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Farm Efficiency and Productivity Growth: The Effect of Commodity Prices

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ABSTRACT

Crop prices can affect farm productivity through input-output decisions. This study assesses the relationship between crop prices and productivity changes among a sample of Kansas farms. The changes in total factor productivity are evaluated using a nonparametric approach with a Malmquist productivity index and potential drivers of technical efficiency and productivity change are analyzed. Farms with higher leverage and greater diversification are likely to be more efficient and experience productivity change. Lower productivity occurred during years with higher crop prices, suggesting that innovation is more likely to occur when margins are tight.

KEYWORDS

data envelopment analysis, efficiency change, Kansas, Malmquist index, prices, productivity change

INTRODUCTION

The agricultural sector has undergone notable changes. An increase in the demand for crops in the early 2000s for use in biofuel production was one reason for a significant increase in nominal crop and livestock prices (Babcock, 2012; Demirer et al., 2012; Dicks et al., 2009; Serra & Zilberman, 2013). According to Sumner (2009), prices of important agricultural commodities in 2008 saw the largest nominal price increases when compared to similar events over the past several decades. The need for the agricultural sector to meet an increasing demand for agricultural products, coupled with high crop prices, provided incentives for farmers to expand crop production. Some producers responded by increasing supply on the extensive margin by increasing the area planted (Brown et al., 2014). However, when land resources are scarce, supply growth must also come from productivity growth (Alston et al., 2009; Rajagopal et al., 2007). Given farmers' allocations of crop land, farmers can increase their production on the intensive margin by altering crop patterns and intensifying input use (Hausman et al., 2012).

An important policy implication is how market conditions and other external factors affect productivity growth in the agricultural sector. While farms respond to shocks in the market, little is known about its relationship to productivity change. The main objective of this study is to evaluate the changes in total factor productivity and its components (efficiency and technical change) for a sample of Kansas farms using an input-oriented nonparametric approach with a Malmquist productivity index, and to study potential factors associated with farm efficiency and productivity change. This study seeks to understand the relationship between the increase in commodity prices observed from 2008 to 2011 and changes in productivity. This period was characterized by significant increases in crop prices (Figure 1). We also evaluate how farmers' demographics and farm management characteristics are associated with changes in farm productivity. A secondary objective is to analyze the factors associated with technical efficiency, and whether farm efficiency is maintained over time or if farm performance changes from year to year (i.e., performance is year-specific). The results in this study will provide information on how farmers might adjust production due to changing commodity markets and about other potential farm-level factors associated with productivity change. This information could be used by extension and policy makers to identify farms lagging behind and to develop outreach programs aimed at addressing the factors limiting farms' growth.

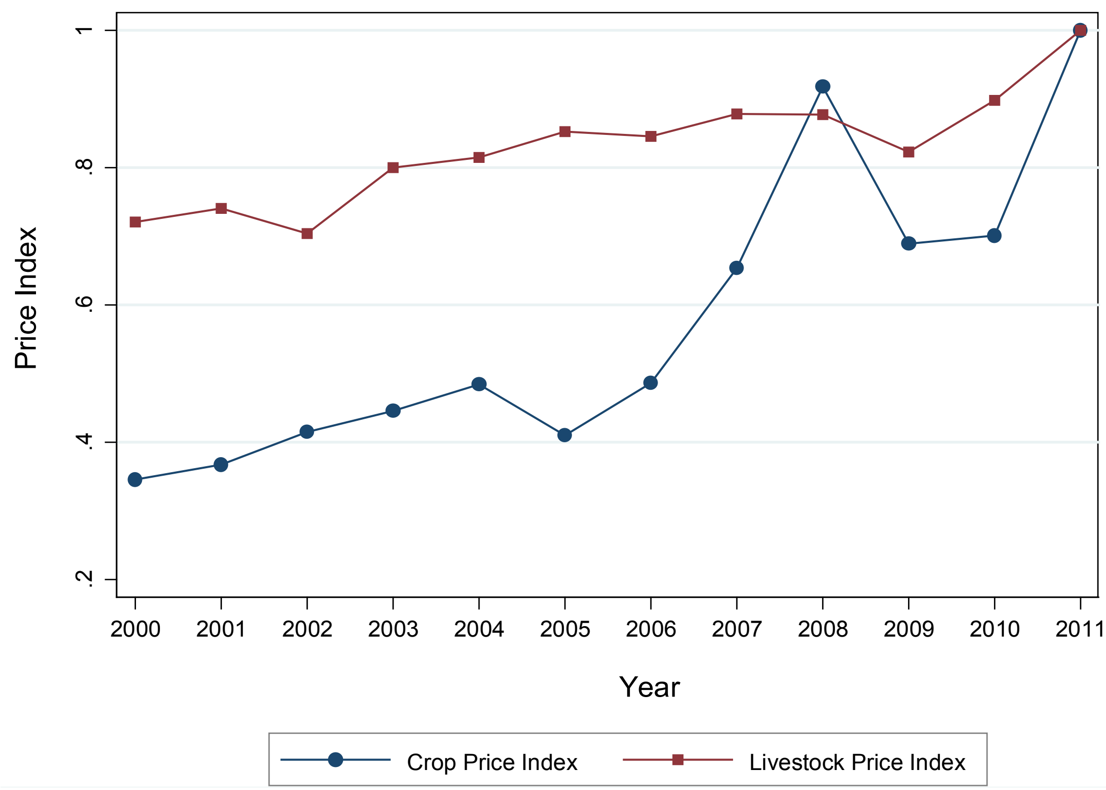

Figure 1. Crop and livestock index normalized by 2011 prices, 2000–2011.

