EFFICIENCY BENEFITS OF GM TECHNOLOGIES?
EVIDENCE FROM SOYBEANS & IMPLICATIONS FOR POLICY

Robert D. Weaver[1], Jarmila Curtiss[2], Bernhard Brummer[3]

May 24, 2005

Paper presented at
9th International Conference
on
Agricultural Biotechnology: Ten Years After
organized by the:
International Consortium on Agricultural Biotechnology Research
(ICABR)
and the:
Catholic University of Leuven
CEIS - University of Rome "Tor Vergata"
Center of Sustainable Resource Development, University of California at Berkeley
Economic Growth Center, Yale University
Ravello (Italy) July 6 10, 2005

Keywords: Technical efficiency, technical change, technological change, technical inefficiency, genetically-modified, transgenic
JEL Classification: D240, O330

1) Corresponding Author: Professor, Penn State University, State College, USA r2w@psu.edu
2) Institute for Agricultural Development in Central and Eastern Europe, Halle, Germany
3) Assistant Professor at Institute of Agricultural Economics, Georg August Universitat Gottingen

ABSTRACT

After nearly a decade of application, the benefits to producers and society of GM technologies have proven complex and variable across the heterogeneous settings that characterize global agricultural systems. One aspect that has received little attention has been the implications of GM technologies for technical efficiency, particularly for inputs and practices that affect the environment. The nature of these effects is especially relevant when considering arguments for or against the use of such technologies, or for their use in developing country contexts. At its root, this issue is a important and general problem in the economics of innovation, i.e. the assessment of change in inefficiency associated with a new technology. If technical inefficiency is viewed as a result of persistent management error that reflects intrinsic characteristics of a technology, then a change from one technology to another may involve a change in that inherent technical inefficiency. The problem of measurement is complicated by a difference in the state of learning associated with the old vs. new technologies. This paper defines inherent technical inefficiency as persistent. A production process that produces joint private and public goods is presented.

The paper first considers distinct types of GM technologies and how they may affect technical efficiency in use of environmentally impacting inputs and practices. Next, the paper presents a stochastic frontier approach to evaluate the extent of difference between the frontiers associated with a GM versus a non-GM technology. Estimates of change in technical efficiency are presented. For an application, the paper analyzes the efficiency of soybean production with respect to grain output and environmental impact and compares two technologies ~ a new technology using genetically modified (GM) herbicide resistant varieties versus the old, herbicide-based, non-GM technology. A shift to GM technology has been argued by physical scientists to result in changes in private good input and output flows, as well as changes in environmental effects.

Results indicate that while physical science predicts little to no productivity change between the two technologies, a measurable difference in technical efficiency is apparent. These results establish a new pathway through which GM technologies may offer important opportunities to alter the impacts of agriculture on the environment. Implications for policy and regulation are drawn for developing country agricultural systems.

EFFICIENCY BENEFITS OF GM TECHNOLOGIES: EVIDENCE FROM SOYBEANS & IMPLICATIONS FOR POLICY

After nearly a decade of application, the benefits to producers and society of GM technologies have proven complex and variable across the heterogeneous settings that characterize global agricultural systems. One aspect that has received little attention has been the implications of GM technologies for technical efficiency, particularly for inputs and practices that affect the environment. The nature of these effects is especially relevant when considering arguments for or against the use of such technologies, or for their use in developing country contexts. At its root, this issue is a important and general problem in the economics of innovation, i.e. the assessment of change in inefficiency associated with a new technology. If technical inefficiency is viewed as a result of persistent management error that reflects intrinsic characteristics of a technology, then a change from one technology to another may involve a change in that inherent technical inefficiency. The problem of measurement is complicated by a difference in the state of learning associated with the old vs. new technologies. This paper defines inherent technical inefficiency as persistent. A production process that produces joint private and public goods is presented.

The paper first considers distinct types of GM technologies and how they may affect technical efficiency in use of environmentally impacting inputs and practices. Next, the paper presents a stochastic frontier approach to evaluate the extent of difference between the frontiers associated with a GM versus a non-GM technology. Estimates of change in technical efficiency are presented. For an application, the paper analyzes the efficiency of soybean production with respect to grain output and environmental impact and compares two technologies ~ a new technology using genetically modified (GM) herbicide resistant varieties versus the old, herbicide-based, non-GM technology. A shift to GM technology has been argued by physical scientists to result in changes in private good input and output flows, as well as changes in environmental effects.

Results indicate that while physical science predicts little to no productivity change between the two technologies, a measurable difference in technical efficiency is apparent. These results establish a new pathway through which GM technologies may offer important opportunities to alter the impacts of agriculture on the environment. Implications for policy and regulation are drawn for developing country agricultural systems.

TECHNICAL CHANGE, PRODUCTIVITY, AND EFFICIENCY

The focus of study of technical change has been sharply placed on productivity growth, although great care has been taken to decompose unexplained change in output into productivity, scale changes (see e.g. Wheelock and Wilson, 1999), capacity utilization (e.g. see Kalirajan et al. 1996), allocative efficiency, scale, and technical efficiency. The possibility of slow learning or other stickiness has led to consideration of the difference between the observed and best practice frontiers, see Kumar and Russell (2002). More recently, consideration of environmental effects has been added to the list of "productivity parts" of interest in decompositions, see e.g. Reinhard et al. (1999). While this literature is well-known and well-organized, cracks remain through which some issues have fallen. The question of how change in technology affects persistent technical inefficiency is one such issue. The intuition of this effect is illustrated in Figure 1. In general, the hypothesis is simple. Each technology has an intrinsic propensity for technical inefficiency. In Figure 1, this is illustrated as a change in the extent and distribution of inefficiency.

