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Technical efficiency of U.S. Western Great Plains wheat farms using stochastic frontier analysis

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Technical efficiency of U.S. Western Great Plains wheat farms using stochastic frontier analysis

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ABSTRACT

Technical efficiency (TE) is an important measure of farm performance. This study measured the TE of wheat farms across six states in the U.S. Western Great Plains based on production and farm management-specific variables. Significant factors positively influencing efficiency were insecticide use, farm size, and tillage. Alternatively, government payments, crop insurance, off-farm income, and crop share rates had negative effects on efficiency. Kansas and Oklahoma farms were more efficient than Nebraska and Wyoming farms in the sample. Average TE score of 0.56 indicates a substantial gap between average producers and the most efficient ones located near the TE frontier. Benchmarking the highly efficient farms provides best-management practices enabling lessefficient farms move closer to the efficient frontier. Extension specialists and collaboration among farms could transfer the skills and techniques through workshops, webinars, fact sheets, and social media pages.

ARTICLE HISTORY

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KEYWORDS

Elasticity of production; production function; technical efficiency (TE); wheat production

1. Introduction

Wheat production in the Western Great Plains (WGP) has played an important role in U. S. agriculture (Vitale et al., 2019). The WGP has historically produced most of the hard red winter wheat and other small grain crops in the US (Clark, 1958). Farms in the WGP have been challenged, however, by factors such as low crop prices, increasing input prices, changes in consumer preferences, and loss of technological competitiveness compared to rival crops such as corn and soybean (OWVRN, 2019). Currently, only 30% of wheat farms in the WGP earn positive profits while others incur losses (Ali, 2002; USDA, n.d.). Climate change is an emerging threat, leading to more extreme weather events including a higher frequency of drought, stronger thunderstorms, warmer temperatures, more extreme flooding, and an expected shift in production toward the northern part of the country from Kansas to North Dakota (Environmental Protection Agency, 2017; Olmstead & Rhode, 2011; Stewart et al., 2018).

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A fundamental way to enhance profitability is to increase managerial efficiency (Kaplan & Norton, 1992). Identifying root causes of inefficiency will help increase profitability of wheat production in the WGP and is a primary focus of this article. Beyond the farm, societal benefits from increased wheat production efficiency include greater returns from public funding, lower food prices, and global exports to enhance global food security (Mekonnen et al., 2015). Management literature has developed a variety of methods to assess and measure managerial performance across both strategic and tactical dimensions. The Balanced Scorecard method focuses primarily on the internal strategic performance of an individual firm across both financial and nonfinancial criteria, typically including financial fundamentals, i.e., return on investment, debt to asset, equity, customer and stakeholder satisfaction, business internals (strategy and goals), and learning and growth (Dye, 2003; Kaplan & Norton, 1992). In the general business setting, methods such as the Balanced Scorecard and multivariate factor analysis have been developed to sector measure firm performance (Hoque, 2014; Tawse & Tabesh, 2022). In agriculture, numerous studies have applied balanced score card to agriculture (Chen et al., 2020; Paustian et al., 2015).

Benchmarking methods measure and assess managerial performance by comparing one or more of firm's output to those achieved by any or all of the following: competitors, industry standards, and best performance (Alem et al., 2018, 2018; Bojnec & Latruffe, 2008). Since its development by Xerox in the 1980s, benchmarking has been applied within a broad range of industries: health care, marketing, supply chain, energy, investment decisions, hotel business, public transportation, manufacturing, and customer service (Hilmola, 2011; Routroy and Pradhan, 2013). Technical and economic benchmarks are established based on the min-max principle of generating maximum output from either a given set of inputs or by minimizing input levels (Heather, 2002; Allen, 2005; "West et al., 2022). Typically, a best performance frontier is estimated and individual firm's performance is measured by its distance (deviation) to the frontier. While several approaches have been developed for the empirical estimation of efficiency, including parametric and non-parametric approaches, no single method has been found to be unambiguously superior to other options (Aigner et al., 1977; Charnes et al., 1978; Farrell, 1957).

Two of the most popular benchmarking methods that have emerged from the literature are econometric methods such as stochastic frontier analysis (SFA), which estimate production functions to establish frontiers of best performance, and non-parametric methods such data envelopment analysis (DEA), that utilize math programming to establish best performance frontiers. Coelli et al. (2003) suggested that if the benchmarking data includes considerable random errors then SFA is preferred over DEA when estimating efficiency benchmarks. Because this study is based on farm survey data, SFA was considered more appropriate than DEA to account for randomness when estimating technical efficiency.