LITERATURE REVIEW

Various studies have estimated productivity change for U.S. agriculture using state-level panel data for food and feed crops, fruits, vegetables, nuts, animal products, and other farm-related outputs from the U.S. Department of Agriculture Economic Research Service (USDA ERS) (O'Donnell, 2012; Tauer & Lordkipanidze, 2000; Wang et al., 2015). Some of these studies have found that productivity change is driven primarily by technical change (O'Donnell, 2012). Ball, Hallahan, and Nehring (2004) studied the convergence of productivity growth in U.S. agriculture and found evidence suggesting catching-up of states that were initially not efficient. Other studies conducted at the country and state level have focused on investigating the effect and importance of agricultural research and development on productivity growth (Alston et al., 2011; Jin & Huffman, 2016).

Other studies have estimated productivity change at the farm level and have examined the effect of exogenous factors on productivity change using different approaches. Yeager and Langemeier (2011) used regression analysis to study the effect of input ratios and income shares on Kansas farmers' factor productivity and its components. Hassanpour et al. (2011) used a pooled logit model to examine the impact of socioeconomic and biotechnical factors on the probability of productivity chance for trout farms in Iran. Odeck (2007) used both DEA and stochastic frontier analysis to estimate efficiency and productivity change in Norwegian grain production, using a tobit model to investigate the effect of farm size on productivity change. The effect of capital structure on the productivity growth of Dutch farms was examined by Zhengfei and Lansink (2006) using a Malmquist productivity index in a dynamic panel data model.

For the state of Kansas, productivity change has been evaluated by Yeager and Langemeier (2011), Mugera et al. (2012a), and Mugera et al. (2012b). Results of the study by Yeager and Langemeier (2011), using data for 135 farms from 1979 to 2008, suggested that farms did not catch up to the growth rate of the more efficient farms (i.e., evidence of divergence) during the period examined. Their findings also indicate that productivity grew for the first 20 years of the sample but decreased for the last 10 years. Mugera et al. (2012a) studied the convergence of productivity growth of labor for Kansas farms using data from 1993 to 2007. They found evidence of convergence in labor productivity, indicating that farms that were less efficient at the beginning of the sample period displayed rapid growth rates due to catch-up in efficiency. Another study by Mugera et al. (2012b) found declining efficiency change and increasing labor productivity driven mainly by technical change and factor intensity in a sample of Kansas farms.

The studies discussed above have examined total factor productivity, how productivity is affected by farm characteristics, and the convergence of productivity growth. These studies have consistently found heterogeneity in farm efficiency stemming from farmer and farm characteristics. For example, larger and more diversified farms have generally been associated with higher technical efficiency scores (Alvarez & Arias, 2004; Featherstone et al., 1997; Mugera & Langemeier, 2012). Productivity has also been found to have a gradual relationship with the age of the farm operator, where it increases and then decreases (Tauer & Lordkipanidze, 2000). Other factors, such as access to credit and agricultural subsidies, have also been found to affect productivity (Ciaian et al., 2012; Skevas & Lansink, 2014). Crop output prices also influence crop supply and could affect farm productivity through input-output decisions. While evidence in the literature suggests farmers alter land allocation and input use in response to price signals (Ciaian & Kancs, 2011; Haile et al., 2014; Liang et al., 2011; Lywood et al., 2009), understanding how this impacts farmers' productivity is also important. This study assesses the relationship between crop and livestock prices and changes in productivity for a sample of farms in Kansas. The association between other farmer and farm management characteristics and technical efficiency and productivity change is also explored.

METHODS AND DATA

The performance of farms can be analyzed using efficiency and productivity measures. In general, technical efficiency can be expressed as the ratio of aggregate outputs to aggregate inputs (Cooper et al., 2007). Efficiency can be measured using parametric techniques such as stochastic frontiers or nonparametric approaches such as data envelopment analysis (DEA). It is also possible to examine changes in productivity over time using a Malmquist productivity index that measures productivity changes of a farm between two adjacent periods. Malmquist productivity indexes have been widely used to study productivity in the agricultural sector. Both parametric (Atsbeha et al., 2012; Ferjani, 2011; Lissitsa & Odening, 2005; Vassdal & Holst, 2011) and nonparametric approaches (Ball et al., 2004; Mugera et al., 2012a, 2012b; Newman & Matthews, 2007; Tamini et al., 2012; Xiao et al., 2012; Yeager & Langemeier, 2011) have been used. DEA has been a widely used method to examine efficiency and productivity in agriculture and for public policy (Emrouznejad & Yang, 2018).

Technical Efficiency and Malmquist Productivity Index

This study analyzed the change in productivity of a set of i farms (i = 1,…, N) for a set of periods ($t = 1,\ldots,T$). Farm j has vectors of inputs and outputs denoted respectively by $(x_1^t,\ldots,x_K^t)$ and $(y_1^t,\ldots,y_M^t)$ where $x^t, y^t \in \boldsymbol{R}^+$. The production possibility set S^t containing the feasible set of inputs transformed into a set of outputs for each time period t is defined as $S^t = \{(x^t, y^t): x^t \ \textit{can produce}\ y^t\}$ (Shephard, 1970). The production possibility set expressed in terms of the input distance function is represented by $D_i^t(x_i^t, y_i^t) = \sup\{\theta:(x^t \mid \theta, y^t) \in S^t, \theta > 0\}$ (Shephard, 1970). In an input-oriented approach, the distance function represents the factor by which the input vector must be scaled down to be on the efficient frontier. If the input and output sets belong to the production possibility set $(x^t, y^t) \in S^t$, then $D_i^t(x^t, y^t) \le 1$, and $D_i^t(x^t, y^t) = 1$ if and only if (x^t, y^t) is on the frontier.

