

Firm Efficiency and Information Technology Use: Evidence from U.S. Cash Grain Farms

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We implement stochastic frontier analysis techniques to show the effects of information technology use on firm efficiency. Results from a sample of 1,865 U.S. cash grain farms reveals that information technology use within the farm business moved farms significantly towards the efficiency frontier. Also moving farms towards the efficiency frontier were the use of written long-term plans, advanced input acquisition strategies, and increased farm labor hours relative to total labor hours. In contrast, an increase in the debt to asset ratio was associated with movements away from the efficiency frontier.

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The invention, innovation, and diffusion of communication and information technology (CIT) and the commercial opportunities of the Internet attracted considerable attention of investors and the popular press in the latter half of the 1990's. Many attribute this level of attention to overly-optimistic expectations about what the technology has delivered or could deliver in terms of improved productivity and increased efficiency. A USDA survey reports that, in 2000, 24 percent of farmers used the Internet as part of their farm business, and online transactions (purchases and sales) totaled \$665 million. Put in perspective, relative to the general economy, the Internet has penetrated farms at a comparable rate, but online transactions in agriculture are lagging (Hopkins and Morehart, 2001).

While aggregate analysis above can be used as evidence of how “big” CIT is for the agricultural economy, it does not address its “importance” to firms or its marginal contribution to efficiency, nor which type of firms are benefitting. For example, innovation in CIT is relatively rapid, and often requires a high degree of learning and adaptation on the part of users. The effects, therefore, may be observable in how the firm is managed before it is observed in the profits or the productivity of the sector. A study by Paul David (David, 1990) attests to the complexity of the cycle of adoption, innovation and diffusion of new technologies. David found that in the early 20th-Century productivity impacts generally trailed electricity adoption by decades, and draws an analogy to the current productivity paradox associated with computerization and information technology. Large technical systems are often slow to change in short time scales, and the changes that do occur are happening at the micro level before they can be observed at the macro level. Learning spillovers to the non-adopting population, subsequent innovations in management, and discrete asset replacement strategies all may delay adoption, innovation and diffusion of new technologies.

The outline of the paper follows. First, we discuss the scale of e-commerce in the general business economy using the most recent aggregate data and compare it to use within the agricultural economy. Second, we present a conceptual model of technical efficiency. Then, we describe our approach to measuring firm-level efficiency using data on economic measures of inputs and outputs along with several efficiency-related management practices with varying levels of adoption throughout the farm population. Finally, we relate our results to the overall question of the importance of CIT to the agricultural sector.

CIT in the U.S. Business Economy

CIT impact is often measured by the size of electronic business transactions. In the period from 1995 to 1999 when investment in CIT was at its greatest and the “hype” about potential benefits from the technology was at its highest, there were no aggregate data available on its relative size. Therefore, many people equated CIT impact from the financial market performance of firms most heavily involved in CIT. The use of this strategy was relatively short-lived, although arguably those most engaged in CIT “anti-hype” still practice the craft. In the past year, data have become available that do a better job of gauging the size of CIT and consequently assist in sorting out the “hype” and the “anti-hype”. Most of this data come from four separate surveys carried out by the U.S. Census Bureau in 1999 and 2000 (DOC, 2002) including the Annual Survey of Manufacturers; the Annual Trade Survey; the Service Annual Survey; and the Annual Retail Trade Survey. None of these surveys covers the agricultural production sector, although comparable aggregate data can be derived from the 2000 ARMS survey.

Table 1 shows the data collected as part of the e-stats initiative of the U.S. Census

Bureau. Although definitions of e-business vary between the different sectors as a result of survey conventions, at a very gross scale e-business grew 10 percent between 1999 and 2000 and at the end of 2000 made up about 7 percent of all economic activity measured by the survey. Significant variability exists within individual sectors, as the manufacturing sector appeared to be the most mature user of the technology (18 percent of all shipments) and service industry (1 percent of total revenue) and retail trade (1 percent of total sales) were the least mature, but fastest-growing, areas of electronic business. Merchant wholesale electronic sales were in between, as 8 percent of sales was online and sales were experiencing double-digit growth.