Given the relatively large number of farms within the agricultural industry, and the availability of representative cross-sectional data from the farming population, benchmarking has typically been the most popular approach used to assess farm managerial performance (Byrnes et al., 1987; Chavas & Aliber, 1993; Featherstone et al., 1997; Mugera & Langemeier, 2011; Olson & Vu, 2009; Paul et al., 2004; Rowland et al., 1998). The similarity in production factors, capital equipment, and marketing channels

imply that technical benchmarks distinguish managerial performance since production outcomes depend overwhelmingly on the timing and intensity of farm operations. Typically, this entails decision-making on seed selection, agronomic practices to maintain soil fertility and protect crops, proper use of mechanization, diversification and crop rotation strategies, and the integration of crop and livestock enterprises into an optimally functioning system.

Since farms are uniquely organized and operated by farm managers, individual differences in managerial performance as influenced by experience, education, preferences, resource endowments generate a distribution of farm efficiency levels. Findings from numerous prior studies indicate that there is no consistent pattern explaining TE (Table 1). Paul et al. (2004) found that small family farms in the U.S. were inefficient, with large farms driving out smaller ones due to their higher competitiveness in terms of size and scope over recent decades, including wheat farms in the WGP. Featherstone et al. (1997) contradicted these findings, however, reporting that the inefficiency of cowcalf operations on Kansas farms was positively related to herd size and degree of specialization, i.e., proportion of cattle income to wheat. Their findings indicate that producers should focus on using capital, feed, and labor more efficiently rather than simply increasing farm size. Langemeier and Bradford (2005) found that the overall efficiency of Kansas farms was positively related to farm size, proportion of time devoted to farming, and gross farm income while inefficiency was positively related to years of farm experiences and acres owned. Mugera and Langemeier (2011) found that efficiency among Kansas Farm Management Association members decreased over the period 1993-2007 and that their efficiency was associated with larger farm sizes but not with specialization.

Our study contributes to the literature by including a comprehensive set of explanatory variables, including variables not included on prior studies as well as those found significant from previous studies, allowing further validation of literature results. We tested 16 farm-specific factors that had a significant effect on TE reported in previous studies: age (Battese & Coelli, 1995; Featherstone et al., 1997; Paul et al., 2004; Pitt & Lee, 1981), education (Battese & Coelli, 1995), family tenure (Giannakas et al., 2001, Langemeier & Bradford, 2005; Olson & Vu, 2009; Taraka et al., 2012), government payments (Giannakas et al., 2001, Latruffe et al., 2017), insurance payments (Giannakas et al., 2001), off-farm income (Olson & Vu, 2009), insecticide use (Giannakas et al., 2001), power and implements machines (Giannakas at al 2001), hiring custom services (Olson & Vu, 2009; Rowland et al., 1998), cash-rented land and crop share rate (Giannakas et al., 2001, Langemeier & Bradford, 2005; Olson & Vu, 2009; Paul et al., 2004), livestock and crop diversity (Giannakas et al., 2001, Mugera & Langemeier, 2011; Olson & Vu, 2009), farm size (Byrnes et al., 1987; Kalaitzandonakes et al., 1992; Mugera & Langemeier, 2011; Olson & Vu, 2009; Paul et al., 2004; Pitt & Lee, 1981) and tillage (Langemeier, 2005).

Our results, as detailed below, found eight significant managerial factors explaining technical efficiency including government payments, insurance payments, off-farm income, insecticide use, crop share rate, farm size, and tillage. The remaining nine variables were not significant: age, education, family tenure, off-farm income, power machines, custom services, crop share rate, livestock, and crop diversity. Previous studies would have benefitted from a more complete set of factors since the omitted variables

				Significant Farm		
Study	Effic. Measure	TE Score ^a	#significant. vars/#vars	Managerial Factors Explaining TE	Data Type/ Model ^b	Study Region/ Product.
Current Study	TE	0.56	8/16	Govt payment, insurance, off-farm Income, insecticide, crop-share, farm-size, tillage, region	Panel/SFA	Western Great Plains/ wheat
Langemeier and Bradford (2005)	Overall	0.83	4/8	Farm income, farm experience, owned acres, percent of time devoted to farming	Panel/DEA	Kansas farms
Featherstone et al. (1997)	TE & others	0.78	3/5	Age, # of beef cows, % of income from beef cow	Cross-sect. /DEA	Kansas/beef cow
Mugera and Langemeier (2011)	TE	0.59	2/2	Specialization and size	Panel/DEA	Kansas farms
Rowland et al. (1998)	TE and others	0.89	3/10	# of litters, pounds of pork produced per litter, hired labor proportion	Panel/DEA	Kansas/swine
Kalaitzandonakes et al. (1992)	TE		1	Farm size with latent variable approach	Panel/DEA, SFA	Missouri/grain
Olson and Vu (2009)	TE and others	0.77	7/8	Farm size (strong), debt asset ratio, experience, non-farm ratio, tendency ratio, land/ labor ratio, hired ratio, specialization	Panel/DEA	Minnesota farms
Byrnes et al. (1987)	TE	1.04		Farm size	Cross-sect. /DEA	Illinois/grain
Chavas and Aliber (1993)	TE & others	0.85– 1	2/5	Intermediate and long run debt to asset ratios	Panel/DEA	Wisconsin farms
Paul et al. (2004)	TE & others	0.93	5/8	Age, rented land, portion of GM corn and soybean, farm size	Panel/SFA, DEA	U.S. farms
Pitt and Lee (1981)	TE	0.60– 0.70	3/3	Age, size, ownership	Panel/SFA	Indonesia/ weaving
Giannakas at al. (2001)	TE	0.66– 0.83	10/14	Participation in top management program, crop insurance, government payment, land tenancy, family operated farm, debt to asset ratio, specialized farms, use of seed and chemical inputs, the use of machinery capital, soil types	Panel/SFA	Saskatchewan, Canada/ wheat
Battesse and Coelli (1995)	TE	N/A	3/3	Age, schooling, year	Panel/SFA	Indian village/ paddy farms
Latruffe et al. (2017)	TE	N/A	5/7	Subsidies, labor, input and output prices	Panel/SFA	Europe/dairy

