4-2002

An Analysis of Grain Production Decline During the Early Transition in Ukraine: Bayesian Inference

Lyubov A. Kurkalova
Iowa State University

Alicia L. Carriquiry
Iowa State University, alicia@iastate.edu

An Analysis of Grain Production Decline During the Early Transition in Ukraine: Bayesian Inference

Abstract

The first years of reforms in the former Soviet Union resulted in a sharp decline in agricultural production. Several reasons for the fall have been advanced, including a drop in state deliveries of production inputs, labor and management migration from the largescale collective system to the private sector, and the transition-related break in old production ties and networks. Little is known, however, about the relative contribution of all these factors to the decline in production efficiency. In this study, we quantify the contributions of weather variability, decline in input quantities, and changes in technical efficiency to the decline in Ukrainian grain production over 1989-1992. We model the stochastic production frontier using a three-level hierarchical model, and estimate its parameters from within a Bayesian framework. In the model, the time-varying technical efficiency depends on farm-specific factors. Non-informative or diffuse prior distributions are chosen where possible. We find that the decline in the use of production inputs accounts for over half of total output decline, while weather effects account for about 35% of the decline. The rest is attributable to a decline in the technical efficiency of collective farms during the transition years.

Disciplines

Statistics and Probability

Comments

This preprint was published as Lyubox Kurkalova and Alicia Carriquiry, "An Analysis of Grain Production Decline During the Early Transition in Ukraine: Bayesian Inference," American Journal of Agricultural Economics (2002): 1256-1263, doi: 10.1111/1467-8276.00387.

An Analysis of Grain Production Decline During the Early Transition in Ukraine: Bayesian Inference

Lyubov A. Kurkalova and Alicia Carriquiry *

April 30, 2002

Kurkalova is an associate scientist, and Carriquiry is a professor, Department of Statistics, and associate provost, both at Iowa State University and Center for Agricultural and Rural Development, Ames, Iowa 50011.

Contact author:
Lyubov A. Kurkalova
CARD
Iowa State University
560A Heady Hall
Ames, IA 50011 – 1070

Voice: (515) 294-7695
Fax: (515) 294-6336
E-mail: lyubov@iastate.edu

Introduction

The first years of reforms in the former Soviet Union resulted in a sharp decline in agricultural production. Between 1989 and 1992, Ukrainian gross agricultural product dropped some 20%, and the output of grain, which is produced mostly in the collective sector, went down some 25% (World Bank). Several reasons for the fall have been advanced. In addition to weather variation across years, there was a drop in state deliveries of production inputs, especially fertilizer and pesticides (World Bank). The emergence of private opportunities resulted in labor and management migration from the large-scale collective system (Csaki and Lerman), thus reducing the average labor quality in the sector. The ability of farms produce efficiently was also affected by the transition-related break in old production ties and networks (Blanchard and Kremer). While all three explanations of production differences between years (weather variability, input quantities decline, and loss of production efficiency) are plausible, little is known about the relative contribution of these factors to the overall decline in production. Identifying the reasons for the decline in agricultural output in countries like Ukraine is important to predict the likelihood of success of new policies and initiatives, such as accession to the European Union (Macours and Swinnen). We attempt to fill in the gap and improve the understanding of the decline in grain production in early transition Ukraine.

Much of the literature devoted to the analyses of the changes in agricultural production in the former Soviet Union focuses on the later transition years and uses data aggregated both across outputs and farms (e.g., Sotnikov, and Sedik, Truebold, and Arnade). Macours and Swinnen used country-level agricultural production data from several Central and Eastern European countries and found that severe drought and reductions in production factor use accounted for around 10% and 80%, respectively, of total output decline between 1989 and 1995. Kurkalova and Jensen, who used farm-level survey data of Ukrainian farms, estimated that the decline in input quantities and technical efficiency decline contributed about half each to the overall drop of grain production between 1989 and 1992. Neither of the last two studies provided standard errors on the estimates of the shares of the components of output decline. Yet knowing the standard errors is important as underestimating the estimation error may lead to unrealistically precise inferences. This paper extends the analysis of Kurkalova and Jensen by (1) focusing specifically on the decomposition of output decline into its components, and (2) explicitly modeling of the effect of weather on grain production.