THE CASE OF GM TECHNOLOGIES

Two types of genetically modified (GM) crop varieties have emerged: those with insecticide activity and those that are tolerant of chemical pesticides. In the first case, insecticide activity constitutes a substitute for application of insecticides. However, the timing and function of the activity differs substantially. For BT crops, damage control is continuous and starts with the occurrence of insects attacking the plant. Under conventional systems, routine application can be pursued as a preventive strategy, though this is inherently inefficient when the actual damage risk is difficult to estimate. Alternatively, application can occur after observation of insects at some threshold level of infestation. Again, this approach is inherently inefficient. For herbicide resistant crops, the implications of GM technologies are more complex. For both types of GM crops, the nature of their impacts is clearly different from a simple yield augmenting, factor neutral change typically associated with a new variety or hybrid. However, the exact nature of the technical change is subject to substantial debate, uncertainty, and variation across growing conditions and crops. The yield effect is exemplary. The yield impact of transgenic soy depends on weed control as well as the extent of adaptation of conventional varieties. Past studies have not found a striking difference in yields that can not be unequivocally assigned to weed control differences, or plant growth or damage effects from application methods. Going a step further, transgenics provide opportunity for substantial changes in management practices, timing, flexibility, and intensity of input use, see Ervin et al. (2000).

Fernandez-Cornejo and McBride (2000) found for the period 1996-98 that use of ht cotton led to significant yield and net return increases, though no significant herbicide use changes. Alternatively, for ht soy they found small increases in yield, no change in net returns, and significant decreases in herbicide use. Their results varied substantially across farms and regions. Although evidence from analysis of farm-level experience is not available, the flexibility in timing of use of herbicides and of field practices for ht soy would suggest efficiency gains could be realized compared to conventional practices for soy.

Public benefits in the forms of both short- and long-term environmental benefits are a potentially important dimension of the adoption of transgenics. Ervin et al. (2000) note that substantial environmental benefits may be associated with transgenic crops, though they also note ecological negative effects have been suggested by some research. Further, as might be expected for any innovation, some uncertainty remains concerning the extent and nature of these effects. Recent USDA data shows that herbicide-tolerant seed slightly reduced the average number of active ingredients applied per acre, while slightly increasing the average amount applied per acre, see ERS (1999a)

In the long-term, it was expected that transgenic crops would facilitate introduction of pesticides that imply reduced environmental risk. While rapid adoption of such crops suggests strong incentives may be in place to motivate these decisions, the interplay of private vs. public effects in these decisions is not clear. Based on ERS/USDA estimates, the expansion of ht soy in the U.S. followed rapidly after 1997 and was accompanied by increased use of glyphosate (ERS 1999b) and decreased use of other herbicides leading to a net reduction in total weight applied. ERS (1999a) indicated that ht soy allowed reduced a.i. application.

A more specific look at farm level survey data suggests that changes in production practices for ht soy include a shift toward conservation tillage, a notable reduction in the number of active ingredient herbicides used with a sharp focus on glyphosate; and finally, that the planting window has become much wider offering substantial flexibility for timing of planting, weed control, and movement toward no-till planting that eliminates tillage and other field preparation activities. From 1989 to 1998 the acreage of soybeans planted with conservation tillage methods increased from 30% to 54%, see Carpenter and Gianessi 1999. These changes appear to offer reduction in fuel use.

Changes in practice include shifts to no-till planting, pre-emergence herbicide use, change in the type of active ingredients used, and perhaps substantial changes in environmental impacts of crop practices. Carpenter and Gianessi reviewed shifts in practices citing in particular the role of transgenic soybeans as a natural extension of an evolution toward increased use of post-emergence herbicides, simplification of weed control programs, and improved effectiveness of active ingredient applications, see e.g. Pike, McGlamery, & Knake (1991). This shift in practice had substantial implications for tillage practices that had focused on field preparation, and post-emergence tillage. Given post-emergence herbicides, adoption of conservation tillage was facilitated, leading to over 50% adoption by 1998, see Kapusta & Krausz (1993) and Conservation Tillage Information Center (1999). This shift was further extended by introduction of herbicide tolerant soybeans that allow post-emergence, broad spectrum herbicide application at nearly any stage of plant growth. A more subtle change associated with the shift to post-emergent herbicides has been a reduction in row spacing, significantly reducing cultivation, improved weed control due to canopy closure, and increasing land area yield. The key innovation offered by transgenic soybeans is the reduction of crop damage (e.g. stunting, delayed canopy closure) from herbicide application, see Padgette, et al. (1996) and increased effectiveness of weed kill, see Rawlinson & Martin (1998). This latter effect follows directly from tolerance that allows effective dosage to be determined with consideration of crop damage relaxing constraints in conventional systems with respect to timing (early in weed emergence).

Together, these changes in practice offer a complex shift from those associated with conventional variety. Given the complexity in this shift, it is of interest to consider the implications of the shift on technical efficiency. Here, interest lies in considering whether the flexibility and associated managerial control offered by GM technologies provides a pay-off in terms of reduced technical inefficiency.

