1. Introduction

Technical efficiency is the ability of the firm to produce the maximum output from its resources. One firm is more technically efficient if it produces a level of output higher than another firm with the same level of input usage and technology. Measures of technical efficiency give an indication of the potential gains in output if inefficiencies in production were to be eliminated. Recent measures of technical efficiency in the Soviet Union have been incongruous with the presumption that bureaucratic obstacles in the command-economy system inherently foster waste in resource utilization and inefficiencies in production. Koopman (1989), in his analysis of time-series data of aggregate Soviet Republic agricultural production, estimated that the average level of technical efficiency in Soviet agriculture is almost 94 percent, with little variability among the republics. Similar results were found by Danilin et al. (1985) in a 1974 cross-section sample of Soviet cotton refining plants. They found a mean level of technical efficiency of 92.9 percent, with little dispersion in the sample.

These relatively high estimates of technical efficiency suggest that Soviet agriculture cannot appreciably increase output by eliminating inefficiencies in production. This implies that Soviet managers use their resources nearly to their full potential. Thus, increases in output will not result simply by adopting policies that encourage more efficient use of resources. Rather, removal of institutional constraints, infusions of technology, and improvements in the resource base may be required.

Consequently, the current level of Soviet technical efficiency, especially in agriculture, has direct implications for the success of the reforms and restructuring under way in the Soviet Union.

The purpose of this paper is to present further evidence on the level of technical efficiency in Soviet agriculture. Estimates are presented of technical efficiency in agricultural production in the Stavropol Region during the 1986-1988 period. The Stavropol Region is located in the North Caucasus of the Russian Republic, between the Black and Caspian seas. For this region, farm-level technical efficiency estimates are generated for five crops: grain (except corn), corn for grain, sunflowers, sugar beets, and vegetables.

2. Background to Computational Methods

Stating an estimated level of a firm's technical efficiency implies that the 100 percent level of technical efficiency is known. Since the pioneering work of Farrell (1957), the frontier production function has been used to approximate the technically feasible potential--or 100 percent level--of technical efficiency. Deviations from the production frontier give indications of the level of inefficiency in production.

Estimates of technical efficiency derived from frontier production functions are appraised relative to "best practice" production methods, rather than some measure of engineering potential. This provides a relative measure, since efficiency is judged in comparison to a peer group of firms. These firms are assumed to face similar technological, behavioral, and institutional constraints. Therefore, for Soviet agricultural industries, the level of technical efficiency may be above or below international standards even though it is found to be relatively high in comparison to peer firms.

Farrell provided both the initial conceptual framework and the computational methods for production frontiers, and thus a means to measure firm-level efficiency. His computational methods have continued to be refined and modified. A recent advance was the independent development of the stochastic frontier production function by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). This function contains a composite error structure that allows for variation in the frontier across firms caused by random factors affecting production, as well as by inefficiency that pulls the firm's output below its frontier.

The composite error structure of the stochastic frontier production function gives a sounder conceptual basis for estimates of technical efficiency. However, while it is an improvement over previous works, the stochastic frontier had an initial weakness that limited its value in applied work: firm-level estimates of technical efficiency could not be generated. Only an estimate of the mean level of efficiency for firms in the industry could be obtained. Jondrow et al. (1982) remedied this by developing two predictors that assumed the parameters of the stochastic frontier were known. The methods of Jondrow et al. have been generalized by Battese and Coelli (1988).

The stochastic frontier methodology has been applied successfully on various data sets with alternative estimators and modifications by Battese and Corra (1977), Lee and Tyler (1978), Pitt and Lee (1981), Jondrow et al. (1982), Bagi and Huang (1983), Huang and Bagi (1984), Schmidt and

Sickles (1984), Battese and Coelli (1988), and others. Reviews of the frontier and efficiency measurement methodology can be found in Forsund, Lovell, and Schmidt (1980) and Schmidt (1985).

In the next section, the structure and estimation of the stochastic production frontier are discussed. The methods and discussion follow directly from Aigner et al. (1977). Estimators for the mean and firm-level technical efficiency also are given. The estimator of firm-level technical efficiency is conditional on the results of the frontier production function estimation. Again, this estimator was developed by Jondrow et al. (1982).