The objective of this study is to quantify the contributions of weather variability, decline in input quantities, and changes in technical efficiency to the decline in Ukrainian grain production over 1989-1992. We formulate a stochastic production frontier model, and estimate its parameters from within a Bayesian framework. The Bayesian approach pioneered in technical efficiency literature by Broeck et al., remedies a weakness of classical inference on firm-level technical efficiency. While maximum likelihood estimates of the components of output decline can be obtained for every firm, obtaining an estimate of the standard error of the estimator of the technical efficiency change can be challenging, as the estimator of firm-level inefficiency is inconsistent. In consequence, theoretical justification for the construction of the corresponding confidence intervals is not strong (Horrace and Schmidt).

Following Koop, Osiewalski and Steel, we formulate a three-level hierarchical model, where the time-varying technical efficiency depends on farm-specific factors. Non-informative or diffuse prior distributions are chosen where possible. The model is estimated on a representative sample of Ukrainian former collective and state farms observed over 1989-1992. Markov chain Monte Carlo methods are used to obtain samples from the distributions of the parameters of interest.

The rest of the paper is organized as follows. We begin with data summary; next three sections present the econometric model, prior distributions, and posterior distributions, respectively. Results are presented in the sixth section followed by conclusions.

Data

The study region is the Mixed (central) soil-climatic zone of Ukraine. The data come from a survey of state and collective farms in two administrative regions (*oblast*), *Kyivska* and *Cherkaska.* Summary statistics for the data used in the analysis are given in Table 1. Kurkalova and Jensen provide more detail about the data.

We supplement the survey data with weather variables constructed from the information provided by the National Climatic Data Center (NCDC). As suggested in Desai, we model the effect of weather on grain yields via two variables, the average March-April and average May-June-July temperatures. Since NCDC provides the information for one station in the area only, that in the city of Kyiv, the weather data in our study varies by years only and not by farms (Table 2).

Econometric model

The stochastic production frontier model we postulate is a three-level hierarchical model similar to that of Koop, Osiewalski and Steel. In <u>*level 1*</u>, the farm's logarithm of output in tons, $\ln(y_{it})$ is modeled as

$$\ln(y_{it}) \mid \underbrace{u_{it}, ?_{1}, ?_{2}, ?_{0}, ?_{1}, \ldots, ?_{5}, ?_{v}^{2}}_{parameters}; \underbrace{z_{1t}, z_{2t}, x_{1it}, \ldots, x_{5it}}_{data}$$

$$\sim N\left(?_0 ? ?_1 z_{1t} ? ?_2 z_{2t} ? \sum_{j=1}^{5} ?_j \ln(x_{jit}) ? u_{it}, ?_v^2\right), \qquad (1)$$

Here the subscript i refers to the i–th farm (i = 1,…,41), the subscript t indicates the t-th year (t = 1989,90,91,92), and notation $N(a, b)$ is used for a Normal distribution with mean a and variance b. The z_{1t} is the average March-April temperature in year t (in C^{o}), z_{2t} is an average May-June-July temperature in year t (in C^{o}), x_{jit} (j = 1,…,5) represent production inputs: land under grain production (in hectares), labor in grain production (in 1,000 hours), organic fertilizer (in 100 tons), chemicals applied for grain production (in tons), and diesel fuel used in grain production (a proxy for machinery services) (in 1,000 liters) respectively. The random component v_{it} is white noise representing effects on firm's output not in the model. The non-negative random variable u_{it} denotes the firm's technical inefficiency, that is, by how much the logarithm of the firm's output falls short of the logarithm of the maximum possible output obtainable given the weather in year t, technology, and the quantities of inputs available. The $?$'s, the $?$'s, the u 's, and the σ_v^2 are the quantities of interest. Conditional on the data and the parameters, the outputs $\ln(y_{it})$ are independent (i.e., conditionally exchangeable) for all i and t.

