , and  $x_j^*$  is the total amount of input  $j$  used. Furthermore, by applying envelope properties and the quotient rule, we can show:

$$(8) \quad \frac{\partial \Pi}{\partial \theta} = \frac{C(\mathbf{y}, \mathbf{w})}{\theta^2}.$$

Using cost data as the endogenous variable, equation (8) can be estimated jointly with a system of supply and input demand equations in (7). However, in models with several inputs and outputs, multicollinearity likely would be a problem in estimating equation (8).

The attraction of the above specification is twofold. First, economic theory is used to determine how technical inefficiency scores may be incorporated into a profit function. Second, the procedure shows that if inefficiency scores are available prior to econometric estimation, they can be specified as an exogenous variable in an output supply and input demand system, and standard econometric methods can be used to estimate the parameters of this system.<sup>3</sup>

<sup>3</sup> Kumbhakar (1996) discusses the benefits and problems parametric methods have had dealing with both technical and allocative efficiency in the context of dual functions.

### Allocative and Technical Inefficiency

Unlike technical inefficiency, allocative inefficiency is a behavioral concept arising when agents do not exactly meet first-order conditions. Toda was one of the first economists to address the issue of allocative inefficiencies on dual functions when he estimated a cost function for Soviet manufacturing industries.

In this section, allocative inefficiency is represented as an additive distortion to first-order conditions. This procedure implies that even when the distortion is the same for each first-order condition, output (input) price ratios fail to equal the marginal rate of transformation (substitution). To see this, consider the profit-maximization problem in equation (4). When there is allocative inefficiency, the first-order condition for each  $y_i$  is:

$$(9) \quad p_i = \theta^{-1} \frac{\partial C}{\partial y_i} + a_i, \quad i = 1, \dots, N,$$

where  $a_i$  represents inefficiency in allocating product  $i$ . Rewriting (9) for each  $y_i$  gives:

$$(10) \quad \theta(p_i - a_i) = \frac{\partial C}{\partial y_i}.$$

By (10), even if each  $a_i$  were the same, the allocative distortion would change the relative price ratios. Therefore, it is assumed behavioral mistakes do not neutralize each other. The resulting profit function is represented by:

$$(11) \quad \Pi^*(\theta(\mathbf{p} - \mathbf{a}), \mathbf{w}) = \max_{\mathbf{y}} \mathbf{p}'\mathbf{y}^* - \theta^{-1}C(\mathbf{y}^*, \mathbf{w}).$$

Thus, in this model, technical inefficiency interacts with output prices multiplicatively, while allocative inefficiency interacts additively. Taking the derivative of profits with respect to the price of output 1, for example, results in the following:

$$(12) \quad \frac{\partial \Pi^*(\theta(\mathbf{p} - \mathbf{a}), \mathbf{w})}{\partial p_1} = y_1 + \sum_{i=1}^n p_i - \theta^{-1} \frac{\partial C(\mathbf{y}^*, \mathbf{w})}{\partial y_i} \frac{\partial y_i}{\partial p_1^*} \frac{\partial p_1^*}{\partial p_1},$$

where  $p_1^* = \theta(p_1 - a_1)$ .

When allocative inefficiency exists, output prices do not equal marginal cost divided by technical inefficiency. This prevents the indirect terms in equation (12) from dropping out. However, using equation (9) and substituting  $a_1$  into the difference term in parentheses, we obtain:

$$(13) \quad \frac{\partial \Pi^*(\theta(\mathbf{p} - \mathbf{a}), \mathbf{w})}{\partial p_1} = y_1 + \sum_{i=1}^n a_i \theta \frac{\partial y_i}{\partial p_1^*},$$

since all  $\partial p^*/\partial p_i = \theta$ .

The above conditions hold for all output price derivatives. Similarly, the derivatives with respect to changes in input prices are given by:

$$(14) \quad \frac{\partial \Pi^*(\theta(\mathbf{p} - \mathbf{a}), \mathbf{w})}{\partial w_j} = \left( \frac{-x_j}{\theta} \right) + \sum_{j=1}^n a_j \theta \frac{\partial y_j}{\partial w_j}.$$

The output supply and input demands in (13) and (14) can be easily estimated<sup>7</sup> including the  $a_i \theta (\partial y_i / \partial p_i^*)$  term with the derivative of the profit function. The parameter

making up the subcomponent term,  $(\partial y / \partial p_i^*)$ , can be derived analytically from the supply and demand functions.

### **An Empirical Application: Russia During Transition**

#### *Data*

To apply this model, data are used from 73 Russian oblasts (equivalent to states or provinces) for 1994–95. While Russia's transition to a market economy has been ongoing, the years 1994 and 1995 represented a unique period when the agricultural sector faced market prices, but retained elements of a planned economy. Studies of this period have demonstrated that technical inefficiencies were prevalent in Russian agriculture (Brock; Sotnikov; Sedik, Trueblood, and Arnade).

Oblast-level prices and quantities of crops or crop categories, as well as the prices and quantities of inputs used in crop production of corporate (i.e., state and collective) farms, are all taken or derived from official sources (Russian Ministry of Agriculture; Goskomstat of Russia). Corporate farms produce approximately half the value of Russian agriculture, and account for approximately 90% of grain and sugar beets production and slightly less than half the livestock production. A significant amount of Russian agricultural output is produced on small private plots. Production from private plots is mostly not included in these data.

The output data consist of quantities and prices for five production categories: grains, sugar beets, potatoes, vegetables, and livestock. The input quantity data consist of land, labor, fertilizers, oil, fuels, electricity, and tractors. Input price data were available for labor, fertilizers, oil, fuels, and electricity. Labor, oil, fuels, electricity, and fertilizer were modeled as variable inputs, while tractors and land were modeled as quasi-fixed inputs.