Table 1. Summaries of farm managerial factors explaining on technical efficiencies (TE) from prior studies.

^aStudies measures TE based on a variety of criteria. Thus, this study cited a representative TE score.

^bSFA denotes stochastic frontier analysis including econometrics models, DEA denotes data envelopment analysis or linear programming models.

could have altered their reported significance levels. For example, in our review of 12 TE studies most closely related to WGP farms, none included farm management operations such as insecticide and tillage, both of which our study identified as having significant and positive effects on TE (Table 1). Omitting farm management practices could be

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relevant since half of the studies identified general farm manager attributes such as age, experience, or education as significant, findings that could change if an expanded set of factors were included. Having more specific factors such as input use provides extension and stakeholders with more specific issues to focus on compared to age, experience, etc.

Our data collecting method surveyed a sample of 564 from 141 farms that remained consistent over a multiyear period and is considered more robust than previous studies by enabling time-varying efficiency effects to be captured at the farm level rather than through regional aggregation. Relying on aggregate data potentially ignores individual farm differences and hence unlikely to provide accurate results on farm-specific efficiency measures. Dynamics in crop portfolios, input choices, production outcomes, and economic returns were thus captured over a multiyear period. This study also improves on previous studies by including a larger study region, the WGP of the U.S., composed of six states: Colorado, Nebraska, Kansas, Oklahoma, Texas, and Wyoming. Previous studies have thus been limited by focusing on small geographical regions within a single state, making it difficult to accurately translate findings to more broadly defined agro ecological landscapes (Table 1).

Hence, the objectives of the study are to (1) measure TE for wheat farms in the WGP; (2) identify significant factors explaining TE performance across WGP wheat producers; and (3) provide suggested policy initiatives to enhance TE in the WGP.

2. Background: crop production in the WGP

The WGP of the U.S. is a diverse region characterized primarily by short, mixed, and tallgrass prairies. Producers employ mixed-farming strategies growing crops with cattle and other livestock obtaining complementary benefits from their interactions and managing risk. Most farms are family-oriented and rely heavily on machinery. To maintain soil fertility, and to improve weed control, farms rotate their crops, generally planting three crops on a 2-year rotation to increase crop production compared to wheat monoculture (Andow, 1991; Gardiner et al., 2009). Typical cropping patterns are winter wheat-cornfallow, winter wheat-sorghum-fallow, winter wheat-proso millet, and winter wheat-cornproso millet-fallow (Elliot et al., 2006). Table A1 from our survey result shows that most of the farms grew wheat annually with average planted acres 1,341 acres during the 4-year survey period. Sorghum, proso-millet, and corn were popular crops rotated with wheat.

The choice of farming practices is expected to have a significant effect on TE as their intensity and timing vary by producer. A primary agronomic constraint is soil moisture. Crop yields in the WGP depend heavily on weather due to low precipitation with annual rainfall averaging from 15 to 30 inches but is often sporadic and subject to substantial evapotranspiration during hot summer months. Traditionally, fields are plowed (or chisel-disked or disked) three or six times to loosen soil and increase its water efficiency, but also leaves soil prone to erosion. To improve soil and water conservation, some farms have adopted reduced till or no-till methods. Insects and foliar pests are common problems in the WGP. To control pest problems, farms typically apply chemicals, e.g., herbicides, insecticides, and fungicides but intensity and economic thresholds triggering use vary by producer. When available, insect and disease-resistant crop varieties can be planted for enhanced protection but usually incur higher up-front costs and yield tradeoffs making adoption an individual decision.

Economic planning is also important in maintaining farm efficiency. Producers in this region often participate in crop yield insurance, forward contracting, and government subsidy programs to increase and stabilize income. Their varied use across the farming community suggests that strategies are either farm dependent or are being inefficiently used. Prior research has often identified economic efficiency as a significant determinant explaining income disparity across farms, particularly for wheat, including this study as shown in the next section (Table 1). Farms typically operate on rented land contracted by either a cash rent or sharecrop agreement. Tenure can be an important factor: Langemeier and Bradford (2005) found a significant difference in TE between owned and rented land with rented land positively related to TE. In our survey, 42% of the farms contract with a sharecrop agreement, which could provide further insight into whether the contract terms further TE implications.