The high use of electronic business within the manufacturing sector is attributed to long-standing use of Electronic Data Interchange (EDI) technology. In particular, the transportation equipment group reported that 46 percent of total shipments resulted from electronic orders from customers in 2000. Among merchant wholesalers, 40 percent of drug orders were placed electronically, the highest rate within the merchant wholesale group. Among service industries the travel arrangement and reservation services group reported 23.5 percent of total revenue was the result of electronic contact with customers. In the retail sector, nonstore retailers (in particular electronic shopping and mail-order houses) had the highest rates of use of electronic purchases, at 19.8 percent of total sales. In fact, firms listed as electronic shopping mail-order houses were responsible for about three quarters of total e-commerce sales of the sector.

Use of electronic commerce in agriculture is smaller compared to the general economy in both absolute and relative terms. Electronic purchases and sales by farms in 2000 totalled \$665 million, or about 0.3 percent of all purchases and sales by farms. Online purchases totaled \$378 million, covering machinery and equipment, farm supplies, crop inputs, livestock inputs, and office and computer equipment. Purchases

of crop and livestock input together were 35 percent of total online purchases, and each was smaller than machinery and equipment purchases and general farm supply purchases. Online sales by farmers totaled \$287 million - \$191 million in livestock sales and \$96 million in crop sales.

Although using CIT for completing transactions online is relatively rare, many farms use the Internet within their business for a number of different reasons, including price tracking (82 percent), using agricultural information services (56 percent), accessing information from USDA (33 percent), communicating with other farmers (31 percent) and crop advisors (28 percent), and maintaining and transmitting records and data online record keeping and data transmission (31 percent). Although many other farm households may use the Internet for personal rather than business use, the ARMS data do not encompass these activities.

Technical Efficiency Model

While aggregate statistics can reflect the size of e-commerce they reveal little about either how big it might become or how important the technology currently is. In this study, we address the issue of how important adoption of CIT is to the agricultural economy, by looking at the impact of CIT adoption on firm-level efficiency. The potential of CIT is made explicit in the concept of information and knowledge and efficient allocation. Desires, resources, and technology are dispersed in the population; therefore coordination of economic activity is the only way to achieve economic efficiency. Hayek (1946) pointed out the relevance of information to traditional views of physically-based constraints on good and service production. Our treatment of firm-level efficiency provides a view that largely avoids the conflicting voices of “hype” and “anti-hype” related to CIT today.

The measurement of firm level technical efficiency has become commonplace with the development of frontier production functions. There are several extensive reviews of empirical applications in agricultural economics (Battese, 1992); (Bravo-Ureta and Pinheiro, 1993) and (Coelli, 1995). Approaches used have been deterministic, where all deviations from the frontier are attributed to inefficiency, or stochastic, which is a considerable improvement, since it is possible to discriminate between random errors and differences in inefficiency. This distinction is particularly important when comparing the farm efficiency given weather, pest, and related production uncertainties.

Another important consideration in frontier analysis is the ability to investigate the sources of inefficiency. In order to avoid the contradiction implicit in the two-stage approach to determining technical efficiency (see (Reifschneider and Stevenson, 1991) and (Khumbakhar et al., 1991)), we apply the stochastic frontier model, of the type independently proposed by (Aigner et al., 1977) and (Meeusen and Van den Broeck, 1977), extended to simultaneously include characteristics of the firm that explain the inefficiency, following the work of (Battese and Coelli., 1995). The general form of the model is expressed as:

$$(1) \quad Y_i = x_i\beta + (V_i - U_i) \quad , i = 1, \dots, N,$$

where Y_i is the production of the i^{th} firm; x_i is a vector of input quantities of the i^{th} firm; β is a vector of unknown parameters; the V_i are random variables which are assumed to be *iid.* $N(0, \sigma_v^2)$, and independent of the U_i , which are non-negative random variables that account for technical inefficiency in production and are often assumed to be *iid.* $|N(0, \sigma_u^2)|$.