The Malmquist productivity index developed by Caves et al. (1982) is defined in terms of the distance function of two adjacent periods and can be represented as the geometric mean of the indexes between two periods as follows (Färe et al., 1992):

$$
\begin{aligned}
&MI(x^{t+1}, y^{t+1}, x^t, y^t) \\
&\quad = \left[\frac{D_i^t(x_i^{t+1}, y_i^{t+1})}{D_i^t(x_i^t, y_i^t)} \times \frac{D_i^{t+1}(x_i^{t+1}, y_i^{t+1})}{D_i^{t+1}(x_i^t, y_i^t)}\right]^{\frac{1}{2}}, \qquad (1) \\
&t = 1,\ldots,T-1
\end{aligned}
$$

where $D_i^t(x_i^{t+1}, y_i^{t+1})$ represents the distance function for time $t+1$ measured with respect to the frontier in time t and $D_i^{t+1}(x_i^t, y_i^t)$ represents the distance function for time t measured with respect to the frontier in time $t+1$. The Malmquist index measures the change in productivity between two time periods and can be decomposed into two primary components, efficiency change and technical change.

$$\text{Efficiency Change} = \frac{D_i^{t+1}\left(x_i^{t+1}, y_i^{t+1}\right)}{D_i^t(x_i^t, y_i^t)}, \quad t = 1, \ldots, T-1 \tag{2}$$

$$\text{Technical Change} = \left[\frac{D_i^t(x_i^t, y_i^t)}{D_i^{t+1}(x_i^t, y_i^t)} \times \frac{D_i^t\left(x_i^{t+1}, y_i^{t+1}\right)}{D_i^{t+1}\left(x_i^{t+1}, y_i^{t+1}\right)}\right]^{\frac{1}{2}}, \quad t = 1, \ldots, T-1 \tag{3}$$

The efficiency change is the ratio of the efficiencies in time $t+1$ and time t, and measures whether a farm is moving away from or closer to the efficient frontier (Equation 2). When the efficiency change index is greater than one, it indicates efficiency progress from period t to period $t+1$, while an index equal to one indicates stagnation, and an index less than one indicates movement away from the frontier. The second term corresponds to the technical change or frontier shift (Equation 3). A technical change value greater than one indicates progress in the technology used by the farm unit, while values equal to or less than one represent no change or technical regression, respectively.

The distance functions within the Malmquist index were estimated using DEA, a nonparametric approach (Färe et al., 1989). The advantage of this method is that it does not require a specification of the functional form of the distance function or the distribution of the errors. The estimation of the Malmquist index requires the estimation of four linear programming problems. Following evidence for farms in Kansas, we assume a constant returns to scale (CRS) technology. Guesmi et al. (2015) concluded that farms in Kansas, on average, operate under constant returns to scale, based on estimated input and output elasticities. The distance functions were computed using the following linear programs (Färe et al., 1989):

$$\begin{aligned} &[D_i^t(x_i^t, y_i^t)]^{-1} = \min_{\theta_i, z_1, \ldots, z_N} \theta_i \\ &\text{subject to: } \theta_i x_{n,i}^t \geq \sum_{i=1}^{N} z_i x_{n,i}^t \qquad n = 1, \ldots, K \\ &y_{m,i}^t \leq \sum_{i=1}^{N} z_i y_{m,i}^t \qquad m = 1, \ldots, M \\ &z_i \geq 0 \qquad i = 1, \ldots, N \end{aligned} \tag{4}$$

$$\begin{aligned} &\left[D_i^t(x_i^{t+1}, y_i^{t+1})\right]^{-1} = \min_{\theta_i, z_1, \ldots, z_N} \theta_i \\ &\text{subject to: } \theta_i x_{n,i}^{t+1} \geq \sum_{i=1}^{N} z_i x_{n,i}^t \qquad n = 1, \ldots, K \\ &y_{m,i}^{t+1} \leq \sum_{i=1}^{N} z_i y_{m,i}^t \qquad m = 1, \ldots, M \\ &z_i \geq 0 \qquad i = 1, \ldots, N \end{aligned} \tag{5}$$

where z_i is an input scaling factor. The distance function $D_i^{t+1}(x_i^{t+1}, y_i^{t+1})$ can be computed by replacing t with $t+1$ in the linear problem in Equation 4. The intertemporal distance function of time $t+1$ evaluated with respect to the technology frontier of time t can be computed by solving the linear program in Equation 5, while the distance function of time $t+1$ evaluated at the technology frontier of time t can be computed by replacing t for $t+1$ and $t+1$ for t in that same linear problem.

Second Stage Regressions

The technical efficiency and productivity change estimates were used in a second stage regression to study the relationship between exogenous factors and farm performance.