In <u>*level 2*</u>, the technical inefficiency is modeled as an exponential random variable:

$$u_{it} \mid \underbrace{?_1, \ldots, ?_7}_{parameters}; \underbrace{w_{1it}, \ldots, w_{7it}}_{data} \sim Gamma\left(1, \prod_{j=1}^{7} ?_j^{w_{jit}}\right) \qquad (2)$$

Here $w_{1it} = 1$ for all i and t, and the $w_{jit}, j = 2,\ldots,7$, represent the factors affecting inefficiency. Notation $Gamma(a, b)$ is used for a Gamma distribution with mean a/b and variance a/b^2. The nonnegative $?$'s are the quantities of interest.

Following Kurkalova and Jensen, we included the following six factors in the model: the ratio of non-agricultural workers to the total number of workers on the farm, the number of agricultural workers per hectare of agricultural land, manager's age, and year indicators for 1990, 1991, and 1992. Since the focus of this study is the output change decomposition rather than explanation of technical efficiency, we refer to Kurkalova and Jensen for an in-depth discussion of the effects.

Dichotomous w's significantly lessen computational burden as the corresponding conditional posterior distributions are of standard form (Koop, Osiewalski, and Steel). In consequence, we constructed the following dummy variables: w_{2it} is one if the ratio of non-agricultural to total workers on the farm i in time t is greater than the sample median, and zero otherwise; w_{3it} is one if the number of agricultural workers per hectare of agricultural land on the farm i in time t is greater than the sample median and zero otherwise; w_{4it} is one if the age of the farm's manager is higher than the sample median age and zero otherwise; w_{5it} is one if the year is 1990 and zero otherwise, w_{6it} is one if the year is 1991, and w_{7it} is one if the year is 1992 and zero otherwise.

In *level 3*, the priors for the parameters $?_0, ?_1, ..., ?_5, ?_1, ?_2, ?_v^2$ and the hyper-parameters $?_1, ..., ?_7$ are specified.

The Bayesian approach to estimation combines the information about model parameters that is available from all sources. Information contained in the data is summarized in the likelihood function. Prior knowledge (or lack thereof) about model parameters is summarized into the prior distributions chosen for those parameters. Bayes' Theorem provides a mechanism to combine both sources of information into the posterior density of the quantities of interest. In stochastic frontier models, we are also interested in the firm efficiencies, which are functions of u_{it}'s.

Prior distributions

We used non-informative prior distributions when possible:

$? _k \sim Unif(??, ?), \quad k ? 0,...,5; \; ?_k \sim Unif(??, ?), \quad k ? 1,2;$

$?_v^{?2} \mid p_1, p_2 \;\sim\; Gamma ? p_1, p_2 ?; \quad ?_j \;\sim\; Gamma(a_j, g_j)$,

where $a_j ? g_j ? 1$ for $j ? 1$, and $a_1 ? 1, \quad g_1 ? ? \ln(r^*)$, with an $r^* ? ?0,1?$.

Notice that the choice of improper prior distributions for some of the parameters still results in an integrable posterior distribution. A Gamma prior distribution is a widely used choice for the inverse of the variance parameters in normal models (Gelman et al.). Fernandez, Osiewalski, and Steel have shown that the parameter p_2 must be positive, as otherwise the posterior distribution in the inefficiency model does not exist. We set p_1=1, p_2=0.01, implying that a priori, the expected value of $?_v^{?2}$ was equal to 100. The relatively non-informative prior distributions of $?$'s are chosen following Koop, Osiewalski, and Steel. If the explanatory variables w_j, $j ? 2,...,7$, have no effect on the distribution of u_{it}, then the prior median efficiency would be r^*. The parameter r^* was chosen to be 0.8, because this is the value reported in many studies of technical efficiency of (post-) Soviet agriculture (e.g., Sedik, Truebold, and Arnade, Johnson et al., Sotnikov).

Posterior distributions and Gibbs sampler

The joint posterior distribution that results from combining the likelihood function and the prior distributions is an unwieldy multivariate function. Thus, derivation of the posterior marginal distributions of the parameters is not analytically tractable. We use a numerical approach, the Gibbs sampler, which permits obtaining a sample from the joint posterior distribution of all parameters by taking random draws from only full conditional distributions (see, for example, Gelman et al., for a detailed description of this technique). The u_{it}'s are included into the set of the random quantities for which we obtain the joint posterior distribution using Gibbs sampler.