In the second part of the model, the inefficiency term, U_i , which represents factors under the control of the farmer, is made an explicit function of k explanatory vari-

ables, z_k . The U_i are independently (but not identically) distributed as non-negative truncations of the normal distribution of the form:

$$(2) \quad U_i \sim N[\gamma_0 + \sum_k^M \gamma_k z_{k,i}, \sigma^2].$$

The maximum-likelihood estimates for the parameters of the stochastic frontier model, defined by equations (1) and (2) can be estimated by using a computer program “FRONTIER 4.1” written by Coelli (1996).

Data and Estimation Approach

Farm business financial data come from the USDA’s Agricultural Resource Management Survey (ARMS), which is administered and maintained by the National Agricultural Statistics Service and the Economic Research Service (Economic Research Service, 2002). In addition to financial information, the ARMS survey collects structural characteristics and operator attributes from a sample of more than 10,000 farms stratified into 13 sales classes for each of the 48 contiguous states. The ARMS survey is also multi-phase, requiring the use of a complex weighting strategy in order to aggregate at the state, regional, or national level. Responses in ARMS are expanded according to the probability of being selected, so that each response represents the surveyed farm and other businesses that are like it.

The data used in this study were restricted to cash grain farms. These farms are defined as having 50 percent or more of their total value of farm production from cash grain commodities such as corn, wheat, oats, rice, soybeans, and others. The analysis was limited to this relatively homogeneous subset of the ARMS in order to preserve the conceptual basis of the frontier application. The most recent ARMS covers the

2000 calendar year with a sample size of 1,865 grain farms¹.

An important element of efficiency analysis is the definition of output and inputs. Specification bias in farm-level frontier analysis can occur as a result of the choice of which variable to include and exclude from the specification, the level of aggregation for each variable, and the amount of structure imposed on the input-output relationship. Most farms produce more than one output, even when specializing in the production of a particular commodity. One way to accommodate for this is to use monetary output measures such as gross receipts, value added, or total value of output. When such monetary output measures are used, the interpretation of efficiency scores reflect a mixture of both technical and allocative efficiency.

In this study, output is the total value of farm production. Output is measured as quantity produced times state average price for major crops. Where acreage and production are not reported (such as vegetables, fruit, nursery products and livestock) gross receipts are used. Output is defined so as to include the value of production under contract for livestock commodities and crops.

Input heterogeneity is another potential source of specification bias. This effect can be minimized by using monetary input measures for production inputs, including economic information on fixed and variable capital. This approach, however, does change the interpretation of inefficiency by producing scores that reflect production efficiency (both price and quantity effects) rather than technical efficiency (quantity effects only). There were five major input groups defined as crop-related input costs, labor costs, capital costs, other variable expenses, and fixed costs. Crop-related input costs were the annual expenses for purchases of seed and fertilizer. Labor costs represent the expenses for hired labor plus the value of unpaid family and operator labor. Capital costs were expenses for repairs and maintenance of capital items and

¹Although the sample is capable of being expanded to represent the entire population, for our purposes of estimating the efficiency frontier we treat each observation equally.

depreciation. Other variable expenses includes the amount spent during the year for items such as electricity, utilities, fuel, feed custom work, and farm supplies. Fixed expenses is the amount paid for interest, leases, insurance, and taxes. In order to explicitly account for the effects of farm size all variables were divided by total acres operated. Sample means for the variable used in the frontier model are presented in table 2.