Farm Technical Efficiency

A dynamic probit model was used to estimate the relationship between farms' characteristics and their likelihood of lying on the efficient frontier. The model used controls for the dynamics of farmers' past history, that is, the effect that being efficient in one period exerts on the likelihood that a farm is subsequently able to be among the most efficient farms in future periods (state dependence). The effect of state dependence can be tested by including the lag of the dependent variable as a covariate. There are two issues that, if not addressed, could result in the overestimation of the effect of state dependence: the correlation of the unobserved individual effects over time and the endogeneity of the initial condition (the first observation in the dataset does not coincide with the start of the stochastic process). Wooldridge (2005) proposed a conditional maximum likelihood estimator for the dynamic random effects model that deals with the initial condition problem and unobserved heterogeneity. This formulation considers the distribution of the dependent variable conditional on the initial value of the dependent variable and exogenous variables. The latent dependent variable can be written as:

$$y_{it}^{*} = \gamma y_{i,t-1} + \boldsymbol{x}_{it}^{'}\boldsymbol{\beta} + \eta_t + \alpha_i + u_{it}; \quad i = 1, \ldots, N; \quad t = 2, \ldots, T \tag{6}$$

where i indexes farms ($i = 1, \ldots, N$) and t indexes time ($t = 1, \ldots, T$). The observed outcome y_{it}, is a binary response where farms that were efficient in a particular year were assigned a value of 1[1]; $\mathbf{x}_{\mathbf{it}}$ is vector of explanatory variables; η_t are year intercepts; α_i represent individual specific time invariant heterogeneity; and u_{it} is the error term such that $u_{it} \sim N(0, \sigma_u^2)$. Following Wooldridge's approach, the density for α_i can be specified as $\alpha_i \mid y_{i0}, \boldsymbol{x}_i \sim N(\delta_0 + \delta_1 y_{i0} + \boldsymbol{x}_i^{'}\boldsymbol{\delta}, \sigma_a^2)$, where $x_i = (x_{i1}, x_{i2}, \ldots, x_{i,T})$ contains a set of period specific indicators of the time-variant explanatory variables included to allow α_i and $\mathbf{x}_{\mathbf{it}}$ to correlate in all time periods. If α_i is $\alpha_i = \delta_0 + \delta_1 y_{i0} + \boldsymbol{x}_i^{'}\boldsymbol{\delta} + a_i$ with $a_i \mid (y_{i0}, \boldsymbol{x}_i) \sim N(0, \sigma_a^2)$, and considering the distribution of the dependent variable conditional on the initial value y_{i0} and $\mathbf{x}_{\mathbf{it}}$, the latent variable can be rewritten as

$$y_{it}^{*} = \gamma y_{i,t-1} + \boldsymbol{x}_{it}^{'}\boldsymbol{\beta} + \eta_t + \delta_0 + \delta_1 y_{i0} + \boldsymbol{x}_{it}^{'}\boldsymbol{\delta} + a_i + u_{it} \tag{7}$$

The resulting likelihood function is the same as the standard random effects probit model with the initial value of the dependent variable and yearly indicators of the time-variant variables used as covariates. Asymptotic standard errors are bootstrapped and average partial effects across the distribution of α_i were estimated following Wooldridge (2005).

Productivity Change

We examined the factors that affect farm productivity change in a dynamic panel data model. Due to the panel structure nature of the data arising from the estimation of productivity change over time, there may be dynamic effects that should be considered. In this study, the effect of previous productivity performance on current productive change was controlled for by including prior measures of productivity change from period $t-1$ and $t-2$. The specification of the estimated regression is as follows:

$$y_{it} = \gamma_1 y_{i,t-1} + \gamma_2 y_{i,t-2} + \boldsymbol{x}_{it}^{'}\boldsymbol{\beta} + a_i + u_{it} \tag{8}$$

where y_{it} is the farm's productivity change (MI); $\mathbf{x}_{it}$ is the vector of explanatory variables; a_i are time-invariant farm-specific effects such that $\alpha_i \sim IID(0, \sigma_\alpha^2)$; and u_{it} is an idiosyncratic error term such that $u_{it} \sim IID(0, \sigma_u^2)$.

A problem encountered when using the lagged dependent variable as an explanatory variable is the dynamic panel bias caused by the correlation between y_{it-1} and the individual effects in the error term. The Arellano and Bover (1995) and Blundell and Bond (1998) approach based on a system generalized method of moments (GMM) was used to correct for this potential bias. This approach deals with the dynamic panel data bias and allows for the inclusion of covariates that are potentially endogenous. In the system GMM, equations in differences that are instrumented with lagged values of the variables (as in Arellano & Bond, 1991) are combined with level equations instrumented with lagged differences of the variables. If an explanatory variable is thought to be endogenous, GMM-style instruments can be used. Following Zhengfei and Lansink (2006), both short-term and long-term debt to asset ratios were treated as endogenous in this study. Endogeneity arises because as farmers' productivity improves, their creditworthiness and ability to obtain loans also increases. A set of year dummy variables were included to control for time effects (Roodman, 2009). To avoid proliferation of instruments, only lags of two years were used as instruments for each time period. Asymptotic standard errors are bootstrapped.

Data

The data used in this study correspond to a balanced panel consisting of 331 Kansas farms for the period 2000–2011. The data were obtained from farmers enrolled in the Kansas Farm Management Association. Detailed information on the data can be found in Langemeier (2010).

Aggregate observation for two outputs (crops and livestock) and five inputs (crop inputs, livestock inputs, labor, fuel, and other inputs) were used for estimation of farms' technical efficiency and productivity change. Crop output comprises feed grain, hay, forage and small grains production. Livestock output corresponds to beef, dairy and swine. Labor input corresponds to the number of workers including hired and unpaid labor. The estimate for crop input is an aggregate of seed, fertilizer, herbicide, insecticide, crop marketing and storage, and crop insurance inputs used in production. The fuel input comprises fuel used for activities related to vehicles, machinery and equipment, and irrigation energy. Inputs corresponding to the livestock input include dairy inputs, feed, veterinarian services, marketing, and breeding. Aggregated into the other input category are mainly capital inputs.