The conditional posterior distributions of the quantities of interest, $\bar{u}, \bar{?}, \bar{?}, ?_v^2, \bar{?}$, are used to implement a Gibbs sampler[1]. That is the distributions of $?_i \mid ?_{(?i)}; data$ are used, where $? ? (\bar{u}, \bar{?}, \bar{?}, ?_v^2, \bar{?})$, $?_i$ is a sub-vector of $?$, $?_{(?i)}$ is $?$ without the element $?_i$, and *data* includes $\bar{y}$, $\bar{z}$, $\bar{x}$, and $\bar{w}$. All conditional posterior distributions in the model have standard densities (truncated Normal, multivariate Normal, or Gamma) (Koop, Osiewalski and Steel), and are given in the Appendix.

Briefly, the Gibbs sampler proceeds as follows. A value of each parameter in the model is drawn from its corresponding conditional distribution. The sequence of draws obtained in this manner forms a Markov chain, whose stationary distribution is equal to the marginal posterior distribution of the parameter. Gelman et al. provide the proof for the result above, and list the conditions that must be met for good performance of the method. In practice, we start with "guesses" for the values of the parameters in the model, and proceed sequentially, drawing a value from each of the full conditional distributions described earlier. After a suitably large number of Gibbs steps, the draws from the conditionals can be thought of as draws from the corresponding marginal posterior distributions. While convergence of the chains to their stationary distributions is very hard to assess exactly, the behavior of the chains can be monitored, and "convergence" can then be assumed. Further details on the Gibbs sampler, including

[1] The notation $\overline{x}$ is used for a vector/matrix *x* of the appropriate dimension.

convergence criteria and application to the estimation of technical efficiency modes are available in Koop, Osiewalski, and Steel, and in Osiewalski and Steel.

Implementation of the Gibbs sampler results in a (correlated) sample of draws of the model parameters. In each pass, draws from the decomposition of output change in its components can be constructed for every firm. Specifically, as the rate of change of output over time is defined as $\dot{y}_{it} = \frac{1}{y_{it}}\frac{dy_{it}}{dt} = \frac{d \ln y_{it}}{dt}$, a discrete estimate of the rate of change of output over the years 1989-1992 can be decomposed as

$$\ln(y_{i,92}) - \ln(y_{i,89}) = \underbrace{\sum_{j=1}^{2} \hat{\gamma}_j \left(z_{j,92} - z_{j,89}\right)}_{\text{due to weather variability}} + \underbrace{\sum_{j=1}^{5} \hat{\beta}_j \left(\ln(x_{ji,92}) - \ln(x_{ji,89})\right)}_{\text{due to a change in input quantities}} + \underbrace{\left(\hat{u}_{i,89} - \hat{u}_{i,92}\right)}_{\text{due to a change in technical efficiency}},$$

where a hat over a parameter denotes an estimate. Once the draws are obtained, the posterior distributions of the quantities of interest can be approximated and easily summarized via histograms and descriptive statistics such as means, variances, and percentiles. The Bayesian approach allows straightforward estimation of probabilities of the form $\Pr(\theta \in \Theta)$, where θ is a random quantity of interest, and Θ is a one-dimensional set. For example, we can make statements such as "The probability that a decline in input quantities contributed between 40% and 70% to the overall decline in the production of firm X is Y%".

We generated five independent chains, each of length 5,000, but combined only the last 4,000 draws from each chain to approximate the posterior distributions of interest. Initial values for $\beta_0, \beta_1, \beta_2$ for the five independent Markov chains were drawn independently from $Unif(-10,10)$ distribution. Initial values for the rest of the β's were drawn from $Unif(0,1)$, since these parameters represent the output elasticities. The initial values for $?_{v}^{?2}$ and $\overline{?}$ were drawn independently from the corresponding prior distributions. Overall, results were insensitive to starting values.

The behavior of the chains was monitored with the statistic $\sqrt{\hat{R}}$ (Gelman et al.). Intuitively, the statistic monitors convergence by comparing the within- and between-chain variances. If the chains have converged to their stationary distributions, the value of the statistic is approximately equal to 1. Values larger than 1 indicate that the "noise" in the draws can be reduced by an amount equivalent to the excess of 1 if the chains are allowed to proceed for additional steps. In our application, the values of the $\sqrt{\hat{R}}$ statistic were under 1.05 for all parameters after 5,000 iterations, indicating that additional Gibbs steps would not have resulted in increased precision of our estimates.