A flexible functional form, the translog production frontier, was empirically estimated assuming a truncated normal distribution.

$$\begin{aligned}
& \beta_0 + \beta_1 \ln(EVCROP_i) + \\
& \beta_2 \ln(LABOR_i) + \beta_3 \ln(CAPCST_i) + \\
& \beta_4 \ln(OTHERV_i) + \beta_5 \ln(EFTOT_i) + \\
& \beta_6 \ln(EVCROP_i)^2 + \beta_7 \ln(LABOR_i)^2 + \\
& \beta_8 \ln(CAPCST_i)^2 + \beta_9 \ln(OTHERV_i)^2 + \\
\ln(VPRODTOT_i) = & \beta_{10} (\ln(EFTOT_i))^2 + \beta_{11} \ln(EVCROP_i) \ln(LABOR_i) + \\
& \beta_{12} \ln(EVCROP_i) \ln(CAPCST_i) + \beta_{13} \ln(EVCROP_i) \ln(OTHERV_i) + \\
& \beta_{14} \ln(EVCROP_i) \ln(EFTOT_i) + \beta_{15} \ln(LABOR_i) \ln(CAPCST_i) + \\
& \beta_{16} \ln(LABOR_i) \ln(OTHERV_i) + \beta_{17} \ln(LABOR_i) \ln(EFTOT_i) + \\
& \beta_{18} \ln(CAPCST_i) \ln(OTHERV_i) + \beta_{19} \ln(CAPCST_i) \ln(EFTOT_i) + \\
& \beta_{20} \ln(OTHERV_i) \ln(EFTOT_i) + (V_i - U_i)
\end{aligned}
\tag{3}$$

The following variables are used in explaining technical inefficiency differences across farms:

Z_1 is a dummy variable for internet use

Z_2 is a dummy variable for a written long-term strategic business plan

Z_3 is a dummy variable for the use of input acquisition management strategies, defined so as to include forward purchasing, using a service to source and purchase inputs, or negotiating price discounts either alone or within a group.

Z_4 is the proportion of total operator labor hours spent on farming

Z_5 is the debt-to-asset ratio

The three dummy variable represent managerial actions that may contribute to production efficiency. Each is expected to be negatively related with inefficiency. The variable measuring the amount of labor commitment by the operator should capture the tradeoff between farm and off-farm employment and is expected to be negatively related with inefficiency. The ratio of debt to assets is commonly used to represent financial constraints on production efficiency and is expected to be positively related with inefficiency.

Results

Hypothesis tests can be performed using log-likelihood ratio tests to identify the appropriate functional form and to determine the extent of inefficiency. The generalized log-likelihood statistic for testing the hypothesis that the Cobb-Douglas functional form is preferred was 450.24, which exceeded critical values of the chi-square test statistic with 15 degrees of freedom at the lowest probability levels for Type I error. The generalized log-likelihood statistic for testing the hypothesis that there were no inefficiency effects was 188.76. This far exceeded the critical value for the mixed chi-square distribution. Therefore we do not accept the null hypothesis that there were no inefficiency effects in the translog stochastic production frontier production function for our sample of cash grain farms. This result is further supported by the parameter γ , which must lie between zero and one. A value of γ of zero indicates

that the deviations from the frontier are due entirely to noise, while a value of one would indicate that all deviations are due to technical inefficiency. This specification allows us to test the null hypothesis that there are no technical inefficiency effects in the model, $H0 : \gamma = 0$, versus the alternative hypothesis $H1 : \gamma > 0$. Given the significance of the estimate for γ the null hypothesis is rejected. Further, the size of γ suggests that inefficiencies in production are the primary source of random errors.

The signs of the coefficients on the production frontier are as expected, with cropping inputs reflecting the most elastic output response, followed by labor and other variable expenditures. Elasticity of output with respect to capital and fixed costs were not significantly different from zero. Since our primary objective is to measure firm-level CIT economic impacts, we focus the rest of our discussion of model results on the interpretation of the variables within the inefficiency component of the model.

The coefficient on the Internet use variable was negative, meaning that Internet use decreased firm inefficiency relative to those that did not use the Internet as part of the farm business. This effect was as expected, because one would assume that firms using the Internet as part of their business are doing so because it will be able to assist them in managing their farm operation. This finding also lends some support to the argument from economic theory that better knowledge of markets and prices allows greater coordination of firm decisions to conditions within the overall market equilibrium. To date, the most common use of the Internet within the farm business was for information-gathering activities, rather than the much-discussed electronic purchases and sales.