Variables Used in Second Stage Regressions

Exogenous variables included in the regression analysis of technical efficiency and productivity change are crop income share of gross farm income, farm size measured in acres, land tenure measured as the percentage of rented land, short- and long-term debt to assets ratio, investment in crop machinery as a percentage of fixed assets, age of the farm operator, crop and livestock price indexes, and regional dummies. Descriptive statistics of the data across farms and years are presented in Table 1.

Age was used as a proxy measure for farmers' experience, and it is expected to positively affect productivity. However, if older farmers are more conservative regarding technological innovation decisions, age could also exert a negative effect. Farm size was measured as total acreage operated. Larger farms may have better access to resources (e.g., credit and technology) and can take advantage of technologies of scale. Previous studies have found evidence that larger farmers have better financial performance (Hoppe et al., 2010) and deviate less from production efficiency when evaluated in terms of profit maximization (Foster & Rausser, 1991). The share of crop income in total gross farm income was used as a proxy for farm diversification. While there are benefits associated with farm diversification (Chavas, 2008), gains from specialization could also exist.

The long-term debt to asset ratio was included to investigate the effect of financial leverage and is expected to have a positive effect on farms' efficiency and productivity growth if debt is used to finance investment in technological improvements and cover operational costs. A short-term debt to asset ratio is expected to negatively affect farm performance as short-term debt is costly, and if farmers experience low liquidity their ability to cover immediate operational needs can be limited (Lambert & Bayda, 2005). Investment in farm equipment is expected to have a positive effect. Regional dummies were included to control for unobserved factors like weather, soil characteristics, and managerial differences that result in heterogeneity in production. Eastern Kansas was used as the baseline region. Year dummies were included to capture productivity differences across years due to unobserved factors like year to year variations in weather (i.e., drought years).

Crop and livestock price indexes were included as additional covariates in the productivity change regression to study the association between changing commodity prices and productivity change. Crop and livestock output price indexes are the weighted average of the prices received by farmers for their crops and livestock normalized by 2011 prices. Crop and livestock prices in the sample have been increasing for the period examined, with the crop price index climbing steeply after 2006 (Figure 1). The livestock price index shows a steadier and smaller increase than crop prices during this same period. Although external factors may affect output prices, at the farm level prices are assumed to be exogenous as an individual farmer's output cannot affect prices. Under profit maximization, output prices affect input use decisions and ultimately the firm's output. If farmers' response to higher prices has resulted in improvements in their performance, a positive sign for these variables is expected. However, suboptimal production could also arise as incentives to boost production could drive farmers to apply inputs in excess of the optimal levels.

RESULTS

Farm Efficiency

Summary statistics of the results of technical efficiency, Malmquist productivity index, and efficiency and technical change averaged across farms

Table 1. Summary Statistics for a Sample of Kansas Farms, Averages for 2000–2011

Variables	Mean	Standard Deviation	Percentiles 25th	50th	75th
Outputs					
Crop index	487,131	470,649	187,876	361,495	627,575
Livestock index	94,277	170,773	0	41,439	106,518
Inputs					
Labor index	1.375	0.856	1	1.1	1.6
Crop input index	131,914	128,894	51,026	95,761	169,381
Fuel index	42,188	38,015	20,245	32,357	49,955
Livestock input index	42,157	108,135	945	10,293	32,884
Other inputs (mainly capital)	211,804	151,074	113,779	167,396	264,893
Price Indexes[a]					
Crop price index	0.576	0.210	0.412	0.485	0.697
Livestock price index	0.830	0.139	0.734	0.824	1
Farm Characteristics					
Age	58	10	51	58	66
Crop income share	0.770	0.265	0.642	0.861	1.000
Livestock income share	0.230	0.265	0.000	0.139	0.358
Average total assets	1,230,341	1,036,815	569,492	936,335	1,537,083
Average total debt	258,967	320,259	41,000	150,695	356,942
Debt to asset ratio	0.243	0.232	0.052	0.180	0.374
Noncurrent assets	898,258	805,276	388,108	676,296	1,088,425
Investment	199,573	180,417	84,580	150,821	256,118
Invest to asset ratio	0.278	0.196	0.140	0.227	0.370
Total acres	2,057	1,467	1,125	1,739	2,518
Percentage of rented acres	0.616	0.281	0.442	0.673	0.831
Western Kansas	0.085	0.278	—	—	—
Central Kansas	0.353	0.478	—	—	—
Eastern Kansas	0.562	0.496	—	—	—

[a] Crop and livestock price indexes were normalized with respect to the year 2011.

are reported in Table 2. Results of the efficiency scores provide evidence of the existence of inefficiency in farm production for the sample of farms examined. The average yearly technical efficiency for farms was 0.74, with a maximum of 0.77 and a minimum of 0.69 over the period examined. About 9.1% to 16.6% of the farms were on the efficient frontier in any year. The years with the highest percentage of farmers on the production efficient frontier were 2007 and 2008 with 16.6% and 16.0% of the farms in the sample, respectively.