The output quantities were all measured in tons per year. The input quantities were measured as follows. Land was measured as land sown to the four crop categories on corporate farms. Labor was measured in 1,000 man-days worked in production. Fertilizers were measured in 1,000 tons and were derived from corporate farm purchases using farm expenditures and unit prices. Oil and fuel products, measured in tons, also were derived from purchases by corporate farms using a similar procedure. Electricity, primarily used for hothouse production in northern regions, was measured as 1,000-kilowatt hours from expenditure and unit prices. Tractors were measured in 1,000 HP units.

The output prices were farm gate prices and measured in 1,000 rubles per ton. The grains and livestock prices were weighted average prices in each oblast, where the weights were derived from the value of output of each subcomponent in the category. Input prices were measured in the following way. For labor, average daily wages were calculated by dividing monthly salaries by the number of man-days worked in the month (Russian Ministry of Agriculture). Fertilizer, oil, and fuel prices were available from price publications (Goskomstat of Russia). The published input prices are weighted average prices in each oblast, where the weights are proportional to total input purchases or output sold on each farm in the oblast. For both output and input prices, the central statistical agency, Goskomstat, estimates prices from a sample of 10% of all agricultural enterprises in Russia.

### Output Quotas and Specification of a Profit Function

An important institutional constraint to be addressed was the possible existence of output quotas during the sample period. Under traditional Soviet agriculture, output quotas often were set for agricultural production units (Brock). Arnade and Munisamy concluded Russian agricultural producers in the early post-Soviet period still might have been prone to output targeting. They applied data envelopment analysis (DEA) to a profit-maximizing problem and tested for broad targeting of outputs in Russian agriculture using a procedure similar to that used to test for expenditure constraints (Färe, Grosskopf, and Lee). In their analysis, however, Arnade and Munisamy did not attempt to determine which crops might have been targeted for quotas.

To specify a profit function for Russian agriculture, the approach employed by Arnade and Munisamy was modified to test for the influence of crop-specific output constraints. The tests for output targeting were applied to each of the 73 Russian oblasts for 1994, and then again to the same oblasts in 1995. DEA profit-maximization problems were solved with and without output constraints, and then solution profits and actual profits were compared.

From this comparison, an index was created: a value less than one indicated output targets limited profits, while an index measure close to one implied observed levels of output were consistent with the objective of profit maximization (see Arnade and Munisamy). For sugar beets, the average index measure across all oblasts was 0.96, with 48 oblast regions registering a one. Similarly, for grains, the average across all oblasts was 0.95, with 46 oblast regions registering a one. Averages for potatoes and vegetables, however, were 0.56 and 0.67, respectively, with no region registering a one. Based on this information, we determined vegetables and potatoes should be treated as fixed outputs, while grains and sugar beets should be specified as variable outputs in the profit function for Russian agriculture.<sup>4</sup>

Having established that potatoes and vegetables were fixed outputs, a normalized quadratic functional form was specified. The normalized quadratic form satisfies the properties of the profit function (Shumway, Saez, and Gottret), is flexible, and yet avoids the computational burdens imposed by other functional forms. The following normalized quadratic profit function was specified:

$$\begin{aligned}
 (15) \quad \Pi(\theta \mathbf{p}, \mathbf{w}) = & \sum_{i=1}^3 \beta_i \theta(p_i - a_i) + \sum_{j=1}^4 \beta_j w_j + 0.5 \sum_{i=1}^3 \sum_{k=1}^3 \beta_{ik} \theta(p_i - a_i)(p_k - a_k) \\
 & + 0.5 \sum_{j=1}^4 \sum_{l=1}^4 \beta_{jl} w_j w_l + \sum_{i=1}^3 \gamma_{id} \theta(p_i - a_i) LND + \sum_{j=1}^4 \gamma_{jd} w_j LND \\
 & + \sum_{z=1}^2 \sum_{i=1}^3 \gamma_{zi} Q_z \theta(p_i - a_i) + \sum_{z=1}^2 \sum_{j=1}^4 \gamma_{zj} Q_z w_j \\
 & + 0.5 \sum_{i=1}^3 \sum_{k=1}^4 \beta_{ik} \theta(p_i - a_i) w_k + \sum_{i=1}^3 \gamma_{it} \theta p_i TRC + \sum_{j=1}^4 \gamma_{jt} w_j TRC.
 \end{aligned}$$

The output prices represent aggregate grains, sugar beets, and aggregate livestock. The prices of variable inputs,  $w_j$ , represent fertilizer, fuel, electricity, and oil. All prices were

<sup>4</sup> Vegetables and potatoes may be targeted for household food security concerns.

normalized by the price of fertilizers. The fixed outputs,  $Q_z$ , as noted earlier, are vegetables and potatoes.  $TRC$  represents tractors and  $LND$  denotes land, both quasi-fixed inputs. In the Russian model, each data point represents one oblast observation in one of the two periods (1994 and 1995).

Using the relationship in equation (13), the  $i$ th supply equation is specified as:

$$(16) \quad y_i = \beta_i \theta + \sum_{k=1}^3 \beta_{ik} \theta^2 (p_k - \alpha_k) + \sum_{j=1}^4 \beta_{ij} \theta w_k + \gamma_{it} \theta TRC + \gamma_{id} \theta LND \\ + \sum_{z=1}^2 \gamma_{iz} \theta Q_z - \left[ \sum_{k=1}^3 \beta_{ki} \theta \alpha_k \right].$$

Factoring the  $\alpha_k$  from  $p_k$  in the second term on the right-hand side of (16) and using symmetry ( $\beta_{ik} = \beta_{ki}$ ), the equation to be estimated becomes:

$$(17) \quad y_{ibt} = \beta_i \theta_{bt} - \sum_{k=1}^3 \beta_{ik} \alpha_k (\theta_{bt} + \theta_{bt}^2) + \sum_{k=1}^3 \beta_{ik} \theta^2 p_{kbt} + \sum_{j=1}^4 \beta_{ij} \theta w_{jbt} \\ + \gamma_{it} \theta TRC_{bt} + \gamma_{id} \theta LND_{bt} + \sum_{z=1}^2 \gamma_{iz} \theta Q_{zbt} + \varepsilon_{ibt},$$

where the outputs are represented by  $\{i = 1, 2, 3\}$ , the oblasts are denoted by  $\{b = 1, \dots, 73\}$ , and  $t = 1994, 1995$ .