MEASURING THE TECHNICAL EFFICIENCY IMPLICATIONS OF GM TECHNOLOGIES

Past literature considering comparison of discrete technologies in the agricultural sector has been limited in focus. Extensive literature has considered how managerial organization affects technical efficiency, most recently in transition countries, see e.g. Sarris et al. (1999) or Kong et al. (1999). A decade ago, the Green Revolution sparked interest in assessment of the technical efficiency implications of High Yielding Varieties (HYV) though these studies took a panel approach; see e.g. Coelli et al. (2003). Lansink et al. (2002) used DEA methods to measure technical efficiency differences between organic and conventional farm technologies in Finland.

To proceed, we consider the case of GM technology and present estimates of the change in technical inefficiency inherent between GM and conventional, or non-GM technology. Although several methods are available to measure inefficiency, we adopt with some variation the stochastic frontier (SF) methodology developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). More specifically, we consider the technical efficiency of soybean production with respect to grain output differences for operations using genetically modified (GM) versus those using non-GM herbicide resistant seed. Although as already noted, a shift to GM technology has been argued by physical scientists to result in changes in private good input and output flows, as well as changes in environmental effects, we limit our focus to private effects.

Before proceeding, it is of interest to note the intuition behind our interest in technical efficiency impacts of GM technologies. In brief, if technical inefficiency is observable by a firm, an incentive exists for the firm to seek innovations and new technologies that reduce the cost and productivity losses of such inefficiency. The link between use of information technologies and productivity has been considered by Siegel and Griliches (1992); Siegel (1997); Lehr and Lichtenberg (1998). Others have noted the role of flexibility of technologies, see e.g. Power (1998) or Breznahan and Trajtenberg (1995). The conditionality of technical efficiency on the extent of learning has also been documented by past results, e.g. see Fane (1975) or Ajibefun et al. (1996). Most recently, Coelli et al. (2003) analyzed technical efficiency of high yielding varieties and considered the long recognized role of learning and information as a determinant of technical efficiency. Using a two-step method, they found a strong relationship between information dissemination (via extension effort) and technical efficiency.

The general problem raised by our query is to evaluate the differences in technical efficiency observed across a two sets of firms. Two approaches have been pursued. A two-step method has been widely applied where first technical efficiency estimates are computed based on an SFA specification of a production function. In a separate step, these estimates are regressed on hypothesized determinants such as use of GM seed. This two-step estimation has seen continued use, see e.g. Stefanou and Ueda (2002) or Coelli et al. (2003) despite a number of caveats concerning its appropriateness. Wang and Schmidt (2002) argue that the two-step procedure might lead to severely biased estimates of the technical efficiency effects. Further, the inconsistency between the distributional assumptions made in each of the two stages has been noted.

An alternative to the two step method is a one step method in which the explanation of technical inefficiency is incorporated in the specification of the distribution of the asymmetric component of stochastic error. Here we use the one stage approach to avoid the omitted variable problem inherent to the two-stage estimation. In the literature, two different approaches to one-step estimation have been proposed: Battese and Coelli (1995) addressed these concerns with a one-stage approach where technical inefficiency effects are explicitly expressed as a function of a vector of firm-specific variables and random error and enter as shifters in the distribution of the systematic error in the stochastic frontier model. A further issue of concern is the possibility that technical inefficiency is firm-related, implying that errors associated with a model of the conditional mean of the frontier could be heteroskedastic.

In this paper, we implement the one-stage estimation procedure of the stochastic frontier production model as proposed by Caudill et al. (see also Brümmer and Loy, 2000). For each of two discrete technologies, we suppose the following model:

(1) $y_{it} = f_t(x_{it}; b_t) + v_{it} - u_{it}, \quad i = 1,2,\ldots, N \text{ and } t = 1,2.$

where $v_{it} \sim i.i.d.\ (0, s^2_{vt})$ independent of the u_{it}, $u_{it} = 0$ and $u_{it} \sim N(0, s^2_{u_{it}})^+$ and

(2) $s_{u_{it}} = exp(z_{it} d_t)$

where y_{it} is the output for the i–th firm using the t-th technology; x_{it} denotes a (k×1) vector of values of known function of inputs of the i-th firm at the t-th technology; b_t is a parameter vector; z_{it} denotes a (p×1) vector of firm-and technology specific variables hypothesized to shift the average technical inefficiency, and d is an (1×p) vector of parameters. Of particular interest is examination of empirical evidence concerning the following set of hypothesis and associated parameter restrictions.

H1: All farms face the same technology (i.e. $f_t(x_{it};b_t) = f(x_{it};b_t)$):

(3) $b_t = b, d_t = 0, d_t = d\ , ,s^2_{vt} = ,s^2_v, \ \forall t$

Based on this notation, we define technical efficiency for the i-th firm with technology t as:

(4) $TE_{it} = \exp(-u_{it})$

GM SOYBEANS AND TECHNICAL EFFICIENCY

As a case for study, we consider soybean production data for Pennsylvania collected for the year 1999 through an on-farm survey as part of the 1999 Agricultural Resource Management Survey implemented by the National Agricultural Statistics Service of U.S.D.A. The survey provides data that describe production practices, inputs, and outputs for soybeans including: acreage planted, the use of damage control inputs (pesticides and fertilizers), land use practices, environmental management practices, and the use of genetically modified seeds. This sample consists of n = 125 observations. The data set provides a variety of continuous, polychotomous, and binary indicators and measures of the production process, inputs, and output. Table 1 presents the list of variables included in our model of production, as well as descriptive statistics. Details on the model estimation are presented in the appendix.