The likelihood that a farm produced on the efficient frontier was examined using a dynamic probit model where the dependent variable indicates whether a farm lies on the efficient frontier or has efficiencies greater than or equal to 0.95. Parameter estimates and average partial effects for the dynamic probit model are reported in Table 3. Given that regional dummies are time-invariant, it is not possible to separately estimate their partial effect from their correlation with time-invariant individual heterogeneity. It is only possible to

Table 2. Input-Oriented Technical Efficiency Scores and Productivity Indexes for Sample of Kansas Farms, 2000–2011

Year	Technical Efficiency	% of Farms on the Frontier	Efficiency Change (a)	Technical Change (b)	Malmquist Productivity Index[a] (a) X (b)
2000	0.691 (0.178)	9.06	—	—	—
2001	0.757 (0.159)	14.8	1.156 (0.358)	0.816 (0.128)	0.926 (0.255)
2002	0.763 (0.172)	12.99	1.031 (0.240)	0.898 (0.122)	0.924 (0.241)
2003	0.692 (0.177)	9.67	0.941 (0.302)	1.198 (0.182)	1.111 (0.333)
2004	0.769 (0.156)	13.29	1.177 (0.364)	0.934 (0.215)	1.077 (0.361)
2005	0.749 (0.175)	14.8	1.003 (0.276)	1.188 (0.441)	1.180 (0.599)
2006	0.756 (0.172)	14.5	1.050 (0.309)	0.929 (0.179)	0.955 (0.262)
2007	0.772 (0.174)	16.61	1.055 (0.281)	0.969 (0.173)	1.015 (0.301)
2008	0.773 (0.171)	16.01	1.040 (0.286)	0.924 (0.115)	0.961 (0.295)
2009	0.758 (0.170)	13.6	1.027 (0.405)	1.156 (0.150)	1.191 (0.524)
2010	0.707 (0.181)	11.78	0.974 (0.334)	1.115 (0.140)	1.083 (0.399)
2011	0.740 (0.184)	15.11	1.093 (0.342)	0.778 (0.271)	0.855 (0.453)
Mean	0.744	13.52	1.049	0.991	1.025
Maximum	0.773	16.61	1.177	1.198	1.191
Minimum	0.691	9.06	0.941	0.778	0.855

Numbers in parentheses are standard errors.
[a] The Malmquist productivity index is the product of columns (a) and (b).

Table 3. Results of Dynamic Probit Model—Probability of Farmers Being on the Efficient Frontier

	Dynamic Model Estimates		Average Partial Effects	
	Coefficient	Std. Error	Estimate	Std. Error
Intercept	–0.2988	(0.3632)		
Efficient$_{t=0}$	0.6263***	(0.1151)		
Efficient$_{t-1}$	0.1112*	(0.0666)	0.0282	(0.0182)
Crop share	–1.4499***	(0.3135)	–0.3234***	(0.0772)
Acres	0.0001***	(0.0000)	0.0000**	(0.0000)
Percentage of rented land	0.0782	(0.2888)	0.0174	(0.0638)
Short-term debt to asset ratio	–0.7036	(0.5082)	–0.1569	(0.1439)
Long-term debt to asset ratio	0.8180**	(0.3826)	0.1824**	(0.0877)
Investment	0.3185	(0.4005)	0.0710	(0.0971)
Age	–0.0045	(0.0043)	–0.0010	(0.0012)
Central region	–0.1023	(0.0998)		
Western region	0.3224*	(0.1697)		
Sigma	0.5125	(0.0461)		
Rho	0.2079	(0.0296)		
No. observations	3,641			

Notes: ***, ** and * indicate the estimated coefficients are significantly different from zero at the 1%, 5%, and 10% level of significance, respectively.
The model includes year dummies.
[a] Standard errors calculated using bootstrapping.

examine the direction of its effect. The estimated value of 0.51 for sigma^2 implies that unobserved heterogeneity accounts for approximately 21% of the error variance.

After controlling for individual heterogeneity, the average partial effect of the variable measuring state dependence was not statistically significant, suggesting that it is the farmers' characteristics and not their prior efficiency that determines a farm's current ability to remain efficient. While it would be expected that farmers learn from their previous experience, it may be that the process of learning and know-how that allows them to perform better than their peers is related to both observable and unobservable farmer characteristics. In addition, factors beyond the control of the farmer also play a role in farming efficiency.

This study found a statistically significant difference in farm performance across farm types. Farms with a higher share of income from crops were less likely to be on the efficient frontier. This could indicate that farms with higher income from livestock enterprises tend to be more efficient. In addition, it could reflect the effect of farm diversity. As an enterprise becomes more specialized on crops with a lower share of income coming from livestock, the diversification of the operation decreases and so does its likelihood of remaining efficient. In a study of the efficiency of beef cow farms, Featherstone, Langemeier, and Ismet (1997) found that diversified farms were more technically efficient than specialized farms.

Total acres operated was found to be a positive and statistically significant factor in armers' likelihood to be efficient (Table 3). Larger farms may have better access to resources (e.g., credit and technology) and can take advantage of technologies of scale. For example, Briggeman, Towe, and Morehart (2009) found that the majority of farms suffering credit constraints are small farms. However, results with respect to farm size and technical efficiency are mixed; both negative (Townsend et al., 1998) and positive effects have been found (Alvarez & Arias, 2004). Mugera and Langemeier (2012) and Featherstone, Langemeier, and Ismet (1997) found larger technical efficiencies for larger farms in Kansas.

Results indicate that farmers with higher long-term debt to asset ratio are more likely to be efficient, suggesting that farmers with financial leverage are more likely to produce on the efficient frontier. A study by Chavas and Aliber (1993) found that the intermediate and long-term debt to asset ratio had a positive effect on the technical and allocative efficiency of a group of farmers in Wisconsin. Similarly, a study by Lambert and Bayda (2005) found a positive relationship between intermediate-term debt to asset ratio and technical efficiency for a sample of North Dakota farmers. Both studies attributed this finding to an increase in investment in capital equipment financed through debt. In addition, this result could be explained by the free-cash theory, which stipulates that the burden of debt creates an incentive for managers to operate more efficiently (see Mugera & Nyambane, 2014).