3. The Frontier Production Function Model

The frontier production function depicts the technical relationships between inputs and outputs of the firm. It indicates the maximum output given the set of available inputs and the technology chosen by the firm. Consider the frontier production function:

$$Y_i = X_i\beta + \epsilon_i \qquad i = 1, 2, \ldots N;$$

$$\text{and} \tag{1}$$

$$\epsilon_i = v_i + u_i,$$

where N is the number of firms, Y_{it} is the level of production for the i^{th} firm, and X_{it} is a 1*k vector of the levels of inputs for the i^{th} firm. Included in this 1*k vector of inputs is the value one, which represents the intercept. The levels of Y_i and X_i are assumed to be in logarithmic form for all N firms. β is a k*1 vector of parameters to be estimated, which will in turn give the relationship between changes in the inputs and outputs.

The composite disturbance term, ϵ_i, is divided into two components. The first, v_i, is a symmetric disturbance that is assumed to be identically and independently distributed as $N(0, \sigma^2_v)$. This symmetric disturbance is assumed to be independent of u_i. As the symmetric component, v_i represents uncontrollable factors that may or may not be favorable to the firm. Uncontrollable factors include the weather, pest outbreaks, unpredictable variation in labor and machinery performance, and possibly just luck. Also imbedded in v_i is measurement error in the dependent variable. Simply put, v_i is the standard stochastic disturbance term found in "average" production function estimation.

The second component of the composite disturbance term is a nonsymmetric, nonpositive ($u_i \leq 0$) disturbance that is assumed to be distributed as $N(0, \sigma^2_u)$, truncated from above at zero. Thus, u_i is assumed to be distributed as half normal. It represents the technical inefficiency of the firm. Technical inefficiency is revealed as production shortfalls from the firm's stochastic frontier $[X_i\beta + v_i]$. Since it is nonpositive, the firm's output must lie on or below its frontier, $Y_i \leq X_i\beta + v_i$. It can be thought that u_i includes factors assumed to be controllable by the firm. Such factors include the ill-timed application of inputs, slack labor practices, lack of proper maintenance, and poor management. However, a more general interpretation is that u_i simply represents factors that limit the firm from reaching its output potential.

The model presented (1), allows through v_i, for variation in the frontier across firms and possibly across time on the basis of random events. The frontier production is firm and time specific. It may shift with the random factors--such as weather--that affect the firm's production possibilities. The remaining part of the composite disturbance, u_i, incorporates a conglomerate of factors labeled technical inefficiency.

Estimation of the model provides a standard to judge the technical efficiency of firms in the sample. It gives an estimate of "best practice" technology within the sample of the peer group of firms. Model estimation and efficiency measures are carried out in a two-step process. First, using maximum likelihood techniques, estimates of the production function parameters β are computed jointly with indicators of the variability of the composite disturbance. With the distributional assumptions given above and a sample of N random observations, Aigner et al. (1977) give the log-likelihood function as

$$\ln L(Y \mid \beta, \sigma^2, \lambda) = N \ln \sqrt{2}/\sqrt{\pi} + N \ln \sigma^{-1} \tag{2}$$

$$+ \sum_N \ln [1 - F(\epsilon_i \lambda \sigma^{-1})] - 1/2\sigma^2 \sum_N \epsilon_i^2,$$

where $\sigma^2 = \sigma^2_v + \sigma^2_u$, $\lambda = \sigma_u/\sigma_v$, and F is the standard normal distribution function. The log-likelihood function (2) can be maximized with respect to β, λ and σ^2 with various numerical iterative algorithms. The estimate of λ gives an indication of the relative variability of the controllable and uncontrollable factors that cause inefficiency.

The second stage provides estimates of industry and firm-level technical efficiency, given the estimates of β, λ, and σ^2. The mean level of efficiency within the industry, TE_m, is given by (Lee and Tyler 1978, pp. 387)

$$TE_m = E(e^u) = 2[1 - F(\sigma_u)] \exp(\sigma^2/2), \tag{3}$$

where F is the standard normal distribution function. This gives an estimate of the average level of technical efficiency in the population.