Table 2 presents results of a set of independent specification tests. To examine the nature of differences between the two technologies, we examine differences in the estimated conditional mean as well as in our estimated parameterization of the error structure. In the first test, we examine evidence that supports simplification of the functional form to a Cobb-Douglas. Our data supports rejection of this hypothesis, implying that production elasticities vary over the surface of the production possibilities set. Next, we examine evidence that would support a common conditional mean across GM and non-GM subsamples. We test this pooling hypothesis using the translog production frontier model with a halfnormal systematic and normal random error, thus without the technology and firm specific effects in the error term. Results indicate the restriction of a common conditional mean across a pooled sample could not be rejected (see Test #2 in Table 2). This result suggests that a gain in the efficiency of estimates can be attained by restricting the parameterization of the conditional mean to a common form across the GM and non-GM subsamples. Conditional on a pooled model, we examine evidence of the structure of the technical inefficiency. First, in test #3 in Table 2, we find that the hypothesis that the stochastic error is symmetric and invariant across firms can be strongly rejected. Next, in test #4 in Table 2, we examine and reject the hypothesis that technical inefficiency does not vary across firms. Based on these specification tests, we choose to proceed with the translog parameterization of the production function allowing for an unrestricted conditional mean and error structure.

Estimates based on a pooled sample GM and non-GM data are reported in Table 3. In Table 3, we see that the first-order effects are statistically significant, except for potash use. Also, numerous second-order effects are statistically significant, which underlines the tested significance of the group of parameters for nitrogen and potash use. We further examine the shift of intercept due to the use of contour farming as it can proxy the terrain slope and thus the differences in production conditions. The negative parameter sign for contour farming suggests lesser production potential likely due to inferior production conditions on terrains where contour farming is necessary. Testing the frontier shift due to drastic technological changes by adopting GM technology was motivated, however, including the GM dummy variable in the production frontier did not prove to improve the model specification. GM technology thus does not significantly increase the maximum attainable yields.

However, as results with respect to the variance of the error structure of the model reported in the bottom portion of Table 3 show, GM technology is a statistically significant determinant of the asymmetric error. Recall the parameters in the error model indicate variation of the technical inefficiency with respect to particular characteristics of the firm. We find that use of GM seed is estimated to reduce technical inefficiency though this effect is statistically significant, the hypothesis of zero effect could be rejected at the 10% significance level. We conjecture that as 84 of the 88 GM technology users were using this technology for the first year, their management of the technology may not fully reflect intrinsic potential impacts on efficiency; still the feasibility of this technology seems already to play a role.

To quantify the magnitude of the effect, average technical efficiency scores in total and separately for the two technologies are reported in Table 4 and the distributions of estimated scores are graphically presented in Figures 2. On average, firms are achieving around 67 % of their production potential. The firms which adopted GM technology utilize slightly higher share, while non-GM seed users only 65 %. The difference between the producers is better demonstrated in Figure 1. Despite the fact that GM technology does not significantly shift the frontier, it is the firms using GM technology which determine the production potential.

Further results of the inefficiency effect model disclosed that tilling, chopping, moving to other discrete practices used to control pests in the field have in general a negative effect of technical inefficiency, thus positive effect on technical efficiency. However, the opposite is true for the GM technology. Tilling is a practice which decreases the performance of this technology. This finding is consistent with other above cited studies which found that performance of GM technologies is conditioned on the change of production practices, e.g. no-till planting.

Table 5 presents the partial production elasticities with respect to each input variable and also presents estimated scale elasticities. We present results for elasticities based on approximation around the geometric mean. The scale elasticity is computed as the sum of the partial output elasticity with respect to each input. In the mean of the sample, the estimated partial output elasticity is non-negative with respect to each input, but significant only for land and standardized seed rate. For the group of fertilizer users, the partial production elasticity with respect to potash and nitrogen are negative. This is consistent with a violation of monotonicity as is expected for this type of input at particular ranges of use. The results are consistent with the interpretation that firms in the sample are on average within a range where further increase in potash and nitrogen would reduce output. The mean of estimated scale elasticities are very close to one, consistent with constant returns-to-scale.

POLICY IMPLICATIONS & CONCLUSIONS

Results presented a case to illustrate that in addition to a shift in the conditional mean of output, or yield, a change in technology may result in a change in technical efficiency. In this case, GM technology is found to reduce technical inefficiency. Given that many of the inputs involved in soybean production contribute to negative environmental impacts, these results suggest one aspect of the environmental impacts of GM technologies may follow from the indirect effect associated with a change in technical efficiency.

The implications of a shift to GM technology for technical efficiency have been considered from a number of perspectives. Results presented here suggest that technical efficiency may play a role in providing an incentive for adoption of GM technologies. While it is often the case that new technologies offer a strong incentive for adoption through increased productivity and private net benefit flow, it is also the case that the advantages offered by some new technologies are primarily reduction in inefficiency. Further, it is most often that new technologies involve a change in complexity of operations that requires management to invest in learning, new equipment, or new materials use. In this paper, we consider an example of such a technology. While data limitations restricted our ability to consider the full range of differences across GM and conventional technology, our results provide new insight into the role that technical efficiency can play in producer adoption of new technologies. Further, results suggest that the implications of such a change in technical efficiency may extend to include environmental and other public effects.

REFERENCES

Aigner, D. J., Lovell, C. A. K. and Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models, Journal of Econometrics, 6, pp. 21-37.