Results

Results are summarized in Table 3. The estimated positive effect of spring temperatures and the negative one of summer temperatures on grain production is consistent with agronomic science. While higher spring temperatures help melt snow and promote winter plant growth, high temperatures after planting of the spring crop deprive the germinating seeds of moisture and, therefore, reduce yields. Desai found similar effects on a 22-year time series of grain yield data for the pre-transition *Kyivska oblast* (one of the regions surveyed in our data). The magnitudes of the output elasticities are also in general agreement with previous studies on crop production in the former Soviet Union (Johnson et al., Kurkalova and Jensen, Sedik, Truebold, and Arnade).

By construction, the $?$'s different from one indicate a significant effect on technical inefficiency. A value of $?_{j}\ ?j\ ?\ 2,\ldots,7?$ greater than one indicates a negative effect of the corresponding variable on technical inefficiency, and thus a positive effect of the variable on technical efficiency. As seen from Table 3, most of the inefficiency effects are different from one, and in agreement with the analysis of Kurkalova and Jensen.

The positive effect of the proportion of non-agricultural workers in total farm employment on technical efficiency is consistent with better farm-provided infrastructure that may have played a positive role in keeping up technical efficiency during the transition-related dismantling of production networks. The number of agricultural workers per hectare can be thought of an indicator of past farm performance – the better the farm performed the more people remained on it over time. The estimated effect thus indicates that the farms that were doing better in pre-transition times are also doing better in terms of technical efficiency during early transition. Sedik, Truebold and Arnade also note the importance of initial conditions on predicting farm efficiency performance during transition. The estimated positive effect of manager's age, a proxy for experience, indicates that human capital is an important factor in achieving technical efficiency; this is consistent with studies of efficiency of agricultural production worldwide (Battese, and Bravo-Ureta and Pinheiro). The median of the posterior distribution of the average (across farms and years) technical efficiency was found to be 0.911 with a standard deviation of 0.019.

The estimates of the average across farms components of output decline are largely negative (Table 3). We estimated the posterior distributions of the proportions of the components of output decline in total output decline for every farm in the sample, and those of averages across farms. That is, we estimated the posterior distributions of both prj_i and $\overline{prj}$, where $prj_i = sj_i / (s1_i + s2_i + s3_i)$, $j = 1,2,3$, $i = 1,...,41$,

$s1_i = \sum_{j=1}^{2} \hat{?}_j \left(z_{j,92} - z_{j,89} \right), \; s2_i = \sum_{j=1}^{5} \hat{?}_j \left(\ln(x_{ji,92}) - \ln(x_{ji,89}) \right), \; s3_i = \hat{u}_{i,89} - \hat{u}_{i,92}$, and

$\overline{prj} = \frac{1}{41} \sum_{i=1}^{41} prj_i$.

The biggest share of the total decline corresponds to the decline in the quantities of inputs: the median of $\overline{pr2}$ is estimated to be 0.55 with $\Pr\left(0.4 < \overline{pr2} < 0.8\right) = 0.91$, and for 15 farms in the sample, $\Pr\left\{ pr2_i ? 0.5 \right\} ? 0.90$. The next biggest share of the total decline is that due to weather: the median of $\overline{pr1}$ is 0.34 with $\Pr\left(0.1 < \overline{pr1} < 0.6\right) = 0.86$. The smallest share of the output decline is due to a decline in technical efficiency: the median of $\overline{pr3}$ is estimated to be 0.10 with $\Pr\left(0 < \overline{pr3} < 0.3\right) = 0.76$, and for some 30 farms in the sample $\Pr\left\{ pr3_i ? 0.3 \right\} ? 0.70$. Note that making such farm-level inference from a classical prospective would be much harder to do because of inconsistency of the ML estimator $\hat{u}_{i,t}$ and nonlinearity of the quantities of interest.