3. Methodology: conceptual framework

This study was designed to measure farm TE and to identify farm-specific factors that explain TE. The most widely used and accepted approach is to use econometrics to measure TE through estimating a production function representing a frontier of maximum output obtained from an observed set of firms. Firm inefficiency is hence the deviation from a firm's output to the frontier. Early methods used deterministic methods to estimate the frontier but have been generally found to be restrictive. Aigner et al. (1977) and Meeusen and van den Broeck (1977) independently developed the stochastic frontier approach in which firm inefficiency is measured using a stochastic variable. The earliest SFA models used cross-sectional data and half-normal distributions to measure inefficiency. The literature has since flourished with numerous extensions of the model as summarized in Forsund, Lovell and Schmidt (1980), Schmidt (1986), Battese (1992) and Greene (1993).

Two important extensions relevant to our study are model formulations that is first measure technical efficiency using time-varying effects, i.e., panel data, and second explain technical inefficiency through a set explanatory variables hypothetically linked to management factors (Battese & Coelli, 1992, 1993, 1995; Giannakas et al., 2001; Pitt & Lee, 1981; Taraka et al., 2012). A general SFA model under these two extensions is formulated as

$$Y_{it} = X_{jit}\boldsymbol{\beta} - u_{it} + v_{it} \tag{1}$$

where Y_{it} is a NT x 1 vector of the log of output for farm *i* and year *t*, where i = [1, 2, ..., N-1,N] and t = [1, 2, ..., T-1,T]. X_{jit} is a NT x K matrix of the log of inputs for input *j*, farm *i* and year *t*, where j = (1, ..., K), is a K × 1 vector of parameters to be estimated, u_{it} is a positive error term to account for inefficiency of farm *i*, v_{it} is a symmetric random error distributed normally with mean 0 and constant variance, and u_{it} and v_{it} are assumed to be independent.

Literature has investigated various functional forms for u_{it} to accommodate either or both time-varying effects (panel data) of efficiency as well as to explain inefficiency using management-related variables. This allows for the simultaneous estimation of both the

stochastic production frontier and regressors explaining inefficiency, an improvement over earlier two-stage estimation approaches that suffered from econometric issues. Pitt and Lee (1981) propose a time invariant approach to explain technical inefficiency, u_i :

$$ui = |Ui| \tag{2}$$

$$U_i \sim N(\boldsymbol{\mu}, \boldsymbol{\sigma}_u^2)$$
 (3)

where u_i is assumed to be a truncated normal distribution. A distinguishing feature of Pitt and Lee's approach is that firm-specific inefficiency is a random effect.

Battese and Coelli (1995) propose u_{it} as a time-varying truncated normal distribution: $uit = \mu + w$ (4)

$$u_{it} \sim N(\mu, \sigma_u^2)$$
 (5)

subject to the following inequality to maintain positivity of u_{it} .

$$w \ge -\mu$$
 (6)

Using a scaled regression model, inefficiency of farm *i* is explained using

$$u_{it} = \delta z_{it} + w \tag{7}$$

where w is a truncated normal whose point of truncation is given by δz_{it} , δ is a vector to be estimated, and z_{it} includes any demographic and economic variables to contribute to inefficieny. In this form, Equation 7 allows for time-varying efficiency that is determined, through its truncation, by the explanatory variables.

Alvarez et al. (2006) were the first to propose using a scaling approach to explain technical inefficiency that allows for time-varying effects. Their formulation includes a truncated normal distribution that scales an overall effect of individual farm management, as explained by exogenous variable z_{it} , as follows:

$$uit(zit, \delta) = h(zit, \delta) \cdot u_{it}^*$$
(8)

where $h(z_{it}, \delta) \ge 0$, $u_{it}^* \ge 0$ has a distribution independent of z_{it} , and δ is a scaling parameter. As explained in Alvarez et al. (2006), scaling splits $u_{it}(z_{it}, \delta)$ into two intuitive terms with greater practical meaning than Battese and Coelli (1995). Hence, u_{it}^* is interpreted as the firm's fundamental efficiency which captures inherent managerial skills assumed randomly distributed. The exogenous variables z_{it} explain how well a manager's inherent skills have been transformed into a stock of human capital through education, farm experience, peer learning, and extension information. Alvazer et al. (2006) used an exponential form for u_{it} :

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$$\boldsymbol{\mu}_{it} = \boldsymbol{\mu} \cdot exp(zit\boldsymbol{\delta}). \tag{9}$$

3.1. Estimation

Following Battese and Coelli (1992, 1993, 1995), a Translog production frontier function SFA model is used to estimate Equation (1) including for all three alternative formulations for v_{it} :

$$y_{it} = \beta_0 + \sum_{k=1}^k \beta_x x_{kit} + \sum_{k=1}^k \sum_{j=1}^k \lambda_{kj} x_{kit} x_{jit} + v_{ij} - u_{it}$$
(10)

where y_{it} is logged output of farm *i* in year *t*, x_{jit} is logged input *j*, λ_{kj} are regression parameters to be estimated, and v_{it} and, u_{it} are defined previously. Equation (10) is estimated using maximum likelihood for all three model specifications: Pitt and Lee (1981), Battese and Coelli (1995) (BC95), and Alvarez et al. (2006). The estimation procedure for the BC95 is provided in this section: estimation procedures including software implementation for the other models are well described in the literature (LIMDEP, 2021).