Ajibefun, I.A., G.E. Battese, and A.G. Daramola. "Investigation of Factors Influencing the Technical Efficiencies of Smallholder Croppers in Nigeria." Centre for Efficiency and Productivity Analysis (CEPA) Working Papers, No. 10/96, Department of Econometrics, University of New England, Armidale, 1996.

Alexander, C., J. Fernandez-Cornejo, and R.E. Goodhue (2002),"Determinants of GMO use: a survey of Iowa maize-soybean farmers' acreage allocation", Market Development for Genetically Modified Foods edited by Santaniello, V., R.E. Evenson, and D. Zilberman, CABI publishing, New York, NY.

Battese, G. E., and Coelli, T. J. (1992) Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India, Journal of Productivity Analysis 3:1/2 (June), pp. 153-69.

Battese, G. and Coelli, T. (1995). "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function and Panel Data", Empirical Economics, Vol. 20, 325-332.

Benbrook, C.M. (2001),"Do GM crops mean less pesticide use?", Pesticide Outlook, pp.204-207.

Bresnahan, T. and Trajtenberg, M. (1995). "General Purpose Technologies: Engines of Growth?", Journal of Econometrics, Vol.65, 83-108.

Brümmer, B. and J.-P. Loy (2000). The Technical Efficieny Impact of Farm Credit Programs: A Case Study of Northern Germany. Journal of Agricultural Economics 51 (3): 405–418 (September).

Bullock, D. S., and Nitsi., E. I. Roundup Ready soybean technology and farm production costs: measuring the incentive to adopt. American Behavioral Scientist 44(April 2001), 1283-1301.

Cameron, L.A. (1999),"The importance of learning in the adoption of high-yielding variety seeds", American Journal of Agricultural Economics 81, pp.83-94.

Carpenter J. & Gianessi L. (1999). Herbicide tolerant soybeans: Why growers are adopting Roundup Ready varieties. AgBioForum, 2(2), 65-72. Available on the World Wide Web: http://www.agbioforum.org

Caudill, S.B., J.M. Ford, and D. M. Gropper (1995). Frontier Estimation and Firm-Specific Inefficieny Measures in the Presence of Heteroskedasticity. Journal of Business and Economic Statistics 13 (1): 105–111.

Clark, E.A. (1999),"Ten reasons why farmers should think twice before growing GE crops", Plant Agriculture, University of Guelph. accessed by http://www.plant.uoguelph.ca/faculty/eclark/10reasons.html.

Coelli, T., R. Sanzidur, and T. Colin. (2003) U Queensland; U Manchester; Imperial College London Journal-of-International-Development. 15(3): 321-33

Coelli, T. and George E. Battese. "Identification of Factors Which Influence the Technical Inefficiency of Indian Farmers." Australian Journal of Agricultural Economics 40(2) (1996): 103-128.

Conservation Tillage Information Center. (1999). Conservation tillage survey data. Retrieved June 4, 1999 from the World Wide Web: http://www.ctic.purdue.edu/Core4/ConsTillage.html.

Desli, E., S. Ray, S. Kumbhakar. "A Dynamic Stochastic Frontier Production Model with Time-Varying Efficiency" Working Paper 2003-15 September 2002

Dosi, Giovanni (1988). "Sources, Procedures, and Microeconomic Effects of Innovation", Journal of Economic Literature, September, Vol. XXVI, 1120-1171.

ERS (1999a) "Genetically engineered crops for pest management." Economic Research Service. U.S.D.A.

ERS (1999b) "Impacts of adopting genetically engineered crops for pest management." Economic Research Service. U.S.D.A.

Ervin, D., S. Batie, R. Welsh, C. Carpentier, J. Fern, N. Richman, and M. Schulz (2000). *Transgenic Crops" An Environmental Assessment.* Policy Studies Report. Wallace Center for Agricultural and Environmental Policy. Winrock International.

Fane, George. "Education and the Managerial Efficiency of Farmers." The Review of Economics and Statistics 57(4) (November 1975): 452-461.

Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans (2000),"Farm-level effects of adopting genetically engineered crops in the U.S.A.", Proceeding of NE-165 Conference, June 24-25, 1999, Washington DC, pp.57-74.

Fernandez-Cornejo and McBride (2000) "Adoption of Bioengineered Crops." AER-810. Economic Research Service. U.S.D.A.

Fine, C. and Freund, R. (1990). “Optimal Investment in Product-Flexible Manufacturing Capacity”, Management Science, April, Vol. 36(4), 449-466.

Kalirajan. K. P., M. B. Obwona; S. Zhao A Decomposition of Total Factor Productivity Growth: The Case of Chinese Agricultural Growth before and after Reforms *American Journal of Agricultural Economics* Vol. 78, No. 2 (May, 1996), pp. 331-338

Kapusta, G. and Krausz, R.F. (1993). Weed control and yield are equal in conventional, reduced-, and no-tillage soybean (Glycine max) after 11 years. Weed Technology, 7(2), 443-451.

Kodde, D.A. and Palm, F.C. (1986). Wald Criteria for Jointly Testing Equality and Inequality Restrictions. Econometrica 54: 1243-1248. test 3

Kong, X., R. E. Marks, G. H. Wan (1999) Technical Efficiency, Technological Cha nge and Total Factor Productivity Growth in Chinese State-Owned Enterprises in the Early 1990s

Kumar,Subodh and R. Robert Russell
Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence. The American Economic Review, Vol. 92, No. 3. (Jun., 2002), pp. 527-548.