Conclusion

This study aims to quantify some of the reasons for the grain output decline in the early years of transition in Ukraine. We find that the decline in the use of production inputs accounts for over a half of total output decline, while weather effects account for about 35% of the decline. The rest is attributable to a decline in the technical efficiency of collective farms during the transition years. The choice of the Bayesian paradigm for estimation was made to improve the reliability in the estimation of standard errors of functions of model parameters. Because we used non-informative priors where possible, posterior medians of parameters are roughly comparable to those that might have been obtained within a frequentist framework. In this paper, we did not model individual farm weather due to lack of data. However, the analysis showed that explicit modeling of weather effects is important and improves technical efficiency analysis. More detailed weather data may improve the precision of estimation.

An intriguing extension of this work is to model explicitly the decline in factor use. The quantities of inputs used in production went down because of the break down of state distribution systems and growing prices, and may have been determined significantly by individual farm responses. Explicit modeling of input quantities used would require farm-level information on input prices, uncertainties in delivery systems, and other information on factors affecting acquisition of production inputs during the early transition.

Acknowledgment

We are deeply thankful to Mark Steel for his valuable comments and for his indispensable help with Gibbs sampler.

References

Battese, G.E. "Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics." *Agr. Econ.* 7(1992):185-208.

Blanchard, O., and M. Kremer. "Disorganization." *Quart. J. Econ.* 112(1997): 1091-1126.

Bravo-Ureta, B., and A.E. Pinheiro. "Efficiency Analysis of Developing Country Agriculture: A Review of the Frontier Function Literature." *Agr. Res. Econ. Rev.* 22(1993):88-101.

Broeck, J. V.D., Koop, G., J. Osiewalski, and M.F.J. Steel. "Stochastic Frontier Models: A Bayesian Perspective." *J. Econometrics* 61(1994): 273-303.

Csaki, C., and Z. Lerman. “Land Reform in Ukraine.” World Bank Discussion Paper No. 371, World Bank, Washington, D.C., 1997.

Desai, P. “Weather and Grain Yields in the Soviet Union.” Res. Report No. 54, International Food Policy Research Institute, Washington, D.C., Sept. 1986.

Fernandez, C., Osiewalski, J., and M.F.J. Steel. “On the Use of Panel Data in Stochastic Frontier Models with Improper Priors.” *J. Econometrics* 79 (1997): 169-193.

Gelman, A., J.B. Carlin, H.S. Stern, and D.B. Rubin. *Bayesian Data Analysis.* London: Chapman and Hall, 1995.

Horrace, W.C., and P. Schmidt. “Confidence Statements for Efficiency Estimates from Stochastic Frontier Models.” *J. Product. Anal.* 7(1996):257-282.

Johnson, S.R., A. Bouzaher, A. Carriquiry, H. Jensen, and P.G. Lakshminarayan. "Production Efficiency and Agricultural Reform in Ukraine." *Amer. J. Agr. Econ.* 76(1994): 629-635.

Koop, G., J. Osewalski, and M.F.J. Steel. “Bayesian Efficiency Analysis through Individual Effects: Hospital Cost Frontiers.” *J. Econometrics* 76(1997): 77-105.

Kurkalova, L.A., and H.H. Jensen. “Technical Efficiency of Grain Production in Ukraine.” *CARD Working Paper 00-WP 250*, August 2000.

Macours, K., and J.F.M. Swinnen. “Causes of Output Decline in Economic Transition: The Case of Central and Eastern European Agriculture.” *J. Comparative Econ.* 28(2000): 172-206.

National Climatic Data Center (NCDC). *Climatic Database*. Available on-line at http://cdo.ncdc.noaa.gov/plclimprod/plsql/poemain.poe (accessed April 2002).

Osiewalski, J., and M.F.J. Steel. “Numerical Tools for the Bayesian Analysis of Stochastic Frontier Models.” *J. Prod. Anal.* 10(1998): 103-117.

Sedik, D.J., M.A. Truebold, and C. Arnade. "Corporate Farm Performance in Russia, 1991-1995: An Efficiency Analysis." *J. Comp. Econ.* 27(1999): 514-533.

Sotnikov, S. (1998). "Evaluating the Effects of Price and Trade Liberalization on the Technical Efficiency of Agricultural Production in a Transition Economy: The Case of Russia." *Eur. Rev. Agr. Econ.* 25(1998): 411-430.

World Bank. *Ukraine: The Agriculture Sector in Transition*. Washington, D.C.: World Bank, 1994.