In Jondrow et al. (1982), the estimate of u_i is the mean or the mode of the conditional expectation of u_i, given ϵ_i. The conditional expectation of u_i, given ϵ_i, is

$$E(u_i | \epsilon) = (\sigma_u \sigma_v / \sigma \, [(f(\epsilon_i \lambda/\sigma)/1 - F(\epsilon_i \lambda/\sigma)) - (\epsilon_i \lambda/\sigma)], \tag{4}$$

where f is the standard normal density function and F is the standard normal distribution function. The expected value for the i^{th} firm can be obtained by substituting the residual from the estimation of (1) into (4). The measure of technical efficiency for the i^{th} firm, TE_i, can then be obtained by substituting (4) into

$$TE_i = \exp(u_i). \tag{5}$$

This is approximately equivalent to the ratio of the production level for the i^{th} firm to production if the technical efficiency is zero ($u_i = 0$). This measure uses the firm's own frontier as the benchmark to measure technical efficiency. The measure is not dependent on the values of the inputs used by the firm.

4. Application to Data from the Stavropol Region

The stochastic frontier production function model was applied to crop production data from collective and state farms in the Stavropol Region from the period 1986 through 1988. The data are from 115 state and collective farms that produced the five principal field crops in the region. The five field crops, analyzed seperately, are grain (except corn), corn for grain, sunflowers, sugar beets and vegetables. The farms are located in 11 of the total 34 districts in the Stavropol Region and are geographically dispersed throughout the region.

Grain, which is mainly winter wheat, is the primary crop in the region. Corn for grain, sunflowers, and especially sugar beets have smaller shares of total crop production. Vegetables, while a minor crop in terms of acreage, are produced on nearly every state and collective farm. The sample districts represent about 40 percent of the total grain production in the Stavropol Region in 1987.

The sample size for each crop and year depends on cropping patterns, production plans, rotational practices, and data omissions. Collectives and state farms that specialized in livestock, viniculture, and other specialized enterprises were omitted from the sample, even though they often have small amounts of crop production. Most of the farm-level crop production and input use data were obtained from the Regional Statistical Bureau in the region's capital, Stavropol. The bureau is the regional center of the Central Statistical Administration. Mineral fertilizer data for 1988 were collected from three regional agro-chemical stations in Shpakovskoe, Budionnovsk, and Cherkessk.

The basic model used for all five crops is the following four-input production function:

$$Y = F(A, K, L, M), \ i = 1, \ldots, N, \qquad (6)$$

where N is the number of observations (farms) and

Y = output (centners);

A = sown area (hectares);

K = capital, cost of depreciation and machinery technical repairs (thousand rubles);

L = direct labor applied (man-hours); and

M = mineral fertilizer nutrients (N, P, and K) applied (centners).

Output for grain, corn used for grain, and sunflowers is measured after "finishing," and thus the usual downward adjustment of bunker-weight values to reflect excess moisture, impurities, and foreign matter is not necessary. The flow of capital services is measured by the cost of depreciation and machinery technical repairs, which is derived from 1981-1983 structure-of-cost data for the region (Sovet po ekonomichesku i sotsialnomu razvitiyo pri Stavropolskm Kraikmeye KPCC statisticheskoye upravleniye Stavropolskovo Kraya 1984). For each crop, the 1981-1983 average percentage of cost due to depreciation and technical repairs was multiplied by the total cost of production to obtain this capital services proxy.

The Stavropol Region has been segmented into five climatic zones, which are distinguished by precipitation and temperature variability (see Nikonov 1973 for details). Structure-of-cost data were available for grain and vegetable production for each of the five climatic zones. For sugar beets, structure-of-cost information was available only for the region as a whole. For corn used for grain and for sunflowers, the structure-of-cost data for grain was used. Sample averages are given for the five crops' dependent and independent variables, along with sample size for each crop (Table 1).

5. Results of Stochastic Frontier Estimation

The stochastic frontier production functions were estimated separately for each of the five crops. The estimation strategy was the same for each crop. The translog functional form was used to provide the approximation to the production frontier. The translog functional form is given as

$$\ln Y_i = \alpha_o + \sum\alpha_i(\ln X_i) + \sum\beta_{ii}(\ln X_i)^2 + \sum\sum\beta_{ij}(\ln X_i)(\ln X_j) + \epsilon_i, \qquad (7)$$

where Y_i is output, X_i is the inputs defined previously (A, K, L and M) and ϵ_i is the composite disturbance term. Initial starting values for the maximum likelihood estimation were obtained with ordinary least squares (OLS). OLS provides consistent and unbiased estimates of all the parameters, except the constant term. The OLS-estimated intercept term is negatively biased.