Lansink, A., K. Pietola, and S. Bäckman (2002) Effciency and productivity of conventional and organic farms in Finland 1994–1997. Eur Rev Agric Econ 2002 29: 51-65.

Lehr, W. and Lichtenberg, F. (1998). “Computer Use and Productivity Growth in US Federal Government Agencies, 1987-92”, The Journal of Industrial Economics, Vol. XLVI (2), June, 257-279.

Meeusen, W., and van den Broeck, J. (1977). “Efficiency Estimation from Cobb-DouglasProduction Functions with Composed Error”, International Economic Review, Vol. 18 (2), 435-444.

Padgette, S.R., Re, D.B., Barry, G.F., Eichholtz, D.E., Delannay, X., Fuchs, R.L., Kishore, G.M. & Fraley, R.T. (1996). New weed control opportunities: Development of soybeans with a Roundup Ready gene. In S.O. Duke (Ed.), Herbicide-Resistant Crops (pp. 53-84). Boca Raton: CRC Press.

Pike, D.R., McGlamery, M.D., and Knake E.L. (1991). A case study of herbicide use. Weed Technology, 5(3), 639-646.

Rawlinson, J. and Martin, A. (1998, November 10). Weed management strategies in soybeans. Unpublished manuscript, University of Nebraska at Lincoln.

Reinhard, Stijn, C. A. Knox Lovell; Geert Thijssen. Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms. American Journal of Agricultural Economics Vol. 81, No. 1 (Feb., 1999), pp. 44-60

Sarris, A.H., T. Doucha, and E. Mathijs (1999). Agricultural restructuring in central and eastern Europe: implications for competitiveness and rural development Eur Rev Agric Econ 1999 26: 305-329.

Siegel, D. (1997). “The Impact of Computers on Manufacturing Productivity Growth: A Multiple-indicators Multiple-causes Approach”, Review of Economics and Statistics, Vol. 79, 68-78.

Siegel, D. and Griliches, Z. (1992). “Purchased Services, Outsourcing, Computers, and Productivity in Manufacturing”, in Z. Griliches ed., Output Measurement in the Service Sectors, Chicago: Chicago University Press, 429-458.

Stefanou, S. and T. Ueda (2002) "From Whom Do Farmers Learn? An Analysis of Technical Efficiency Determinants for the Indian Green Revolution" presented at Asia Conference on Efficiency and Productivity Growth. July 19-20, 2002 Academic Activity Center, Academia Sinica http://www.sinica.edu.tw/~teps/A3-2.pdf

Wang, H.-J. and P. Schmidt (2002). One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels. Journal of Productivity Analysis 18: 129-144.

Wheelock, D.C. and Paul W. Wilson. (1999) Technical Progress, Inefficiency, and Productivity Change in U.S. Banking, 1984-1993 Journal of Money, Credit and Banking Vol. 31, 2 :212-234

Table 1: Variable Definitions

Variable	Description	Variable type	Unit
Production Frontier			
Y	Yield	Continuous	bushels per field
x_1	Natural logarithm of land	Continuous	acres
x_2	Natural logarithm of stand. seed rate	Continuous	lbs per field
r_1	Potash use	Dummy	YES = 1, NO = 0
r_2	Nitrogen use	Dummy	YES = 1, NO = 0
z_1	Natural logarithm of total potash use	Continuous	pounds per field
z_2	Natural logarithm of total nitrogen use	Continuous	pounds per field
p_1	Use contour farming	Dummy	YES = 1, NO = 0
Technical Inefficiency Effect			
s_1	Type of seed variety	Dummy	GM =1, NGM = 0
s_2	Use of tilling, chopping, mowing, etc. to control pest in the field	Dummy	YES = 1, NO = 0
s_3	Size of farm - gross value of sale	Dummy	Over $ 250,0001 = 1, otherwise 0
s_5	Livestock production - largest category of gross income from livestock prod.	Dummy	livestock = 1, crop = 0
s_6	Specialization - largest category of gross income from grain and oilseeds prod.	Dummy	Grain and oilseeds = 1, otherwise 0

Table 2: Results of Hypotheses Testing

Hypothesis tested	Null hypothesis	χ^2-statistic	$\chi^2_{0.95}$ (df)
#1 Simplification of functional form to Cobb-Douglas	$a_{mj} = b_{nk} = w_{mn} = 0$ $m = j = 1,2$ and $n = k = 1,2.$	44.595	18.307 (10)
#2 Common conditional mean for translog functional form with halfnormal systematic and normal random error	$a_m^{GM} = a_m^{NGM}$; $b_0^{GM} = b_0^{NGM}$; $q^{GM} = q^{NGM}$	16.020	28.869 (18)
#3 Inefficiency does not vary across firms	$d_1 = \ldots = d_6 = 0$	12.663	12.592 (6)
#4 Asymmetric stochastic inefficiency does not exist	$g = d_0 = \ldots = d_6 = 0$	38.092	16.274 (9)[a)]

*, **, and *** indicate the significance of the effect at the 10%, 5% and 1% significance level, respectively.

[a)] This statistic has a mixed χ^2 distribution. This test involves one inequality restriction on γ and seven equality restrictions on $d_0 = d_1 \ldots = d_6 = 0$. The upper bounds for the mixed χ^2 distribution are employed from Table I in Kodde and Palm (1986, p. 1246).