Productivity Change

Productivity change was measured using the Malmquist productivity index (Table 2). Productivity indexes greater than one indicate progress (i.e., productivity growth), values of one indicate stagnation, and values less than one indicate regression between two adjacent years. The average productivity index across farms and years was 1.025, indicating a productivity growth of 2.5% per year for the sample of farms examined. Estimates from USDA ERS for aggregate agricultural output for the period 1948–2011 indicate an annual productivity growth of 1.49% in the United States during this period (Wang et al., 2015). Variations in the productivity index are observed from year to year in our study, but greater variation can be observed across individuals. The maximum average yearly growth was 19% (observed in 2009), while the minimum observed value is -14% (observed in 2011). This result could reflect the negative effect of the 2011 drought on yields in Kansas. Looking into the efficiency component of the productivity index, farms exhibited an average efficiency growth of 4.9%. Generally, farms exhibited efficiency growth in all but two years (2003 and 2010). This result indicates that farms are moving closer to the efficient frontier (i.e., catching up). The average annual productivity change index was 0.991, indicating technical stagnation during the period examined. We observe a drop in the technical change (frontier shift) from 2010 to 2011, after observing a growth of 12–16% during the previous two years. Productivity growth during the period examined is mainly attributable to efficiency growth.

Table 4. Productivity Change (Malmquist Index) Regression Analysis Results

	Coefficient	Std. Error
Intercept	2.1640***	(0.3550)
M_{t-1}	–0.3700***	(0.1290)
M_{t-2}	–0.0865*	(0.0446)
Crop price index	–0.8960***	(0.2600)
Livestock price index	0.1940*	(0.1150)
Crop share	–0.1260**	(0.0520)
Acres	0.0000	(0.0000)
Percentage of rented land	–0.0832	(0.0826)
Short-term debt to asset ratio	0.2280	(0.1790)
Long-term debt to asset ratio	0.1930*	(0.1120)
Investment	–0.0108	(0.8790)
Investment$_{t-1}$	–0.0312	(1.0470)
Age	0.0003	(0.0008)
Central region	–0.0062	(0.0137)
Western region	0.0361*	(0.0190)
Year dummies	Yes	
No. observations	2,979	
AR(1) test (p-value)	–2.930	(0.003)
AR(2) test (p-value)	–0.750	(0.456)
Sargan test (d.f., p-value)	56.17	(45, 0.123)
Hansen test (d.f., p-value)	48.79	(45, 0.323)

Notes: ***, ** and * indicate the estimated coefficients are significantly different from zero at the 1%, 5%, and 10% level of significance, respectively. MI = Malmquist productivity index. The model was estimated using the xtabond2 module in Stata11 (Roodman, 2009) using the Windmeijer (2005) finite-sample correction. The model includes year dummies.

Regression results for the model examining productivity change via the MI using a dynamic panel data model are reported in Table 4. Results of the Sargan and Hansen test for overidentifying restrictions confirmed the validity of the instruments used (Table 4). The parameters on the lags of productivity change are negative and statistically significant. Farms with high productivity change are getting closer to the efficient frontier due to catch-up to the most efficient farms. More efficient farms appear to have less opportunity for improvement in subsequent periods. Econometrically, this is a result of negative intertemporal serial correlation from the calculation of cross-period indexes (Zhengfei & Lansink, 2006). As pointed out by Zhengfei and Lansink (2006), the production possibility set $D_o^{t+1}(x_o^{t+1}, y_o^{t+1})$ in the numerator for the estimation of productivity change from time t to $t+1$ (Equations 1–3) rotates to the denominator in the estimation of the productivity growth from time $t+1$ to $t+2$. These results are related to the concept of convergence that postulates that farmers who lag behind operations on the frontier can exhibit larger increases in productivity as technologies diffuse and farms catch up (Ball et al., 2004). Larger potential increases in productivity for farms that initially experience lower productivity could also be the result of a positive spillover effect of knowledge and management strategies from the most productive farms.

It is important to note that while past productivity progress is negatively related to current changes in productivity, this does not imply lack of efficiency; rather, it informs us that a farm's opportunity for growth is reduced compared to their peers as the farm grows closer to the production frontier. For example, a farm that caught up to the efficient frontier in the previous year (exhibited growth) is not able to experience additional growth as it has already attained the maximum level of efficiency given the technological frontier available. Given that innovation in the agricultural sector results in shifts in the production frontier, efficient farmers can attain productivity growth through frontier shifts when they adopt new technologies. For this reason, investment in research and technological development is important for achieving long-term productivity growth in the agricultural sector (Fuglie & Wang, 2012).

The long-term debt to asset ratio was found to be positively and significantly correlated with productivity change. This result is consistent with previous research in the literature that found evidence suggesting a positive relationship between financial leverage and productivity growth (Ciaian et al., 2012; Zhengfei & Lansink, 2006). Credit constraints could affect resource allocation decisions and input usage and could limit farmers' ability to undertake investment in technological innovation. Credit limitations could result in lower efficiency levels (Briggeman et al., 2009; Lambert & Bayda, 2005; Petrick, 2004). Contrary to expectations, however, investment in crop machinery as a percentage of total assets was not statistically significant. A possible explanation is that investments in other type of capital or technological innovations (e.g., improved seed varieties, facilities, etc.) not included could have a large effect on efficiency.

An increase in the share of income from crops was associated with a lower growth. This result suggests that farms that were more specialized in crop production attained a lower increase in productivity than farms that include livestock production. The results in this study also suggest that farms located in western Kansas had a larger productivity change than farms located in the eastern region of the state. A good portion of the land under production in western Kansas is irrigated. Irrigated crops have generally larger crop yields than dryland crops (Rogers & Lamm, 2012), which could explain why farmers in this region exhibit higher productivity.