Next, a statistical test was conducted of whether the functional form is translog or Cobb-Douglas. Model (7) was reestimated with the restrictions that all β_{ii} and β_{ij} are equal to zero. Under these parameter restrictions, the Cobb-Douglas functional form is the result.

Table 1. Sample average and standard deviations of dependent and explanatory variables

Crop	Output (centners)	Sown area (hectares)	Capital (th. rubles)	Labor (man hours)	Fertilizer (centners)
Grain	125438	5089	165.7	76076	6271
	(79932)	(3240)	(93.01)	(62891)	(6658)
Corn	24104	867.4	44.14	27834	1528
	(22740)	(661.6)	(34.72)	(35830)	(1239)
Sunflowers	9894	764.6	22.83	8785	1005
	(7554)	(720.1)	(16.17)	(7294)	(893.5)
Sugar Beet	167863	618.7	82.19	117511	2854
	(137145)	(308.2)	(50.87)	(119297)	(2273)
Vegetables	8193	62.9	59.59	66456	382.2
	(21010)	(136.2)	(572.3)	(242165)	(876.7)

Note: Standard deviations are in parentheses.

The validity of these restrictions is tested with a likelihood ratio test. The test statistic is the negative of twice the likelihood ratio, which is asymptotically distributed as a Chi-square with parameter m, where m is the number of restrictions imposed to define the restricted model. This test statistic is equivalent to the negative of two times the difference of the restricted and unrestricted log-likelihood functions. The null hypothesis is rejected if the test statistic is greater than the critical value. The test statistics for the five crops are given (Table 2).

During the three crop years of the sample (1986, 1987, and 1988), favorable weather prevailed in the Stavropol Region. The level of moisture was above average and crop conditions were considered good. Nevertheless, the presence of shifts in the frontier production functions due simply to periodicity was examined. The functional form chosen from the results of the previous likelihood ratio test was expanded to include intercept shift dummy variables for two of three sample years, 1987 and 1988. The validity of intercept shifts was also tested with the likelihood ratio test. Other than the inclusion of the fixed-year effect, firm-level efficiency was assumed to be invariant over time. This seems reasonable given that the sample contains three consecutive years of observations and that these years fell in the same five-year plan (12th Five-Year Plan). The tests statistics for the inclusion of intercept shifts are summarized in Table 2.

What follows are the results for each crop, discussed in turn. Discussion focuses on the model selection process and the implied elasticities of the final model chosen for each crop. In the next section, frontier estimates are used to generate population and firm-level

Table 2. Likelihood ratio test statistics

Crop	Null hypothesis[a]		
	All B_{ii} and B_{ij} = 0 (m=10)[b]	1987=0 (m=1)	1988=0 (m=1)
Grain	24.0 **[c]	35.44**	0.13
Corn	39.06**	0.05	-
Sunflowers	17.07	0.07	0.08
Sugar beets	9.70	7.48*	0.78
Vegetables	30.62**	4.54*	5.34*

Note: The likelihood ratio is approximately equal to -2 (log $L(H_o)$ - log $L(H_A)$), where $L(H_o)$ and $L(H_A)$ are the likelihood functions evaluated from the null and alternative hypotheses, respectively.

[a]The restriction that all B_{ii} and B_{ij} equal zero creates the Cobb-Douglas function form from the translog. 1987 = 0 and 1988 = 0 are the tests for the inclusion of separate intercepts in those years.

[b]The degree of freedom, m, is the number of restrictions under the null hypothesis.

[c]Significant at the 99 percent (**) and 95 percent (*) confidence levels.

efficiency estimates. Estimation results are presented (Tables 3 and 4). Table 3 includes the estimation results for the five crops using the Cobb-Douglas functional form. OLS estimates are provided along with the maximum likelihood estimates of the stochastic frontier production functions. The translog functional form was judged superior for grain, corn for grain, and vegetables. The translog stochastic frontier production function results for these crops are given in Table 4.