Written long-term planning of economic strategies is also found to be an important way to decrease inefficiency for farms. A long term business plan involves the development of a set of goals or objectives for the farm that indicate where the farm will be, what it will look like and how it will operate at a future point in time. Typically

the plan includes decisions on what to produce, how to produce it, the scale and methods of operation, marketing channels and linkages, financial and organizational structure. Although used by only 7 percent of the cash grain farms, a long-term plan can be an important manifestation of farmer desire to succeed.

Group buying behavior is a common way to create economies of scale in purchases. Common practices include specific functions for the farm such as purchasing feed or breeding livestock, buying inputs, providing transportation, or marketing functions. Examples would be starting a cooperative or a limited liability corporation. In the model, we found that the use of an input acquisition practice that involved either formal activity (such as starting a limited liability corporation) or informal pooling of purchases through an already-existing cooperative significantly decreased inefficiency among firms.

The ratio of farm hours to total hours is an indicator of farm operator labor hour specialization in the farm sector relative to the nonfarm sector. In the model, specialization within the farm sector decreased inefficiency. This result was expected, given the time-sensitive nature of many production activities. Foremost among these include the sensitivity of crop yield to soil preparation and planting within an optimal time window, but other soil and crop management tasks are also very time-sensitive. While nonfarm employment is not incompatible with efficient production, increased availability of management and labor time for the operator appears to be an important way to decrease inefficiency. Care should be taken to maintain this finding at the level of the allocation of farm operator labor and relative to the productivity of the firm, rather than the level of well-being of the household and the presence of spouse or other family sources of labor off the farm. In many cases, off-farm income is an important determinant of household well-being, although this may be at odds with efficient production at times. Although beyond the scope of this paper, further investigation

would require an analysis of the farm household's production efficiency.

There have been several hypotheses put forth to explain the influence of financial exposure as measured by the debt/asset ratio on financial efficiency. The notion of embodied capital (Chavas and Aliber, 1993), credit evaluation (Nasr et al., 1998), and free cash flow (Nasr et al., 1998) all imply a positive relationship between financial exposure and technical efficiency. Our results conform with the agency cost hypothesis (Nasr et al., 1998) to explain the negative relationship between financial exposure and our broader measure of production efficiency. Monitoring of borrowers by lenders involves transaction costs, that lenders typically pass on to the borrower. Farms that are more highly leveraged are expected to be relatively high cost operations, therefore reducing efficiency. Although the mean debt to asset ratio was 0.19, which is generally considered to be a comfortable amount of debt for a firm to carry, our finding shows that on average the borrowed funds are not providing a high level of return to producers, and the additional capital provided by borrowed funds is a drain on efficient production as valued by the market.

Conclusions

CIT use for cash grain farms was shown to be associated with reductions in inefficiency. The finding is potentially more useful than aggregate measures of adoption and volume of e-commerce transactions because it could be a leading indicator of efficiency impacts on individual firms within the sector. It is unlikely that these effects are unique to farm businesses. Other studies on firm-level efficiency and CIT use could show effects within other sectors. One comparable data source for non-farm businesses that addresses technology use is the 2000 Survey of Small Business Finance, carried out by the Federal Reserve Board.

CIT adoption is only one of several management strategies that can decrease inefficiency for firms. Long-term planning and coordinated strategies for purchasing of inputs are two other management activities that should decrease inefficiency, although both involve some degree of coordination and commitment. While the potential benefits from long-term planning and CIT adoption were similar, the improvement in efficiency from long-term planning was much larger. Labor specialization was shown to have positive efficiency effects for the farm businesses. This result highlights one of the tradeoffs that managers of cash-grain farms make between optimum business efficiency and maximizing household well-being.

We feel that our analysis indicates three areas where further study of CIT and firm performance could usefully address prominent questions of the agricultural sector. Firms, when CIT decreases inefficiency, does it do so across all farm types or primarily for the types who already have relatively easy access to information and knowledge about prices and markets? Or, does it decrease inefficiency among a group of farms that is currently information-constrained? The general purpose nature of the technology indicates that it may be the latter phenomenon rather than the former, but few technologies demonstrate such a lack of bias.