Similarly, using equation (14), the input demands are calculated as:

$$(18) \quad -x_{jbt} = \beta_j \theta_{bt} - \sum_{k=1}^4 \beta_{jk} \alpha_k (\theta_{bt} + \theta_{bt}^2) + \sum_{j=1}^3 \beta_{ji} \theta^2 p_{ibt} + p_{ibt} + \sum_{k=1}^4 \beta_{jk} \theta w_{kbt} \\ + \gamma_{zj} \theta TRC_{bt} + \gamma_{jd} \theta LND_{bt} + \sum_{z=1}^2 \gamma_{jz} \theta Q_{zbt} + \varepsilon_{jbt}, \quad j = 1, \dots, 4.$$

The  $\varepsilon$  terms appended to equations (17) and (18) represent random errors, which are assumed to be independent and identically distributed normal random variables with zero means and constant covariances:

$$(19) \quad E\{\varepsilon_{ibt}\} = E\{\varepsilon_{jbt}\} = 0,$$

$$(20) \quad \left. \begin{aligned} E\{\varepsilon_{ibt}, \varepsilon_{ibt}\} &= \sigma_{ii} \\ E\{\varepsilon_{jbt}, \varepsilon_{jbt}\} &= \sigma_{jj} \\ E\{\varepsilon_{ibt}, \varepsilon_{jbt}\} &= \sigma_{ij} \end{aligned} \right\} \text{ for } b = d \text{ and } t = s; 0 \text{ otherwise.}$$

These assumptions are reasonable and commonly used. They allow for contemporaneous correlation of the errors from different supply and input demand equations within each oblast unit.

Equations (17) and (18) are supply equations which account for both technical and allocative inefficiency. When producers are technically efficient,  $\theta = 1$ , and when they are allocatively efficient,  $\alpha = 1$ . If all producers are both technically and allocatively efficient, then equations (17) and (18) reduce to standard output supply and input demand equations.

### *Inefficiency Calculations*

The techniques widely applied to measuring firm or regional inefficiency fall into two broad categories: (a) the parametric stochastic frontiers approach, which was separately introduced in 1977 by Aigner, Lovell, and Schmidt, and by Meeusen and van den Broeck, and (b) the nonparametric programming approach, introduced in 1957 by Farrell, and subsequently revived as data envelopment analysis (DEA) by Charnes, Cooper, and Rhodes in 1978.

Both classes of models have seen considerable refinement and widened applications over the past 20 years. While each technique has its own advantages and limitations (e.g., see Hjalmarsson, Kumbhakar, and Heshmati), technical inefficiency measures calculated with nonstochastic programming methods can be used as explanatory variables in subsequent econometric analysis without sequential econometric estimation. Thus we use a DEA problem in this analysis to calculate technical inefficiency measures for 73 oblasts across Russia. Statistical tests are not used to determine the level of confidence in each inefficiency score. However, in the next section, standard testing procedures are used to determine the *impact* these scores have on output supply and input demand.

In estimating technical inefficiency, a procedure similar to that reported by Färe and Whittaker is followed in which a model is developed for a farm producing livestock and crops, with the crop output used as on-farm livestock feed (see Färe and Whittaker for details). Technical inefficiency in this study is estimated at the oblast level, and it is assumed corporate farms in each oblast have similar technology. This model also allows crop output to be represented in two components: (a) output used as feed within the oblast, whether through sales or barter arrangements, and (b) output sold outside the oblast. The feed constraint of the Färe and Whittaker model was modified here to account for feed imported by the oblast. Using similar assumptions, a DEA program also was used to calculate allocative inefficiency scores for each oblast (see Coelli, Rao, and Battese).

In calculating technical inefficiency scores, no assumptions about scale economies were made. Instead, inefficiency scores were used to determine the scale economy in each oblast. By comparing the inefficiency scores estimated with different scale assumptions, Byrnes et al. demonstrated it is possible to determine whether there is decreasing, constant, or increasing returns to scale. To make this determination, a program was run three times for each observation—one time each assuming constant (CRS), decreasing (DRS), and variable returns to scale (VRS). In Byrnes et al.'s method, if a particular score is equal when calculated across all scale assumptions, then the observation is considered to be CRS. If DRS and CRS scores are not equal, then the observation is considered to be DRS. If the inefficiency score is equal when calculated under DRS and CRS assumptions, but not equal to the score calculated under the VRS assumption, then the technology is considered to be increasing returns to scale (IRS).

Table 1 reports the calculated technical inefficiency scores under the various scale assumptions, and table 2 presents calculated allocative inefficiency scores. Comparing technical inefficiency scores, agricultural technology at the oblast level in Russia was found to be more commonly characterized by decreasing returns to scale than constant or increasing returns. For example, in 1995, 51 oblasts displayed decreasing returns to scale, 15 showed constant returns, and seven displayed increasing returns.<sup>5</sup> In general,

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<sup>5</sup> Sedik, Trueblood, and Arnade found increasing returns for the crops using a sample for 70 oblasts. The present study differs in that it estimates returns to scale on an oblast-by-oblast basis, uses an alternative method, and examines returns to scale for both crops and livestock.