Grain Estimation Results

Grain production in the Stavropol Region includes winter wheat, winter rye, barley, oats, millet, buckwheat, and peas. Corn for grain is not included in this category. Winter wheat accounts for typically 75 percent of the total grain production. The sample for grain production is 336 observations. The numbers of observations for sample years 1986, 1987, and 1988 are 114, 115, and 107, respectively. The lack of consistency in sample size across years is due almost entirely to data omissions, since grain production is found on every sample farm during the period.

The translog functional forms, with an intercept shift variable for the year 1987, is considered to provide the best approximation of the grain production frontier (see Table 2). The production frontier for grain appears to have shifted outward in 1987--but not in 1988--for a given level of sown area, capital usage, labor, and mineral fertilizer.

For the Cobb-Douglas functional form results (Table 3), the parameter estimates can be directly interpreted as output elasticities. The output elasticities for the translog model, evaluated at sample means, are 0.207

Table 3. Cobb-Douglas stochastic frontier production function results

	Intercept	Dummy	A	K	L	M	λ	σ^2	Log-L
			Grain (N = 336)						
OLS	5.234	-0.159	0.229	0.559	0.071	0.111	–	0.214	43.54
	(0.207)	(0.0260)	(0.0403)	(0.0471)	(0.021)	(0.022)			
Frontier	5.591	-0.155	0.200	0.585	0.070	0.106	1.565	0.287	46.88
	(0.223)	(0.026)	(0.041)	(0.048)	(0.019)	(0.021)			
			Corn for Grain (N = 132)						
OLS	2.800	–	0.582	0.353	0.117	0.106	–	0.444	-77.66
	(0.531)		(0.084)	(0.089)	(0.051)	(0.054)			
Frontier	4.340	–	0.566	0.366	0.084	0.014	4.297	0.685	-66.75
	(0.515)		(0.069)	(0.085)	(0.047)	(0.050)			
			Sunflowers (N = 246)						
OLS	2.577	–	0.565	0.449	0.153	0.009	–	0.362	-96.57
	(0.302)		(0.056)	(0.052)	(0.036)	(0.026)			
Frontier	3.925	–	0.507	0.448	0.095	0.003	5.254	0.577	-75.85
	(0.264)		(0.037)	(0.036)	(0.031)	(0.030)			
			Sugar Beets (N = 91)						
OLS	6.741	0.284	0.416	0.743	-0.068	-0.011	–	0.362	-61.67
	(1.033)	(0.114)	(0.229)	(0.224)	(0.082)	(0.133)			
Frontier	6.926	0.284	0.466	0.700	-0.066	-0.016	0.893	0.560	-61.17
	(1.438)	(0.198)	(0.370)	(0.314)	(0.145)	(0.172)			
			Vegetables (N = 238)						
OLS	0.707	–	0.269	0.428	0.501	0.044	–	0.688	-246.18
	(0.431)		(0.079)	(0.060)	(0.054)	(0.037)			
Frontier	2.675	–	0.287	0.483	0.353	0.058	3.043	1.022	-230.17
	(0.439)		(0.062)	(0.037)	(0.052)	(0.027)			

Note: Standard errors are in parentheses.

Table 4. Translog stochastic frontier production function results

	Grain (N = 336)	Corn for Grain (N = 132)	Vegetables (N = 238)
Intercept	1.087 (2.391)	-6.118 (4.888)	-3.012 (2.323)
Dummy	-0.154 (0.026)	-	-
ln A	1.421 (0.606)	1.246 (1.653)	-0.312 (0.721)
ln K	-1.035 (0.776)	-3.785 (1.952)	-0.214 (0.518)
ln L	0.648 (0.460)	1.818 (0.627)	1.714 (0.635)
ln M	0.164 (0.460)	1.998 (0.886)	0.595 (0.481)
ln A * ln A	-0.253 (0.067)	-0.070 (0.127)	0.036 (0.075)
ln A * ln K	0.519 (0.123)	0.141 (0.259)	-0.033 (0.090)
ln A * ln L	0.071 (0.068)	-0.137 (0.109)	0.108 (0.092)
ln A * ln M	-0.042 (0.081)	0.165 (0.160)	-0.120 (0.063)
ln K * ln K	0.243 (0.092)	-0.285 (0.177)	-0.051 (0.029)
ln K * ln L	-0.015 (0.073)	0.381 (0.150)	0.079 (0.063)
ln K * ln M	-0.016 (0.089)	0.213 (0.209)	0.077 (0.066)
ln L * ln L	-0.045 (0.026)	-0.039 (0.035)	-0.088 (0.045)
ln L * ln M	-0.013 (0.037)	-0.194 (0.096)	-0.060 (0.053)
ln M * ln M	-0.031 (0.019)	-0.145 (0.053)	0.026 (0.021)
λ	1.278	4.486	3.069
σ	0.262	0.592	0.960
Log-L	58.878	-47.218	-214.860