Including year variables in the production function could theoretically account for year-to-year TE change. According to Coelli (2003), this discrimination is only possible when the inefficiency effect is stochastic and has a specific distribution. The year variable can also be included as an exogenous variable to determine factor efficiency effects. In this case, individual years are permitted to affect efficiency differently:

$$L(\theta; \mathbf{y}) = -\frac{1}{2} \left(\sum_{i=1}^{N} T_i \left\{ In 2\pi + In \sigma_s^2 \right\} - \frac{1}{2} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ \left(\frac{(y_{it} - x_{it} \beta + z_{it} \delta)^2}{\sigma_s^2} \right) \right\} - \sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ In \phi(d_{it}) \right\} - \left\{ In \phi(\mathsf{d}^*_{it}) \right\}$$
(11)

where $\Phi(\cdot)$ is a function of the standard normal random variable, $\ln(\cdot)$ is the logarithm function, π is $\delta_s^2 \equiv \delta_v^2 + \delta^2$, $\gamma \equiv \frac{\delta^2}{\delta_s^2}$, $d_{it} = \frac{z_{it}\delta}{(\gamma\delta_s^2)^{\frac{1}{2}}}$, $d^*_{it} = \frac{\mu^*_{it}}{[\gamma(1-\gamma)\delta_s^2]^{\frac{1}{2}}}$, $\mu^*_{it} = (1-\gamma)z_{it}\delta - \frac{1}{(\gamma\delta_s^2)^{\frac{1}{2}}}$

 $\gamma(y_{it} - x_{it}\beta), \ \theta = (\beta^1 \delta^1, \sigma_s^2 \gamma)$, and the remaining symbols are previously defined.

Minimizing the log likelihood function in Equation (11) provides unbiased estimates of the parameters β , δ , σ_S^2 , and γ . Based on these parameters, the conditional distribution $f(u_{it}|\varepsilon_{it})$ can be calculated, where ε_{it} is the residual of the ordinary least squares estimate of $\varepsilon_{it} = v_{it} - u_{it}$. Using the conditional distribution, $f(u_{it}|\varepsilon_{it})$, the TE of each farm is calculated as

$$TE_{it} = E(exp(-u_{it}|\varepsilon_{it}))$$
(12)

where TE_{it} is TE of farm *i* in year *t*.

Based on the stochastic production function in Equation 1, output oriented TE is defined as

$$TE_{it} = \frac{f(x_{jit}; \beta) \exp(v_{it}) \exp(-u_{it})}{f(x_{jit}; \beta) \exp(v_{it})} = \exp(-u_{it})$$
(13)

where TE_{it} measures the ratio of the observed output for farm *i* (the test farm) relative to the frontier farm, given the input vector X_{jit} .

An advantage of SFA is it enables a direct calculation of return to scale (RTS) by taking the first-order derivative of Equation (1) with respect to each input and then summing the elasticity of each input. As discussed above, the elasticity of each input was calculated by taking the first-order derivative of Equation (10) with respect to each input:

$$RTS_k = \frac{\partial y_{it}}{\partial X_{kit}} = \sum_k \beta_k x_k + \delta$$
(14)

where the value of x_k is generally used as the mean of the input k^{th} observation.

The following equation is used to find significant factors affecting efficiency:

$$u_{it} = \zeta + \delta z_{it} \tag{15}$$

where u_{it} is a one-sided disturbance term from the production function, distributed as a truncated N(μ , σ^2), which is a nonnegative disturbance capturing the inefficiency effect. z_{it} includes any demographic and economic variables hypothesized to contribute to inefficiency. ζ , and δ are the parameters to be estimated.

Equations (11) and (15) are estimated simultaneously using maximum likelihood. FRONTIER version 1.1-6 software (Coelli & Henningsen, 2019) and LIMDEP 11 (econometric software 2021) were used for estimating SFA. TE was measured as the value of the output of the *i*th farm relative to the maximum output of an unobserved, fully efficient farm using the same input vector.

A kernel density with logit function (h) was used to examine the efficiency distribution of SFA. A kernel density shows the distribution of a variable non-parametrically without any assumption of the underlying distribution. The horizontal axis in Figure 1(a,b) denotes bandwidth, which is analogous to the bin in a histogram and the vertical axis is a function of frequency observed at bandwidth h:

$$h = 0.9Q/n^{0.2}$$
 (16)

where $Q = \min$ (standard deviation, range/1.5), *n* is the frequency, and the interval is 100.