**Table 1. Technical Inefficiency Estimates for 73 Russian Oblasts, by Region: Joint Crop and Livestock Model (1994 and 1995)**

Regions/Oblasts	1995				1994			
	VRS <sup>a</sup>	CRS <sup>a</sup>	DRS <sup>a</sup>	Scale <sup>b</sup>	VRS <sup>a</sup>	CRS <sup>a</sup>	DRS <sup>a</sup>	Scale <sup>b</sup>
<b>North:</b>								
Arkhangelsk	1.00	0.68	1.00	DRS	0.66	0.49	0.66	DRS
Karelia	0.64	0.63	0.64	DRS	1.00	0.95	1.00	DRS
Komi	0.83	0.83	0.83	CRS	0.83	0.75	0.83	DRS
Murmansk	1.00	1.00	1.00	CRS	1.00	1.00	1.00	CRS
Vologda	0.70	0.45	0.70	DRS	0.70	0.39	0.70	DRS
<b>Northwest:</b>								
Leningrad	0.92	0.53	0.92	DRS	1.00	0.59	1.00	DRS
Novgorod	0.45	0.45	0.45	CRS	0.39	0.38	0.39	DRS
Pskov	0.38	0.37	0.38	DRS	0.40	0.39	0.39	IRS
<b>Central:</b>								
Bryansk	0.40	0.34	0.40	DRS	0.64	0.47	0.64	DRS
Ivanovsk	0.40	0.30	0.40	DRS	0.53	0.45	0.53	DRS
Kaliningrad	0.46	0.46	0.46	CRS	0.64	0.58	0.64	DRS
Kaluga	0.35	0.32	0.35	DRS	0.65	0.54	0.65	DRS
Kostroma	0.41	0.40	0.41	DRS	0.43	0.37	0.43	DRS
Moscow	1.00	0.59	1.00	DRS	1.00	0.82	1.00	DRS
Orlov	0.38	0.26	0.38	DRS	0.58	0.48	0.58	DRS
Ryazan	0.58	0.41	0.58	DRS	0.70	0.48	0.70	DRS
Smolensk	0.33	0.31	0.33	DRS	0.50	0.35	0.50	DRS
Tula	0.60	0.33	0.60	DRS	0.72	0.57	0.72	DRS
Tver	0.32	0.31	0.32	DRS	0.54	0.39	0.54	DRS
Vladimir	0.56	0.47	0.56	DRS	0.61	0.45	0.61	DRS
Yaroslavl	0.41	0.41	0.41	CRS	0.58	0.49	0.58	DRS
<b>Volga:</b>								
Chuvashia	0.58	0.40	0.58	DRS	0.60	0.53	0.60	DRS
Kirov	0.39	0.28	0.39	DRS	0.52	0.31	0.52	DRS
Mari-El	0.46	0.43	0.46	DRS	0.56	0.48	0.56	DRS
Mordovia	0.38	0.37	0.38	DRS	0.61	0.55	0.61	DRS
Nizhniy Novgorod	0.58	0.36	0.58	DRS	0.65	0.45	0.65	DRS
<b>Central Black Soil:</b>								
Belgorod	0.67	0.36	0.67	DRS	0.73	0.51	0.73	DRS
Kursk	0.54	0.33	0.54	DRS	0.73	0.56	0.73	DRS
Lipetsk	0.39	0.22	0.39	DRS	0.67	0.58	0.67	DRS
Tambov	0.73	0.67	0.73	DRS	0.93	0.63	0.93	DRS
Voronezh	0.58	0.32	0.58	DRS	0.65	0.41	0.65	DRS
<b>Volga Valley:</b>								
Astrakhan	1.00	1.00	1.00	CRS	0.65	0.64	0.64	IRS
Kalmykia	0.38	0.37	0.37	IRS	0.84	0.84	0.84	CRS
Penza	0.40	0.38	0.40	DRS	0.73	0.52	0.73	DRS
Samara	0.85	0.69	0.85	DRS	0.84	0.60	0.84	DRS
Saratov	1.00	0.91	1.00	DRS	1.00	1.00	1.00	CRS
Tatarstan	0.97	0.38	0.97	DRS	1.00	0.85	1.00	DRS
Ulyanovsk	0.53	0.43	0.53	DRS	0.56	0.48	0.56	DRS
Volgograd	0.50	0.48	0.50	DRS	0.92	0.70	0.92	DRS

(continued . . .)

**Table 1. Continued**

Regions/Oblasts	1995				1994			
	VRS <sup>a</sup>	CRS <sup>a</sup>	DRS <sup>a</sup>	Scale <sup>b</sup>	VRS <sup>a</sup>	CRS <sup>a</sup>	DRS <sup>a</sup>	Scale <sup>b</sup>
<b>North Caucasus:</b>								
Adygea	0.55	0.44	0.44	IRS	0.73	0.67	0.73	DRS
Dagestan	0.81	0.78	0.81	DRS	0.56	0.53	0.56	DRS
Kabardino-Bal.	0.58	0.53	0.53	IRS	0.69	0.65	0.69	DRS
Karachay-Cher	0.73	0.53	0.53	IRS	0.73	0.72	0.72	IRS
Krasnodar	1.00	0.56	1.00	DRS	1.00	0.78	1.00	DRS
North Osetia	0.71	0.49	0.49	IRS	0.92	0.74	0.74	IRS
Rostov	1.00	0.94	1.00	DRS	1.00	0.67	1.00	DRS
Stavropol	1.00	0.68	1.00	DRS	0.93	0.70	0.93	DRS
<b>Urals:</b>								
Bashkortostan	0.70	0.27	0.70	DRS	0.55	0.45	0.55	DRS
Chelyabinsk	0.56	0.50	0.56	DRS	0.82	0.59	0.82	DRS
Kurgan	0.48	0.40	0.48	DRS	0.77	0.57	0.77	DRS
Orenburg	0.35	0.34	0.35	DRS	0.89	0.71	0.89	DRS
Perm	0.85	0.51	0.85	DRS	0.82	0.47	0.82	DRS
Sverdlovsk	1.00	1.00	1.00	CRS	1.00	0.48	1.00	DRS
Udmurtia	0.55	0.36	0.55	DRS	0.61	0.43	0.61	DRS
<b>West Siberia:</b>								
Altay Krai	0.85	0.54	0.85	DRS	0.81	0.66	0.81	DRS
Altay Republic	1.00	1.00	1.00	CRS	1.00	1.00	1.00	CRS
Kemerova	0.73	0.41	0.73	DRS	1.00	0.52	1.00	DRS
Novosibirsk	1.00	1.00	1.00	CRS	0.78	0.56	0.78	DRS
Omsk	0.81	0.76	0.81	DRS	1.00	0.91	1.00	DRS
Tomsk	0.80	0.49	0.80	DRS	0.56	0.45	0.56	DRS
Tyumen	1.00	0.61	1.00	DRS	0.74	0.44	0.74	DRS
<b>East Siberia:</b>								
Buryatia	0.59	0.55	0.59	DRS	0.62	0.62	0.62	CRS
Chitinsk	0.57	0.57	0.57	CRS	0.54	0.53	0.53	IRS
Irkutsk	0.60	0.31	0.60	DRS	0.91	0.60	0.91	DRS
Khakassia	0.37	0.35	0.35	IRS	0.39	0.38	0.38	IRS
Krasnoyarsk	0.84	0.35	0.84	DRS	0.91	0.50	0.91	DRS
<b>Far East:</b>								
Amur	0.47	0.46	0.47	DRS	0.78	0.59	0.78	DRS
Kamchatka	1.00	1.00	1.00	CRS	1.00	1.00	1.00	CRS
Khabarovsk	0.99	0.98	0.98	IRS	1.00	0.84	1.00	DRS
Magadan	1.00	1.00	1.00	CRS	1.00	1.00	1.00	CRS
Primorye	1.00	1.00	1.00	CRS	1.00	0.84	1.00	DRS
Sakhalin	1.00	1.00	1.00	CRS	1.00	1.00	1.00	CRS
Yakutia	1.00	1.00	1.00	CRS	1.00	1.00	1.00	CRS