Note: Standard errors are in parentheses.

(land), 0.573 (capital), 0.054 (labor), and 0.120 (mineral fertilizer). Returns to scale, evaluated at sample means, equals 0.953. The Cobb-Douglas results imply a larger output elasticity for labor and a smaller output elasticity for fertilizer.

Wyzan (1979), in his analysis of Soviet Republic time-series crop production data, found output elasticities of 0.616 (area), 0.419 (capital), and 0.040 (labor), in grain production. Wyzan found returns to scale for grain, evaluated at sample means, to be 1.057. Wyzan's output elasticities for capital and labor are similar to the current results, but he found a considerably larger output elasticity for land. Wyzan's results also suggest slightly increasing returns to scale, while the current results suggest slightly decreasing returns to scale for grain production.

The parameter λ, the ratio of the standard deviations of the composite error term, is equal to 1.28 for the translog model. This suggests that the unsymmetric disturbance dominates the symmetric component. Unexplained variation in the frontier is attributable more to inefficiency than to statistical noise.

Corn for Grain Estimation Results

The sample size of corn used for grain is 132 observations. The sample includes 53 observations in 1986, 79 observations in 1987, and no obervations in 1988. Output data, either in quantity or value terms, were unavailable. The translog functional form was judged best for approximating the corn production frontier, with no intercept shifts included (see Table 2).

The output elasticities, evaluated at sample means, are 0.658 (area), 0.346 (capital), 0.132 (labor), and -0.106 (mineral fertilizer). The returns-to-scale coefficient, evaluated at sample means, is 1.03. The Cobb-Douglas elasticity results suggest a lower output elasticity for area and labor, and a positive, but not significantly different from zero, output elasticity for mineral fertilizer. The parameter estimate of λ is equal to 4.49. This clearly indicates the dominance of presumably controllable factors in the composite error of the regression.

Sunflower Estimation Results

The sample size for sunflower is 246 observations. The sample includes 83, 80, and 83 observations from 1986, 1987, and 1988, respectively. The frontier representation considered best is given by the parsimonious Cobb-Douglas functional form, with no intercept shifts (see Table 2). The returns-to-scale coefficient is 1.08, which suggests increasing returns to scale for sunflower production. All the elasticity parameters for sunflowers are positive. The output elasticity parameter for mineral fertilizer is not significantly different from zero. The parameter estimate of λ is equal to 5.25, which indicates technical efficiency is a relatively important part of the composite error.

Sugar Beets Estimation Results

Sugar beets are a minor crop in the Stavropol Region and are grown mostly in the central part of the region. The sugar beet sample has 91 observations. For 1986, 1987, and 1988 there are 32, 30, and 29 observations, respectively. The Cobb-Douglas functional form, with no intercept shifts, proves to adequately characterize the sugar beet production frontier (see Table 2).

The output elasticity for labor is negative (-0.021), but insignificant (see Table 3). The output elasticity for mineral fertilizer is also insignificant, but positive (0.022). The output elasticities for area (0.28) and capital (0.47) are both significant. The returns-to-scale coefficient is 1.09, suggesting slightly increasing returns to scale. The ratio of the standard deviations of the error components, λ, is 0.89. This implies that statistical noise is a more important component of the composite error than technical inefficiency.