The livestock price index was positively correlated with productivity during the period of time examined, indicating possible efficiency growth due to better livestock prices during the period examined. Examination of the association between crop prices and productivity change indicates that productivity growth was negatively related to increases in crop prices for the period examined, as reflected by the negative sign on the crop price index (Table 4). While increases in commodity prices could provide incentives for farmers to increase efficiency, it could also provide incentive for farmers to increase input allocation at a suboptimal level. Higher commodity prices could incentivize farmers to move away from their original rotations to a more specialized rotation consisting of high-value crops, and could also cause farmers to use less productive marginal lands for production and to increase input use (Choi & Helmberger, 1993; Ciaian & Kancs, 2011; Malcolm et al., 2009).

In the short-term, farmers could use their inputs mix in a less efficient way as they seek to increase yields and to maximize returns. O'Donnell (2010) suggests that factors that increase profitability, like output price, can result in lower productivity. He suggests that increases in output prices relative to input prices could represent an incentive for farmers to expand their operation to take advantage of profit opportunities. This could result in farmers moving into a region of decreasing returns to scale, reducing their productivity (O'Donnell, 2010). For example, a farmer that reacts to high corn prices may attempt to boost yields by adding fertilizer above the optimal level. In our data, we observe a decline in technical efficiency change from 2006 to 2010 (Figure 2), the same period for which we observed higher crop prices (Figure 1). Statistics by the ERS-USDA (2013) suggest that a productivity decline was observed in 2007 when, motivated by high corn prices and the demand for corn for ethanol production, farmers increased their use of fertilizer and expanded the land under corn production, abandoning their common crop rotation.

CONCLUSIONS

This study estimated farm technical efficiency and changes in productivity using the Malmquist productivity index and its components for a sample

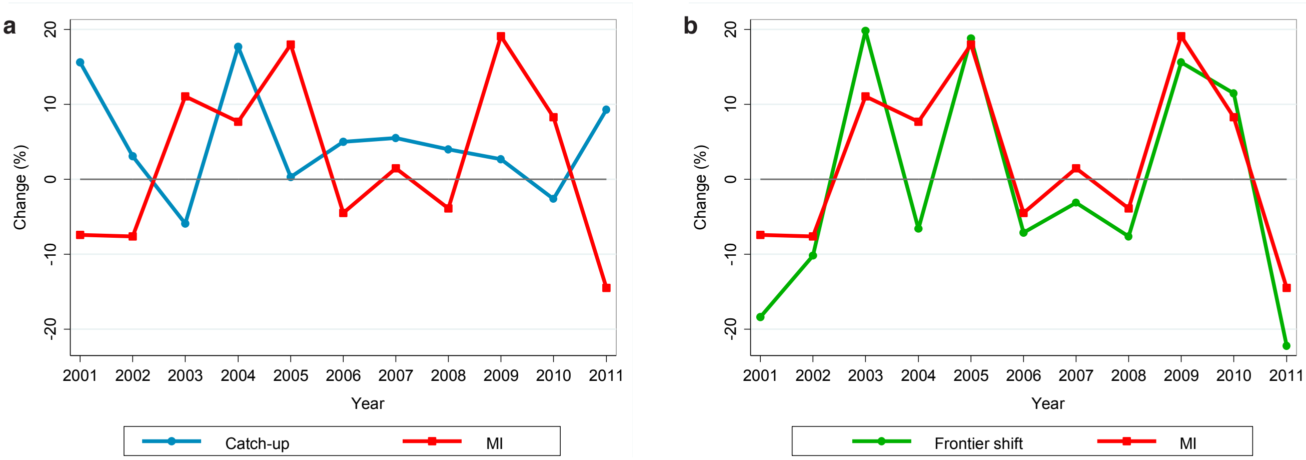

Figure 2. Average annual change across farms in the Malmquist index (MI), and its components catch-up (a) and frontier shift (b), 2001–2011.

of farms in Kansas. The study then examined farm technical efficiency and productivity change using regression analysis. First, we analyzed factors associated with the probability that a farm will be on the efficient frontier (i.e., the farm is efficient). The study found that farms that were more efficient in the past were not necessarily among the most efficient in later periods. In addition, larger farms with livestock income and a higher long-term debt to asset ratio were more likely to be on the efficient frontier.

Second, we analyzed productivity change and its relationship with commodity prices to gain insights about changes in productivity as a result of higher commodity prices during the ethanol boom period that resulted in higher crop prices. While it was expected that increases in commodity crop prices would have resulted in a push to increase productivity, the results in this study did not find supportive evidence. To the contrary, increases in the crop price index had a negative relationship with productivity change. A possible explanation is that farmers may have increased the use of inputs above optimal levels in an attempt to increase crop supply. Thus, farmers may have adjusted their production to take advantage of increases in commodity prices, but those changes in production might be geared toward yield increases and not necessarily optimization of input usage.

This study contributes to the literature by providing some insights about how the productivity of a sample of farms changed in association with higher crop prices experienced during the ethanol boom. This can inform policy makers about how policies that could result in higher farm output prices could potentially affect input allocation and farm productivity in the short-term. Education and outreach efforts could focus on efficient input allocation tools and strategies, particularly when market conditions create incentives for producers to maximize output. Future research could examine the impact of changes in efficiency over time due to commodity prices changes and how they relate to agricultural commodity policies.

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NOTES

1. While efficient farms have efficiency scores equal to one, to consider farms with low deviations from the efficient frontier and for the purpose of this model we included farms whose scores are equal or greater than 0.95.

2. $\sigma_a/(1+\sigma_a)=0.51/(1+0.51)=0.21$.

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