<sup>a</sup> VRS imposes variable returns to scale, CRS imposes constant returns to scale, and DRS imposes decreasing returns to scale.

<sup>b</sup> Scale: By imposing VRS, CRS, and DRS, it is possible to infer which oblast technology is CRS, IRS, or DRS.

both technical and allocative inefficiency displayed much variation, particularly in the Central and Volga valley regions.

**Table 2. Allocative Inefficiency Scores for 73 Russian Oblasts, by Region (1994 and 1995)**

Regions/Oblasts	1995	1994	Regions/Oblasts	1995	1994
<b>North:</b>			<b>North Caucasus:</b>		
Arkhangelsk	0.67	0.33	Adygea	1.00	0.73
Karelia	0.43	1.00	Dagestan	0.45	0.56
Komi	0.48	0.82	Kabardino-Bal.	0.15	0.26
Murmansk	1.00	1.00	Karachay-Cher	0.35	0.73
Vologda	1.00	1.00	Krasnodar	0.54	1.00
<b>Northwest:</b>			North Osetia	0.48	0.92
Leningrad	0.77	1.00	Rostov	0.40	0.58
Novgorod	0.18	0.31	Stavropol	0.48	0.55
Pskov	0.19	0.39	<b>Urals:</b>		
<b>Central:</b>			Bashkortostan	0.47	0.54
Bryansk	0.32	0.19	Chelyabinsk	1.00	1.00
Ivanovsk	0.13	0.26	Kurgan	0.38	0.74
Kaliningrad	0.25	0.64	Orenburg	0.21	0.60
Kaluga	0.18	0.40	Perm	0.37	0.82
Kostroma	0.26	0.43	Sverdlovsk	1.00	1.00
Moscow	1.00	1.00	Udmurtia	0.19	0.42
Orlov	0.26	0.47	<b>West Siberia:</b>		
Ryazan	0.22	0.33	Altay Krai	0.49	0.69
Smolensk	0.17	0.49	Altay Republic	1.00	1.00
Tula	0.41	0.73	Kemerova	0.49	1.00
Tver	0.22	0.54	Novosibirsk	1.00	0.77
Vladimir	0.28	0.48	Omsk	0.80	1.00
Yaroslavl	0.27	0.58	Tomsk	0.34	0.56
<b>Volga:</b>			Tyumen	0.75	0.74
Chuvashia	0.51	0.60	<b>East Siberia:</b>		
Kirov	0.23	0.48	Buryatia	0.36	0.62
Mari-El	0.34	0.56	Chitinsk	0.32	0.53
Mordovia	0.28	0.61	Irkutsk	0.36	0.32
Nizhniy Novgorod	0.33	0.65	Khakassia	0.27	0.90
<b>Central Black Soil:</b>			Krasnoyarsk	0.50	0.91
Belgorod	0.56	0.73	<b>Far East:</b>		
Kursk	0.43	0.73	Amur	0.16	0.45
Lipetsk	0.14	0.31	Kamchatka	0.83	1.00
Tambov	0.64	0.93	Khabarovsk	0.76	1.00
Voronezh	0.46	0.65	Magadan	0.87	0.87
<b>Volga Valley:</b>			Primorye	0.35	0.45
Astrakhan	1.00	0.65	Sakhalin	0.25	0.25
Kalmykia	0.37	0.84	Yakutia	0.84	0.84
Penza	0.28	0.58			
Samara	0.48	0.84			
Saratov	1.00	1.00			
Tatarstan	0.71	0.54			
Ulyanovsk	0.38	0.46			
Volgograd	0.48	0.91			

*Estimation of Output Supply and Input Demand with Technical and Allocative Inefficiency*

While the existence of technical and allocative inefficiency is not unique to Russia, its critical role in the agricultural economy of Russia may be unique where, despite a move to market pricing, institutional constraints and poor management practices persist (Brock; Sotnikov; Sedik, Trueblood, and Arnade). Thus, Russian agriculture is appropriate for demonstrating this investigation's modeling technique.

Having calculated technical and allocative inefficiency, three different models of output supply and input demand were estimated. Model 1 is a standard model in which full efficiency is assumed, model 2 relaxes the efficiency assumption by allowing technical inefficiency, and model 3 relaxes the assumption further to include both technical and allocative inefficiency.<sup>6</sup> In models 2 and 3, technical inefficiency scores representing the appropriate degree of scale (CRS, DRS, or IRS) in each oblast were used. Thus, an exogenous variable is used to account for differences in scale economies in each observation.