Wyzan (1979), using a translog functional form and republic time-series data, found output elasticities of -0.035 (area), (0.013) (capital), and 0.902 (labor). Wyzan estimated the returns-to-scale coefficient, evaluated at sample means, to be equal to 0.896. His results are quite dissimilar to the current results. The output elasticities for area, capital, and labor have completely different magnitudes, and the output elasticity for labor has an opposite sign.

Vegetable Estimation Results

Vegetable production is primarily onions, cabbage, cucumbers, and tomatoes in the Stavropol Region. The vegetable sample includes 238 observations. For 1986, 1987, and 1988 there are 79, 85, and 74 observations, respectively. The translog form with no intercept shifts is considered to provide the best approximation to the vegetable frontier (see Table 2).

The output elasticities for vegetables, evaluated at sample means, are 0.363 (area), 0.585 (capital), 0.230 (labor), and 0.011 (mineral fertilizer). The implied returns-to-scale coefficient is 1.19, which suggests increasing returns to scale in vegetable production. The ratio of the unsymmetric and symmetric disturbances λ is 3.07. This indicates a larger proportion of the unexplained variability of vegetable output is due to technical inefficiency.

Wyzan's (1979) output elasticities for area (-0.051), capital (0.525), and labor (0.958) differ somewhat from the current results. While the capital elasticities are quite similar, labor output elasticity is four times as large as the current estimate, and his estimate of area output elasticity was negative and insignificant. His returns-to-scale estimate of vegetables was 1.405, which indicates increasing returns to scale.

6. Estimates of Technical Efficiency

After estimation and the model selection process, estimates of technical efficiency within the industry overall (3) and at the firm level (5) were generated for each crop. These measures indicate potential output for each crop in the region, given the elimination of technical inefficiencies. The population average and firm-level estimates are summarized for each crop (Table 5).

In the Stavropol Region, technical efficiency in crop production is lower and more variable than the Russian Republic results of Koopman suggest. Depending on the crop, the current results suggest considerable increases in output could be obtained without expanding the resource base.

Table 5. Frequencies and percentages of crop production technical efficiency in the Stavropol Region

Efficiency	Grain		Corn		Sunflower		Sugar Beets		Vegetables	
	Frequency of technical efficiency									
0-10%	0	0.0%	0	0.0%	0	0.0%	0	0.0%	3	1.3%
10-20%	0	0.0%	2	1.5%	4	1.6%	1	1.1%	15	6.3%
20-30%	0	0.0%	3	2.3%	6	2.4%	0	0.0%	14	5.9%
30-40%	0	0.0%	8	6.1%	11	4.5%	0	0.0%	17	7.1%
40-50%	0	0.0%	17	12.9%	19	7.7%	0	0.0%	40	16.8%
50-60%	5	1.5%	14	10.6%	43	17.5%	3	3.3%	36	15.1%
60-70%	20	6.0%	29	22.0%	42	17.1%	10	11.0%	55	23.1%
70-80%	68	20.2%	18	13.6%	40	16.3%	62	68.1%	40	16.8%
80-90%	179	53.3%	32	24.2%	60	24.4%	14	15.4%	17	7.1%
90-100%	64	19.0%	9	6.8%	21	8.5%	1	1.1%	1	0.4%
Total	336	100.0%	132	100.0%	246	100.0%	91	100.0%	238	100.0%
	Level of technical efficiency									
Sample average		82.9%		66.6%		67.7%		75.1%		54.9%
Collective		84.9%		65.7%		69.6%		76.3%		56.2%
State		80.2%		68.4%		64.2%		71.0%		54.0%
Population		83.3%		66.6%		67.0%		76.0%		54.8%

It may be possible to coax greater production out of the current resources if mismanagement, misallocation of resources, and other inefficiencies are eliminated.

Grain production is the most technically efficient crop of those analyzed, and it shows the least dispersion in the sample. The estimated population-average level of technical efficiency for grain production is 83.3 percent. The estimates of firm-level technical efficiency are fairly concentrated in the 80-90 percent range. The minimum level of technical efficiency in the sample is 51.0 percent, and the maximum is 96.1 percent. Only two of the 115 farms have technical efficiency levels above 95 percent. Collective farms are found to be more efficient than state farms.