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Figure 1. (a) Kernel density of the return to scale (upper graph) and (b) kernel density of the technical efficiency (lower graph).

4. Application to surveyed crop farm data in the Western Great Plains

Data for this study were obtained from a series of face-to-face interviews conducted with 141 producers over 4 years (Figure A1). A panel of experts, including county educators from cooperative extension services, managers of farmer-owned cooperatives, agricultural researchers, and executives from producer organizations, was used to identify a representative sample of producers. Bravo-Ureta et al. (2012) emphasize the need for obtaining a random sample of producers to avoid sample selection bias that could limit generalizing TE to the WGP farming population. The survey sample was purposely designed to best represent the overall farm typology in the WGP to minimize sample bias, including a careful selection of farm size, cropping system, and location (Figure A1). The resulting sample included 141 farms from the six states of the WGP, roughly 0.28% of the farming community (NASS, 2016). The modest sample size was necessary since the survey was conducted over a 4-year period (2002-2005) and included a detailed survey that required on-farm visits throughout the year. The survey collected an extensive range of data at a modest number of farms over a multiyear horizon rather than to than a larger sized sample limited by cursory data

Survey findings for revenue, specified production costs, wheat yield, and wheat acreage were compared to survey results published by USDA annual production cost reports

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to minimize concerns over potential sample bias (Table A2). Statistical *t*-tests failed to reject the null hypothesis of equal means for all of the specified revenue and cost variables and wheat yield between the survey and USDA data, providing empirical validation for our survey sample. The only variable where the *t*-test rejected the null hypothesis of equal means was farm size (wheat acres planted). Our sample's average was significantly higher, 1,380 acres, compared to the USDA sample of 395 acres (Table A2). Although our sample contains an unexpectedly larger proportion of bigger farms, the overall effect of farm size on the revenue and cost variables was not significant, implying no apparent scale effect of bigger farms on how they generate revenue and manage production cost. Hence, this comparison implies that our survey sample is generally representative of farming conditions in the WGP, but with a disproportionate number of bigger farms.

For estimating the stochastic frontier production function, total gross revenue for all crops grown on the farm throughout the year was used as the output and expenditures incurred during crop production were used as input. Itemized expenditures include machinery, seed, fertilizer, chemical, labor, land, and miscellaneous costs (Vitale et al., 2019). Certain items specified a more complete accounting of costs, e.g., machinery costs asked producers to list fuel, repairs, depreciation, and interest for owner-operated activities and custom rates when using custom hired operators. Chemicals included the quantity of herbicide, insecticide, and fungicide applied. Labor costs to complete the field operations specified the amount of hired labor as well as family supplied labor valued as an opportunity cost of time spent on farm operations. Land cost was calculated as the value of the county's average cash rent value times the farm's crop acres, including fallow acres. Miscellaneous costs included insurance, operating interest, overhead, and taxes, housing, and interest (THI) (Table A3).

As shown in Table A4, explanatory factors in the efficiency model include demographic variables: producer age, formal years of education, and the number of years the farm had been operated. Government payments, crop insurance, off-farm income, and cattle were also surveyed. Production practices included insecticide, machinery and implements, tillage system(s), custom services, land rental and its tenure (cash versus crop sharing), crop diversity, and farm size. Year and state variables were included in the efficiency calculations to account for variation across time and among locations.

Crop diversity, farm size, and the tillage system were employed as discrete variables based on previous research (Chauhan et al., 2006; Mugera & Langemeier, 2011; Vitale et al., 2019). Crop diversity was classified based on the proportion of the total cropped land used for wheat and fallow land (Vitale et al., 2019). Farms in the upper 25% of this diversity measure were classified as wheat-only, those in the lower 25% as full diversity, and the remaining farms in the middle 50% as some diversity. Farm size was based on a system used by Mugera and Langemeier (2011) in which farms with annual revenue less than \$100,000 were classified as very small farms, revenue from \$100,000 to \$250,000 as small farms, revenue from \$250,000 to \$500,000 as medium farms, and large farms with revenue greater than \$500,000. Three discrete tillage groups were established based on number of tillage passes prior to planting: no-till, minimum till, and conventional till (Chauhan et al., 2006; Vitale et al., 2019). Fields not tilled were grouped as no-till. Fields with one or two passes were designated as minimum till.