Appendix

Throughout the Appendix, $p(?)$ denotes the probability density function of an appropriate random variable, $f_G ?x \mid a,b?$ denotes the probability density function of a Gamma distribution with a mean a/b and a variance a/b^2, i.e. $f_G ?x \mid a,b? ? \frac{b^a}{? ?a?} x^{a?1} e^{?bx}$,

$? ??$ is a Gamma function, and $? ??$ is a cumulative density function of the standard Normal distribution.

The *full conditional posterior of* u_{it} is a truncated Normal distribution:

$$p(u_{it} \mid \overline{?}, \overline{?}, ?_v^2, \overline{?}; y_{it}, z_{1t}, z_{2t}, x_{1it}, \ldots, x_{5it}, w_{2it}, \ldots, w_{7it})$$

$$? \frac{1}{\sqrt{2?}\sqrt{?_v^2}\, ? \, ? \frac{m_{it}}{\sqrt{?_v^2}} ?} \exp ? ? \frac{1}{2?_v^2}(u_{it} ? m_{it})^2 ?, \quad u_{it} ? 0, \text{ where}$$

$$m_{it} ? ? \ln(y_{it}) ? ?_v^2 \sum_{j?1}^{7} ?_j^{w_{jit}} ? ?_0 ? ?_1 z_{1t} ? ?_2 z_{2t} ? \sum_{j?1}^{5} ?_j \ln(x_{jit}).$$

The *full conditional posterior of* $\overline{?}$? $\{?_0, ?_1, ?_2, ?_1, ..., ?_5\}$ is an 8-variate Normal

distribution: $p(\overline{B}\,|\,\overline{u}, ?_v^{?2}; \overline{z}, \overline{x}, \overline{y})$? $\exp\left\{ ? \frac{1}{2} ?_v^{?2} \left(\overline{?} ? \hat{?}\right)' \left(\overline{X}'\overline{X}\right)\left(\overline{?} ? \hat{?}\right) \right\}, \quad \overline{?} ? ? \left(\overline{?}\right),$

where $\hat{?}$? $\left(\overline{X}'\overline{X}\right)^{?1} \overline{X}'\left(\overline{\ln(y)} ? \overline{u}\right)$, ? $\left(\overline{?}\right)$? $\prod_{j?1}^{8} ?(??, ?)$, and $\overline{X}$ is a 164 by 8 matrix

consisting of the rows $\left(1, z_{1t}, z_{2t}, \ln(x_{1it}), ..., \ln(x_{5it})\right)$, t ? 89,...,92, i ? 1,...,41.

The *full conditional posterior of* $?_v^{?2}$ is a Gamma distribution

$$p\left(?_v^{?2}\,|\,\overline{u}, \overline{?}, \overline{?}; \overline{z}, \overline{x}, \overline{y}, p_1, p_2\right)$$

$$? \; f_G\left(?_v^{?2} \,\middle|\, \frac{p_1 ? 164}{2}, \frac{1}{2}\left\{ p_2 ? \sum_{t?89}^{92} \sum_{i?1}^{41} \left[\ln(y_i) ? u_{it} ? ?_0 ? ?_1 z_{1t} ? ?_2 z_{2t} ? \sum_{j?1}^{5} ?_j \ln(x_{jit}) \right]^2 \right\} \right),$$

$$?_v^{?2} ? 0.$$

The *full conditional distribution of* $?_1$ is a Gamma distribution

$$p\left(?_1\,|\,\overline{u}, \overline{?}_{?1?}; \overline{w}; a_1, g_1\right) ? f_G\left(?_1 \,\middle|\, a_1 ? 164, g_1 ? \sum_{t?89}^{92} \sum_{i?1}^{41} u_{it} D_{1it} \right), \quad ?_1 ? 0.$$

Here D_{rit} ? $\prod_{j?r} ?_j^{w_{jit}}$, r ? 1,...,7, i ? 1,...,41, t ? 89,...,92, and $\overline{?}_{??j?}$ denotes $\overline{?}$ without its

j th element.