Table 3. Estimates of Translog Production Frontier Function

Yield per acre			Estimate	Std Error	p-prob
Production Frontier					Prob zero
	Intercept	b_0	0.342	0.070	0.000
Land	x_1	a_1	0.729	0.093	0.000
Seeding rate	x_2	a_2	0.320	0.112	0.005
Potash use	r_1z_1	b_1	0.007	0.048	0.886
Nitrogen use	r_2z_2	b_2	0.031	0.101	0.761
Land	x_1^2	a_{11}	0.328	0.106	0.003
Seeding rate	x_2^2	a_{22}	0.573	0.149	0.000
Potash use	$r_1z_1^2$	b_{11}	0.004	0.029	0.897
Nitrogen use	$r_2z_2^2$	b_{22}	0.011	0.075	0.880
	x_1x_2	a_{12}	-0.605	0.139	0.000
	$x_1 * r_1z_1$	g_{11}	-0.004	0.081	0.965
	$x_1 * r_2z_2$	g_{12}	0.294	0.090	0.001
	$x_2 * r_1z_1$	g_{21}	0.000	0.038	0.990
	$x_2 * r_2z_2$	g_{23}	-0.096	0.053	0.073
	$r_1z_1 * r_2z_2$	b_{12}	-0.167	0.060	0.007
Contour farming?	p_1	q_1	-0.103	0.058	0.080
Sym error	log s_v		-2.466	0.438	0.000
Technical Inefficiency Effect					
log σ_u (mean asym error)	*1*	d_0	0.114	0.193	0.554
GM seed	s_1	d_1	-0.327	0.198	0.101
Tillage	s_2	d_2	-0.432	0.296	0.148
GM x Tillage	s_1 s_2	d_3	0.759	0.350	0.032
Scale binary (neg ➔ more eff)	s_3	d_4	-0.395	0.232	0.091
Specialized livestock (neg➔ more eff)	s_5	d_5	-0.572	0.214	0.009
Specialized grain & oilseeds	s_6	d_6	-0.360	0.218	0.101
	$g = s_u^2/s_s^2$		0.981		
	Var(u)/ Var(total)		0.945		
Log (likelihood)			**-34.685**		

Table 4: Average Technical Efficiency (TE) for Firm Groups

	Total	GM	Non-GM
Average TE	0.667	0.673	0.650

Table 5: Mean Production and Scale Elasticities

	Approximation to mean	
	Mean elasticity	Stand. dev.
Land	0.729	0.093
Standardized seed rate	0.320	0.112
Total potash use	0.007	0.048
- For users of potash	-0.069	0.071
Total nitrogen use	0.031	0.101
- For users of nitrogen	-0.253	0.112
Scale	1.087	0.071