In each model, cross-sectional data representing 73 oblasts for 1994–95 were used to estimate a seven-equation system (three output supply and four input demand equations) with iterative seemingly unrelated regression (ITSUR) with correction for censored dependent variables, which is equivalent to maximum-likelihood estimation. A dummy intercept variable was used to represent a change in time periods.<sup>7</sup> Relative output prices were represented by lagged relative output prices, which implies producers follow naive relative price expectations. Lagging relative output prices reduced the data set to two years (1994, 1995) and 73 cross-sections, but provided the model with an acceptable representation of expected output price. Standard symmetry conditions were imposed in the second-stage ITSUR estimation.

A problem encountered in the econometric estimation was that several Russian oblasts did not grow some of the crops. For example, a few oblasts did not grow grains and about one-third did not grow sugar beets. This problem was addressed by employing a technique developed by Shonkwiler and Yen for modeling censored dependent variables in a system of equations. First, probit models were estimated for the two dependent variables (sugar beets and grains) containing the zero observations. Then, using the appropriate information from the probit models, and restricting the parameters on the probit model to equal their first-stage estimates, the probit equations were included in the system of output supply and input demand equations, which were jointly estimated with the ITSUR procedure.

The estimated parameters of model 2 are presented in table 3 (for brevity, parameter values of output supply and input demand for models 1 and 3 are not shown).<sup>8</sup> The own-price coefficients of model 2, which include technical inefficiency scores, are statistically significant at the 0.05 confidence level in three out of four input demand equations, and in one out of three output supply equations. In both the grains and sugar beet equations, the cross-price coefficients between these two crops are statistically significant. The

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<sup>6</sup> Note, because the profit function maximizes a linear profit equation, the various uses of grain for on-farm feed need not be broken out in a dual problem.

<sup>7</sup> Distinct output supply and input demand functions for each period could have been estimated, but to keep the presentation of results simple, all available data were used to estimate a single system of equations.

<sup>8</sup> The tables for models 1 and 3 are available upon request from the authors. In model 1, all own-price elasticities displayed the expected signs. In model 3—the model with both allocative and technical inefficiency—the parameters were not much different from those of model 2.

**Table 3. Output Supply and Input Demand for 73 Russian Oblasts, Estimated by ITSUR Corrected for Censoring (1994–1995)**

Variable <sup>a</sup>	OUTPUTS			INPUTS			
	Grains	Sugar	Livestock	Labor	Oil	Electricity	Fuel
$\theta 2 * PGRN$	138,820.0 (0.82)	-127,141.1 (-1.72)	-21,109.0 (-0.60)	-234.6 (-0.15)	-443.6 (-0.92)	50,028.1 (0.35)	208,600.0 (2.93)
$\theta 2 * PSUG$	-127,141.1 (-1.72)	161,910.0 (1.92)	25,491.0 (1.29)	800.5 (0.97)	26,838.0 (1.20)	25,052.0 (0.34)	26,875.0 (0.71)
$\theta 2 * PLIVE$	-21,109.0 (-0.60)	2,591.0 (1.29)	2,674,500.0 (0.68)	-107,270.0 (-0.79)	8,672.3 (0.75)	20,117.0 (0.27)	25,130.0 (0.51)
$\theta * WAGES$	234.6 (0.15)	-800.5 (-0.98)	107,270.0 (0.79)	-16,971.0 (-1.71)	354.7 (0.61)	-2,230.2 (-0.76)	-3,555.4 (-1.86)
$\theta * WOIL$	443.1 (0.01)	-26,838.0 (-1.20)	-8,672.3 (-0.74)	354.7 (0.61)	-16,031.0 (-1.08)	18,536.0 (0.41)	39,217.0 (1.73)
$\theta * WELEC$	-50,028.3 (-0.34)	-25,052.3 (-0.33)	-20,117.1 (-0.27)	-2,230.2 (-0.75)	18,536.0 (0.41)	-1,714,300.0 (-4.67)	485,690.0 (3.39)
$\theta * WFUEL$	-208,600.1 (-2.94)	-26,875.0 (-0.71)	-25,130.0 (-0.51)	-3,555.5 (-1.86)	39,217.1 (1.73)	485,690.5 (3.39)	-1,108,800.0 (-9.67)
$\theta * TRACT$	642.7 (13.21)	324.6 (2.73)	98.4 (11.51)	6.67 (16.9)	75.5 (6.06)	97.2 (2.51)	25.7 (1.31)
$\theta * LAND$	-548.1 (-4.77)	-693.6 (-2.94)	-170.3 (-8.40)	-7.48 (-7.98)	-61.2 (-2.07)	-84.2 (-0.91)	-84.0 (-1.81)
$\theta * QPOT$	-0.73 (-3.68)	-0.65 (-1.03)	0.13 (3.57)	-0.008 (-4.69)	0.15 (2.98)	0.72 (4.48)	0.55 (1.20)
$\theta * QVEG$	-4.83 (-6.58)	-0.31 (-0.16)	-0.21 (-1.58)	-0.002 (-2.92)	-0.28 (-1.51)	-1.06 (-1.79)	0.36 (1.21)
$\theta$	-353,430.0 (-2.36)	-95,414.0 (1.65)	-98,536.0 (-3.06)	-10,686.0 (-7.99)	-183,460.0 (-5.00)	-306,060.0 (-2.05)	-327,300.0 (-4.68)
YEAR	-0.0001 (-0.50)	95,414.0 (1.65)	-25,535.0 (-2.04)	-31.0 (-0.06)	212,460.0 (12.36)	-450,130.0 (-7.88)	-38,349.0 (-1.34)

Notes: Numbers in parentheses are *t*-statistics. The system log-likelihood value is -12,967.3. Single equation measures of fit are not generally applicable in systems estimation.