Finally, the *full conditional distributions of* $?_j$, j ? 2,...,7, are also Gamma

distributions:

$$p\left(?_j\,|\,\overline{u}, \overline{?}_{??j?}; \overline{w}; a_j, g_j\right) ? f_G\left(?_j \,\middle|\, a_j ? \sum_{t?89}^{92} \sum_{i?1}^{41} w_{jit}, g_j ? \sum_{t?89}^{92} \sum_{i?1}^{41} w_{jit} u_{it} D_{jit} \right), \quad ?_j ? 0.$$

Table 1. Summary Statistics for Variables in the Stochastic Frontier Production Model of Grain Production

Variable	Units	Mean	St. Deviation	Minimum	1st Quartile	Median	3d Quartile	Maximum
Production	Tons	3,972	2,361	1,219	2,728	3,466	4,356	18,574
Land	Hectares	1,112	517	268	829	970	1,141	2,850
Labor	1,000 hours	32	29	6	17	26	39	219
Fertilizer	100 tons	79	78	14	40	59	86	596
Chemicals	Tons	6.6	3.7	1.6	4.5	5.9	7.5	21.4
Fuel	1,000 liters	93	51	24	66	79	92	285
Ratio of non-agricultural to total workers	Number	0.143	0.053	0.041	0.107	0.136	0.169	0.317
Agricultural workers per agricultural land	Number per hectare	0.141	0.031	0.081	0.119	0.140	0.161	0.245
Manager's age	Years	47	8	30	42	45	54	65

[a] 41 farms, 4 years, 164 observations in total

Table 2. Temperature Data for the Kyiv Weather Station, in C°

Variable	1989	1990	1991	1992
March-April average temperature	7.7	6.9	9.0	5.4
May-June-July average temperature	17.8	16.2	17.5	19.3

Source: authors' calculations using monthly data from NCDC.

Table 3. Bayesian Estimates for Parameters of the Frontier Model

Variable	Parameter	Posterior Distributions [a]		
		Median	St. Dev.	Selected probabilities
Stochastic Frontier	?			
Constant	$?_0$?	5.34	0.65	Pr{ $?_0$? 0} ? 100.0%
April-May Av. Temp.	$?_1$	0.006	0.022	Pr{ $?_1$? 0} ? 61.0%
May-June-July Av. Temp.	$?_2$	-0.044	0.021	Pr{ $?_2$? 0} ? 98.8%
Ln (Land)	$?_1$	0.15	0.13	Pr{ $?_1$? 0} ? 88.5%
Ln (Labor)	$?_2$	0.059	0.027	Pr{ $?_2$? 0} ? 98.5%
Ln (Fertilizer)	$?_3$	0.135	0.032	Pr{ $?_3$? 0} ? 100.0%
Ln (Chemicals)	$?_4$	0.282	0.048	Pr{ $?_4$? 0} ? 100.0%
Ln (Fuel)	$?_5$	0.309	0.093	Pr{ $?_5$? 0} ? 99.9%
Standard deviation	$?_v$?	0.147	0.013	
Inefficiency model	?			
Constant	$?_1$?	20.4	7.1	Pr{ $?_1$? 1} ? 100.0%
Dummy for proportionately higher non-agricultural employment	$?_2$	1.41	0.42	Pr{ $?_2$? 1} ? 90.6%
Dummy for higher agricultural workers per hectare	$?_3$	2.02	0.57	Pr{ $?_3$? 1} ? 99.7%
Dummy for higher manager's age	$?_4$?	1.73	0.66	Pr{ $?_4$? 1} ? 95.2%
Dummy for 1990	$?_5$	0.48	0.56	Pr{ $?_5$? 1} ? 85.3%
Dummy for 1991	$?_6$	0.113	0.052	Pr{ $?_6$? 1} ? 100.0%
Dummy for 1992	$?_7$	0.44	0.56	Pr{ $?_7$? 1} ? 87.2%
Average (over farms) change in Ln (output), 1989-92				
Due to weather		-0.082	0.047	Pr{ *change* ? 0} ? 95.2%
Due to a change in input quantities		-0.202	0.018	Pr{ *change* ? 0} ? 100.0%
Due to a change in technical efficiency		-0.045	0.038	Pr{ *change* ? 0} ? 91.8%

[a] Computed from 20,000 runs of the Gibbs sampler after discarding the first 5,000 draws.