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		Modified				
Variables	BC95 ^a	Pitt-Lee ^b	Alvarez et al. ^c	Pitt-Lee ^d		Sickle et al. ^e
Constant	5.29 ***	2.91	4.66 ***	4.65		-
Land	-0.60	-0.17	-0.08	-0.89 *		-1.47 ***
Machinery	-0.27	0.13	-0.32	-0.46		-1.12 ***
Seeds	1.00 ***	0.22	0.84 ***	-0.08		0.32
Fertilizer	0.03	-0.10	-0.06	-0.07		-0.07 *
Chemicals	0.06	0.07	0.09	0.09		0.18 ***
Labor	0.41	-0.25	0.41	0.11		1.05 ***
Miscellaneous	0.42	1.24 **	0.20	2.08 ***		1.86 ***
Land2	0.19 *	-0.12	0.10	-0.01		0.09
Machinery2	0.17	0.28 *	0.19	0.36 **		0.41 ***
Seeds2	-0.17 **	-0.19	-0.11	-0.17		-0.06
Fertilizer2	0.00	-0.01	0.00	0.00		0.02 ***
Chemical2	0.01 ***	0.00	0.01 ***	0.00		0.01 ***
Labor2	0.03	-0.01	0.05 **	-0.01		0.07 ***
Miscellaneous2	-0.12	-0.13	0.08	-0.09		0.06
Land*machinery	-0.09	-0.31	0.02	-0.17		0.12
Land*seeds	0.09	0.58 ***	0.21 *	0.05 **		0.66 ***
Land*fertilizer	0.01	0.02	0.04 **	0.04		0.04 **
Land*chemicals	-0.03 **	-0.06	-0.07 ***	-0.08		-0.10 ***
Land*labor	-0.14 *	0.19	-0.29 *	0.15		-0.21
Land*miscellaneous	0.03	-0.02	-0.13	-0.14		-0.38 **
Machinery*seeds	-0.01	-0.20	-0.13	-0.18		-0.48 ***
Machinery*fertilizer	-0.01	-0.02	-0.02	-0.03 **		-0.02
Machinery*chemicals	0.02	0.04	0.04	0.05		0.02
Machinery*labor	0.09	0.03	0.16	-0.02		-0.01
Machinery*miscellaneous	-0.12	-0.08	-0.36 *	-0.26		-0.26
Seeds*fertilizer	-0.01	-0.03	-0.03 *	-0.02		-0.00
Seeds*chemicals	0.00	-0.00	0.01	0.01		-0.02
Seeds*labor	-0.09 **	-0.19	-0.20 **	-0.18		-0.22 ***
Seeds*miscellaneous	0.08	0.12	0.16	0.20		0.08
Fertilizer*chemicals	0.00 **	-0.00	-0.00	0.00		-0.00
Fertilizer*labor	0.00	0.03	0.01	0.04		0.02 *
Fertilizer*miscellaneous	0.01	0.03	0.01	-0.00		-0.04 **
Chemicals*labor	-0.01	-0.01	-0.02	-0.02		-0.00
Chemicals*miscellaneous	0.01	0.02	0.01	0.03		0.06 ***
Labor*miscellaneous	0.09	-0.00	0.20	0.01		0.13
Year (shifter)	0.29 ***	0.13 ***	0.17 ***	0.12	***	0.12 **
2003	0.20 ***	0.06 **	0.11 *	0.05	*	0.05 *
2004	0.22 ***	0.10	0.16 ***	0.71		0.09 **
2005						
Gamma ^a	0.47 ***	0.22 ***				
Sigma square	0.04 ***	0.24 ***	0.19 ***	0.14	***	0.19 ***
Log likelihood value	147	40	134	-38		-26
No. of Obs.			564			

Table 2.	Five	different	stochastic	frontier	translog	production	functions.
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^aBC95: Battese and Coelli (1995)'s time-varying inefficiency model.

^bModified Pitt and Lee: Pitt and Lee (1981)'s time invariant inefficiency, random effect model with normal distribution (frontier component residual) - normal truncated distribution(inefficiency component residual).

^cAlverez et al. : Alverez, Amsler, Orea and Schmidt (2006)'s equality constrained scaling model.

^dPitt and Lee (1981)'s random effect model with normal-normal half model.

^eCornwell, Schmidt and Sickles (1990)'s time invariant inefficiency, fixed effect model. ^fGamma is a parameter indicating inefficiency effect.

^gSingle, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level, respectively.

5. Results

5.1. Estimated production function

Five alternative SF production functions were estimated based on our data: BC95 (Battese & Coelli, 1995), Modified Pitt–Lee (Pitt & Lee, 1981; LIMDEP 2021), Alvarez et al. (2006), Pitt and Lee (1981), and Cornwell et al. (1990). Alvarez et al. (2006) list six criteria that can be used to choose the most appropriate model for analysis. Given the common data set used in both the production function and technical efficiency estimations across all models, the log-likelihood (LL) was used as the model performance, and has generally been found to provide the most accurate selection. Based on a comparison of the log-likelihood values, the BC95 model was chosen since it produced the strongest econometric fit (LL = 140.90) to the empirical data than the alternatives, with the Alvarez et al.'s model providing the next best fit (LL = 134), while the other three had substantially weaker explanatory power with LL values ranging from 40 to -23 (Table 2). A subsequent correlation of parameter estimates indicates that the BC95 and Alvarez et al.'s models had similar estimates to one another with a correlation of 0.996 while the other three models were much less correlated to either of these two models as well as to one another.