Figure 1. Technical Change and Technical Inefficiency

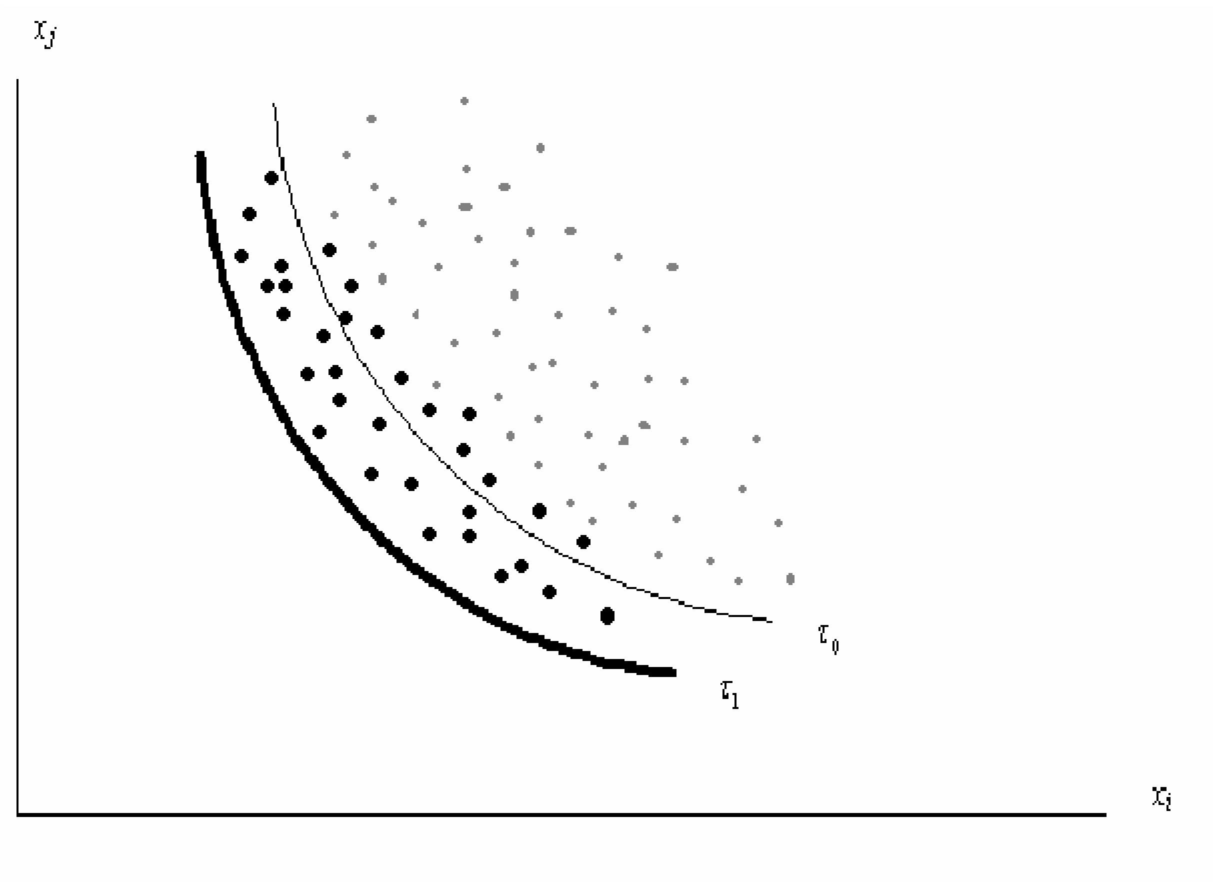
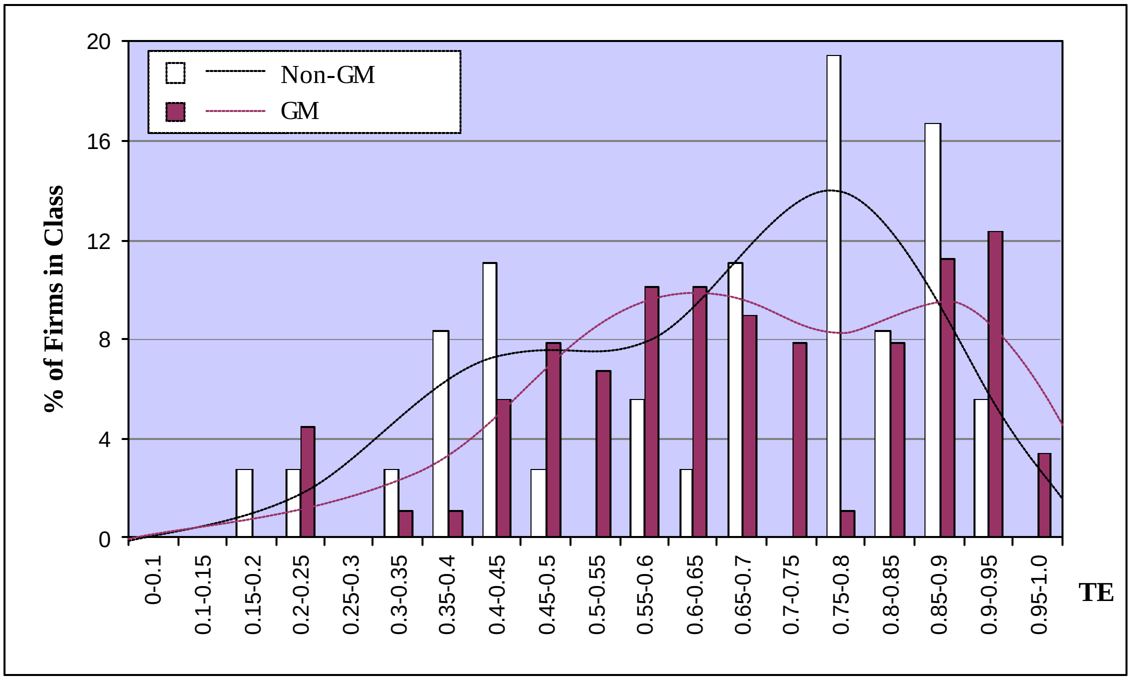


Figure 2. Sample Distribution of Estimated Technical Efficiency Scores (best fit kernel)



APPENDIX

Application

We specify the production function in Equation (1) in translog form as follows:

(5) $$\ln Y_i = b_0 + \sum_m a_m x_{mi} + \sum_n b_n (r_{ni} z_{ni}) + \frac{1}{2}\sum_m \sum_j a_{mj} x_{mi} x_{ji} + \frac{1}{2}\sum_n \sum_k b_{nk} (r_{ni} z_{ni})(r_{ki} z_{ki}) + \\ + \frac{1}{2}\sum_m \sum_n w_{mn} x_{mi} (r_{ni} z_{ni}) + q_1 p_{1i} + v_i - u_i$$

where the distributions of v_i and u_i are defined above in Equation (2), the subscript t is suppressed, and the heteroskedastic asymmetric error variance is written:

(6) $$s_{u_i} = d_0 + \sum_t d_t s_{ti}$$

where s_i are variables which may influence the efficiency of a firm. The likelihood function for this model is (subscripts for the technology t are suppressed on the parameters):

(7) $$L^*(p\,; y) = -(1/2)\sum_{i=1}^{n} T_i \{\ln 2p + \ln s_{it}^{2}\} - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left\{(y_{it} - x_{it} b)^2 / s_{it}^{2}\right\} - \sum_{i=1}^{N}\sum_{t=1}^{T_i}\{\ln \Phi(-d_{it})\}$$

where $T = 2$ and

$$d_{it} = {}^{l_i}\!/_{s_i}\left(y_{it} - x_{it} b\right)$$

$$l_{it} = \frac{s_{u_{it}}}{s_v}$$

$$s_{it} = \left[s_v^{2} + s_{u_{it}}^{2}\right]^{\frac{1}{2}}$$

$$l = \left(a', b', w', q', d', s_v, s_{u_i}\right)'$$

We proceed by estimating the parameters of the frontier production function and the inefficiency model by maximization of this likelihood function. Based on the parameter estimates, we first examine restrictions on the model, before individual farm technical efficiencies are computed and reported. In order to examine the specification, we consider functional form, existence of a stochastic, asymmetric error interpretable as technical inefficiency, existence of a common frontier across firms, and the effect of GM technology on the conditional mean of technical inefficiency.