Second, if CIT is a general purpose technology, it should set into motion larger adjustments within the sector. These adjustments would be in response to the relaxation of constraints that lock in existing patterns of production. One of the most-discussed benefits of CIT, and the Internet in particular, is how it reduces time and location constraints. The potential to affect that geography of agricultural production is one area where overall social benefits could be affected by CIT.

Third, because CIT is a rapidly-developing area, additional data on specific technological innovations will continue to be relevant. The latest data available today reflects the technology available 18 months ago or more. Although nearly all adopters in the

ARMS survey reported using the Internet to gather information, more widespread adoption of specific applications has been limited. As these further implementations of the mature technology occur, the resulting impacts on productivity are likely to change as well.

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Table 1: **Estimated Size of e-commerce in Business**

	2000		1999		% change		e- as % of total	
	Total	e-	Total	e-	Total	e-	2000	1999
Manufacturing (Shipments, \$bn)	4,218	777	4,032	730	5	0	18	18
Merchant Wholesale Trade (Sales,\$bn)	2,750	213	2,540	183	8	17	8	7
Service Industries (Revenue,\$bn)	4,663	37	4,273	25	9	48	1	1
Retail Trade (Sales,\$bn)	3,061	29	2,867	15	7	92	1	1

Table 2: **Variable Definitions and Sample Means**

Definition	Variable name	Mean
Vale of production	VPRODTOT	150.90
Crop-related inputs	EVCROP	56.30
Hired and unpaid labor	LABOR	45.21
Capital costs	CAPCST	39.93
Other variable expenses	OTHERV	40.11
Fixed costs	EFTOT	55.01
Internet Use	INETUSE	0.41
Written long-term plan	LTPLAN	0.07
Input acquisition practice	INPUT	0.84
Farm hours/total hours	FARMHRS	0.86
Debt/asset ratio	DARATIO	0.19

Table 3: **Stochastic Production Frontier Estimation Results**

Variable name	Coefficient	Standard Error	T- Ratio
CONSTANT	1.2826642	0.14794435	8.6699097
EVCROP	0.62129774	0.045623194	13.618024
LABOR	0.4297089	0.066345752	6.476811
CAPCST	0.059333634	0.030219263	1.9634375
OTHERV	0.22071118	0.061794692	3.5716851
EFTOT	0.022592322	0.05582997	0.40466298
EVCROP ²	0.051012158	0.004015413	12.704086
LABOR ²	-0.01496732	0.009460866	-1.5820245
CAPCST ²	0.001571223	0.001720161	0.91341583
OTHERV ²	0.019820068	0.007074125	2.8017697
EFTOT ²	0.031566891	0.005343151	5.9079167
EVCROP*LABOR	-0.04032786	0.011572759	-3.4847228
EVCROP*CAPCST	-0.0170878	0.007009135	-2.4379332
EVCROP*OTHERV	-0.06898776	0.010993873	-6.2751095
EVCROP*EFTOT	-0.03388954	0.010187472	-3.3265898
LABOR*CAPCST	-0.00235423	0.005622827	-0.4186918
LABOR*OTHERV	-0.01528545	0.012363291	-1.2363575
LABOR*EFTOT	-0.00479103	0.011866056	-0.40375912
CAPCST*OTHERV	0.001754637	0.005302688	0.3308957
CAPCST*EFTOT	0.004295569	0.006032228	0.71210324
OTHERV*EFTOT	0.008219325	0.010229163	0.80351883
CONSTANT	-5.18168	1.420231	-3.648477
INETUSE	-0.73985092	0.16259949	-4.5501431
LTPLAN	-5.3021136	0.23403648	-22.655073
INPUT	-0.75852502	0.19230969	-3.9442891
FARMHRS	-3.9383771	0.54786668	-7.1885684
DARATIO	2.1251081	0.35008011	6.070348
SIGMA ²	3.8096112	0.72552484	5.250835
GAMMA	0.98393246	0.003223558	305.2318
log likelihood function			-1008.68
LR test of the one-sided error			478.94