Corn for grain has a lower level of technical efficiency. The population average is 66.6 percent. The firm-level estimates are more dispersed, with a minimum level of 17.4 percent and a maximum of 95.2 percent. Only one farm is above the 95 percent level of technical efficiency. Counter to conventional thinking, state farms are slightly more technically efficient than collective farms in production of corn for grain.

The level of technical efficiency for sunflower production is quite similar to the corn results. The population average is 67.0 percent. The minimum firm-level estimate is 14.6 percent and the maximum is 96.2 percent. Only two farms are above the 95 percent level of technical efficiency. In sunflower production, collective farms are more efficient than state farms.

The technical efficiency estimates for sugar beets are slightly less dispersed in the sample than those for corn or sunflowers. The population average of technical efficiency is 76.0, which is higher than that of corn and sunflowers. The minimum firm-level estimate is 29.8 percent and the maximum is 93.3 percent. Collective farms again are more efficient than state farms.

Vegetable production in the Stavropol Region has the lowest average level of technical efficiency of the crops analyzed, and it displays the most dispersion in the sample. The population-average level of technical efficiency is 54.8 percent. The minimum estimate of firm-level efficiency is 2.0 percent, and the maximum is 92.4 percent.

The estimates of firm-level technical efficiency correspond with conventional wisdom. In general, the farms considered best in the sample districts have the highest levels of technical efficiency. Farms that are considered poor have the lowest levels of efficiency. This relationship holds especially for grain production. The estimates also show that most farms in the sample use their resources efficiently in grain production, the primary crop in the region. Grain production is typically profitable and has less variability in returns than the other, more specialized, crops.

For the other crops, less correspondence is found between farms that are subjectively considered good and high measures of technical efficiency. This is particularly true for vegetables. Vegetable production is labor intensive and requires careful handling during growth and harvesting. Also, vegetable production is sensitive to weather variability. Combining these factors, vegetable production typically yields low or negative returns. Thus, farms may put less emphasis on the production and harvesting of vegetables, and use their resources on more profitable crops such as winter wheat.

Grain production shows the least amount of output potential given the current resource base. However, considerable gains apparently can be made in the output of corn, sunflowers, sugar beets, and vegetables, while maintaining similar levels of land, labor, fertilizer, and machinery. More detailed analysis of the production of these minor crops needs to be completed. Part of the differences in technical efficiency might be explained simply by low precipitation, pest outbreaks, and other random factors. Differences in technical efficiency also may be due to controllable factors, such as the timing of harvest, the allocation of labor during peak production periods, and the overutilization of fertilizer in the highly profitable crops. Once these and other factors are delineated, inefficiencies can be eliminated.

7. Summary of Results

On the basis of cross-sectional, firm-level data, the level of technical efficiency in agricultural production has been found to be lower and more variable than suggested by previous results based on aggregate Republic data. In the Stavropol Region, technical efficiency of grain production is relatively high (average 83.3 percent), and there appears to be little dispersion in the sample. The level of efficiency for corn for grain, sunflowers, sugar beets, and vegetables is much lower, and the variability in the sample is much higher. Thus, in the Stavropol

Region, farms use their resources most wisely in the production of the region's primary crop.

Improved use of existing resources could greatly improve the production of corn, sunflowers, sugar beets, and especially vegetables. However, while grain production is more technically efficient than that of the other crops, improvements can still be realized in the production of grain within the existing resource base. For all crops, this will require more detailed analysis of production decisions and resource allocations in the low-efficiency farms as well as in the farms that successfully manage their resources.

The technical efficiency of the sample farms from the outset was expected to be different. More important than measuring the level of technical efficiency, though, is the need to discover reasons for the differences in technical efficiency; this is more fundamental to improving the resource use and increasing the agricultural output level in the Stavropol Region. This important question remains. However, the answer requires a more adequate information base. An information base on farm management, organizational structure, labor payment methods, and other factors that may affect the use of resources, profitability, and production potential is clearly needed. The ability to judge the consequences and significance of past policy initiatives--such as the introduction of new forms of farm organizations, labor payment structures, and technology (e.g., the intensive technology program)--is severely constrained. This, in turn, limits the ability to devise promising new policy initiatives on the organization of farms and the relationship between management and labor. The path of policy reform may be filled with less peril if such an information base is instituted.

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