<sup>a</sup>  $\theta$  represents the square root of the inefficiency variable,  $\theta 2$ ; both are used as interaction terms with other variables. *PGRN*, *PSUG*, and *PLIVE* are the respective prices of grain, sugar, and livestock, which are normalized on the price of fertilizer. Relative output prices were lagged one period to represent naive relative price expectations. *WAGES*, *WOIL*, *WELEC*, and *WFUEL* are the respective input prices for labor, oil, electricity, and other non-oil fuels. *QPOT* and *QVEG* are the fixed output quantity potatoes and vegetables. *YEAR* is a dummy variable with a value of 0 for 1994 and 1 for 1995.

coefficient on the one “stand-alone” technical inefficiency term in each equation,  $\theta$ , is statistically significant in all the equations. Output supply parameters were small and statistically insignificant, while the input demand parameters were statistically significant.

The implied own-price elasticities for all three models were calculated at the sample mean for the two-year period and are reported in table 4. Model 2's elasticities, the model with technical inefficiency included, are larger in absolute value than those for model 1. Further, more of model 2's elasticities are statistically significant at the 0.01 confidence level compared to the findings for model 1.<sup>9</sup> Model 2's own-price elasticities have

<sup>9</sup> Model 1 (standard model) elasticity estimates would be lower if the true model included efficiency scores. By excluding the efficiency variable, the inefficiency effect may become incorporated into the estimated parameter of price response, resulting in smaller elasticity estimates.

**Table 4. Own-Price Elasticities of Models With and Without Technical and Allocative Inefficiency (1994–1995)**

Description	MODELS					
	[#1] With No Inefficiency (Standard Model)		[#2] With Technical Inefficiency		[#3] With Technical and Allocative Inefficiency	
	Elasticity	Std. Error	Elasticity	Std. Error	Elasticity	Std. Error
<b>Outputs:</b>						
Grains	0.023	0.059	0.055	0.066	0.086	0.066
Sugar Beets	0.025	0.061	0.217**	0.112	0.268**	0.122
Livestock	0.036	0.036	0.036	0.067	0.026	0.057
<b>Inputs:</b>						
Wages	-0.041	0.077	-0.062**	0.030	-0.053**	0.002
Oil	-0.029	0.078	-0.091	0.080	-0.090	0.052
Electricity	-0.356**	0.121	-0.627**	0.130	-0.630**	0.259
Fuel	-0.488**	0.095	-0.841**	0.173	-0.860**	0.117

Notes: Double asterisks (\*) denote significance at the 0.05 confidence level. Cross-elasticities are not shown for the sake of brevity, but are available upon request from the authors.

the expected signs for grains, sugar beets, and livestock (0.055, 0.217, and 0.036, respectively), and indicate there is a slight sensitivity to output prices; the elasticities for grains and livestock are statistically indistinguishable from zero. All input elasticities have the expected negative signs, and several show a clear sensitivity to price (electricity, -0.627; fuels, -0.841). Model 3's output supply elasticities are slightly higher for grains and sugar beets compared with those of model 2 (technical inefficiency only), but the input demand elasticities are practically the same as in model 2. Except for electricity, the elasticity estimates from model 3 are more precise.

The positive response to the price of sugar beets and strong negative response to the prices of electricity and fuel provide evidence confirming Russian producers were responding to some market signals after three years of market pricing. The signs for both the output supplies and input demands were as expected theoretically, though the greatest sensitivity was shown for the demand for electricity and fuels. It makes sense that changes in electricity and fuel prices elicited a stronger response because these two inputs were available to substitute for each other. When interpreting these results, it is important to consider: (a) cross-sectional supply models often do not perform as well as time-series models, and (b) evidence of response to market prices in Russia, even if it is a relatively small response, is of significant interest to policy makers and transition economy researchers.

### A Comparison with a Standard Model

Two different tests were employed to compare model 2 with model 1, and model 3 with model 2. To test model 2 (technical inefficiency model) against model 1 (a standard model), a nonnested test for systems estimation devised by Davidson and MacKinnon was used. However, to test model 3 (technical and allocative inefficiency model) against model 2 (technical inefficiency model), a system log likelihood ratio test was used because model 2 was nested within model 3.

**Table 5. System  $P_1$  Tests (following a  $t$ -distribution)**

Description	[A] $H_0$ : Model 1 (standard model) is the true model	[B] $H_0$ : Model 2 (tech. inefficiency model) is the true model
$P_1$ Value	17.23***	11.24***
Coefficient	0.54	0.11

Notes: Triple asterisks (\*) denote significance at the 0.01 confidence level. The significant  $P_1$  statistic in column [A] rejects the model without technical inefficiency; the significant  $P_1$  statistic in column [B] rejects the model with technical inefficiency. The coefficient represents the degree to which the test moves away from the model. The coefficient 0.54 means implicitly that it attaches close to equal weights to both models in the compound model, while the coefficient 0.11 attaches a weight of 0.89 to the efficiency model and 0.11 to the no-efficiency model.

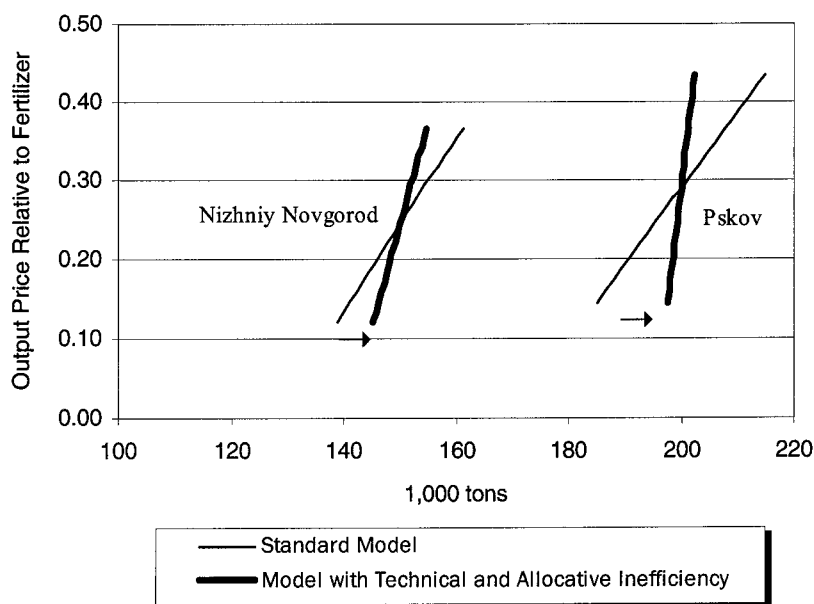
For the first test comparing model 1 with model 2, Davidson and MacKinnon's method for testing nonnested systems of equations was applied, which involved reestimating the ITSUR system and testing the relative performances of fitted values from each model in a composite model. For nonnested models, there are typically four outcomes: rejection of model 1, rejection of model 2, rejection of both models, and nonrejection of either (Greene). However, the Davidson and MacKinnon system " $P_1$ " test has two rejection outcomes: rejection in the direction of the other model, and rejection away from the other model (see Davidson and MacKinnon, p. 304).

The  $P_1$  values in table 5 lead to a rejection of model 1 (a standard model) in the direction of model 2 (technical inefficiency model). When reversing the test, model 2 was rejected in the direction of model 1. However, the relative size of the test coefficients is revealing. When model 1 is the null hypothesis, the relevant coefficient is 0.54, indicating a sizeable move in the direction of model 2. When model 2 is the null hypothesis, the relevant coefficient is 0.11, indicating small movement in the direction of model 1.

Mixed results are not uncommon when applying nonnested tests. In this case, the non-nested systems  $P_1$  test leans in favor of model 2, which includes technical inefficiency scores. A comparison of both models found more parameter estimates and  $t$ -statistics for important price variables were significant in model 2, the model that includes technical inefficiency.

An effort also was made to test the specification of model 3. Because model 2 (technical inefficiency model) is nested within model 3 (technical and allocative inefficiency model), a system log likelihood ratio was used to perform the test. The calculated  $\chi^2$  test statistic (6 degrees of freedom) of 11.0 indicated model 2 could not be rejected in favor of model 3 at the 0.05 confidence level, but could be rejected at the 0.10 confidence level. Thus, if using the 0.05 confidence level, model 2 is the preferred model, but when using a 0.10 confidence level, model 3 can be considered to be the preferable model.

Assuming model 3 is the preferred model, the supply parameters from this model can be used to distinguish supply response among the different levels of technical and allocative inefficiency. Figure 1 shows the grain supply curves for two oblasts in 1994 which produced at a comparable level: Pskov and Nizhniy Novgorod. Using the parameter of price response for grain from model 3, output response was simulated assuming technical and allocative efficiency, and again simulated at observed levels of inefficiency in these



**Figure 1. Hypothetical grain supply response under different price scenarios and efficiency levels: Nizhniy Novgorod and Pskov oblasts, 1994**

oblasts. When full technical and allocative efficiency are assumed, the model's estimated output is greater over a range of prices around the observed mean relative price than when inefficiency exists.

In the case of Nizhniy Novgorod, the output bias would have been about 2.5% for prices 30% above the observed mean relative price; in the case of Pskov, the overstatement would have been about 3.7% (figure 1). The percentage biases would have been larger for the commodities with higher elasticities, such as sugar beets. It is important to note that each oblast has a steeper supply slope in model 3 compared with model 1 because of the interaction effect with price, which enters multiplicatively for technical inefficiency [allocative inefficiency only changes the constant; see equation (16)]. The interpretation is that a lower technical inefficiency score implies there will be a steeper, inelastic supply curve because any price responsiveness is constrained by technical inefficiency. In figure 1, the slope of the supply curve from model 3 is steeper for Pskov, which was relatively more technically inefficient. Aggregating these effects, the assumption of full efficiency in each oblast in 1994 (compared to the sample average 0.76 score) means the predicted grain output would have been overstated by about 2% if relative price levels had been 30% above observed price levels.

## Conclusions

In this study we have demonstrated existing dual relationships can be used to directly relate technical and allocative inefficiency to the profit function, and the relationship can be used in estimating a system of output supplies and input demands. The method presented here focuses on estimating the *effect* technical and allocative inefficiency

scores have on output supply and input demand. Economists may consider using this approach in whole or in part. For example, if consistent data were available, economists could take either existing technical inefficiency scores or existing allocative inefficiency scores and estimate the influence of either of these scores on output supply and input demand. Or they could use this approach to model the joint influence of technical and allocative inefficiency on output supply and input demand.

This analysis focuses on incorporating inefficiency scores calculated with nonparametric methods into a system of output supply and input demand equations. Calculating inefficiency scores using programming techniques has certain advantages. For example, programming methods impose no restrictions on functional forms and do not rely on nonlinear econometric estimation techniques, which may have convergence problems. Programming methods can provide efficiency measures to use as regressors in econometric estimation. However, nonparametric methods do not readily lend themselves to establishing confidence intervals around each inefficiency score.<sup>10</sup> The method introduced here provides a tractable alternative to parametric approaches, which simultaneously estimate efficiency and the parameters of a profit function. This method allows researchers to gauge the effects of inefficiency on supply response and input use.

To illustrate this approach, efficiency scores were calculated in Russian agriculture and the scores were incorporated into an output supply and input demand system. Because Russia's agriculture was modeled over a period in which the economy was in transition, technical and allocative inefficiency were likely to exist. Our findings confirm technical and allocative inefficiencies were widespread. The Russian corporate farms were shown to be slightly responsive to output prices, but more responsive to some of the input prices.

Perhaps in the future, efficiency scores calculated by programming approaches could be viewed as serving a role in cross-sectional econometric models analogous to the role of time variables in time-series models. Or perhaps there may be useful analogs in other fields of economics. For example, experimental economics has shown that consumers often do not have perfect perceptions about price and quality of goods, so they do not engage in cost-minimizing or economically rational behavior. Another example is the cognitive dissonance experienced by researchers in the natural resources field when soliciting consumer willingness-to-pay versus willingness-to-receive values for environmental amenities. These types of disparities might be translated into inefficiency scores and used as variables in various demand models.

[Received August 2001; final revision received March 2002.]

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<sup>10</sup> Some work has been done in the area of establishing confidence intervals for DEA. (See Grosskopf for a survey.)

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