The BC95 translog model identified 14 significant regression variables out of a total of 34, which included linear, quadratic, and interaction terms arising from the seven production inputs, year dummy variables, and regression parameters explaining production function (Table 2). The two production inputs that had the most significant explanatory effect were seeds and land, which were found to be significant (P < 0.05) in three of the translog model's variables. Seeds were significant as both a linear and quadratic term and through the interaction with labor, while land was significant as a quadratic term and through the interaction with both chemicals and labor. Chemicals had two significant interactions, one through land and the other fertilizer. Year, included as a fixed effect, was significant in each year from 2002 through 2005.

Because of use of quadratic and interaction terms, variables included in more than one term could have counteracting effects, weakening its overall significance. In such cases, it is necessary to test significance, and to measure effects, based on the elasticity of each variable. A log likelihood test was conducted to determine the overall statistical significance using the null hypothesis that, for each production input, its value in any of the translog regression variables is 0, including linear, quadratic and interaction terms. Results from the log likelihood test found that five of the seven production input

 Table 3. Mean elasticity of translog production function inputs and return to scale (RTS) by state from

 BC95 model.

	Land	Machinery	Seed	Fertilizer	Chemicals	Labor	Miscellaneous	RTS ^b
Mean of input elasticity	^a 0.26***	0.15***	0.13***	-0.01**	0.04***	0.03	0.02	0.61
Colorado	0.33	0.12	0.16	0.00	0.03	-0.03	0.02	0.63
Nebraska	0.24	0.19	0.02	-0.01	0.04	0.00	0.08	0.56
Kansas	0.28	0.12	0.18	-0.01	0.03	0.03	0.00	0.64
Oklahoma	0.27	0.15	0.04	0.00	0.04	0.04	0.03	0.56
Texas	0.17	0.16	0.24	-0.01	0.05	0.09	-0.04	0.66
Wyoming	0.19	0.19	0.16	-0.01	0.04	0.05	0.01	0.63

^aSingle, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level, respectively. ^bRepresents the sum of the means for the elasticity of the individual inputs. variables had a significant effect (P < 0.05) in the translog production function: land, machinery, seeds, fertilizer, and chemicals, whereas labor and miscellaneous were not significant (Table 3).

Land had the highest elasticity at 0.26, indicating that a unit (% increase) in farm size would increase farm output by 0.26% (Table 3). Machinery and seeds had the second and third highest elasticities of 0.15 and 0.13, respectively. The elasticity of inputs effects suggests that land, machinery, and seeds are the most economically productive inputs in crop production in the WGP. The remaining two production inputs, labor and miscellaneous, were not significant (P > 0.05), indicating they did not meaningfully contribute to farm output (as measured by total crop revenue).

Fertilizer had a slightly negative elasticity value of -0.01 in Texas, Kansas, Wyoming, and Nebraska and was not significant in Oklahoma and Colorado (Table 3). This suggests that either WGP farms are already at efficient fertilizer levels or were not applying fertilizer in a timely manner and/or at optimal rates. The distribution across states in terms of chemicals, labor, and other inputs had much less variation. One noteworthy exception was the negative effect of labor in Colorado (-0.03), suggesting that farms in Colorado are perhaps lagging other states in the training and supervision of labor, and that efforts to improve these areas should be able to increase levels to those found neighboring WGP states.

5.2. Returns to scale (RTS)

Based on Equation (14) of BC95 model, the estimated RTS of each input elasticity shows an average RTS for all production inputs in the WGP was 0.61 (Table 3). Figure 1(a) illustrates that RTS scores had a normal distribution around mean 0.6, but less dispersion with sharp peaks around 0.6. Total crop output (revenue) thus increased less than the total quantity of inputs, indicating crop production in the WGP can be characterized as having decreasing RTS (DRTS). Mugera and Langemeier (2011) and Vitale et al. (2019) have also reported a decreasing RTS in the WGP. DRTS indicates that the wheat farms in the WGP are improperly scaled and that they are oversized and could be explained by the larger number of farms that manage both crops and cattle in integrated farming systems.

lable 4. Mea	n output-orient	ed TE by year and sta	te from BC95	model.
	Mean	Standard Error	Min.	Max.
Year				
2002	0.59	0.21	0.22	1
2003	0.53	0.22	0.21	1
2004	0.55	0.23	0.10	1
2005	0.58	0.23	0.18	1
State				
Colorado	0.51	0.22	0.18	1
Kansas	0.76	0.18	0.38	1
Nebraska	0.41	0.11	0.24	0.65
Oklahoma	0.67	0.22	0.22	1
Texas	0.55	0.20	0.20	1
Wyoming	0.38	0.11	0.10	0.66
Mean	0.56	0.22	0.10	1

5.3. Measuring TE

The mean TE across all six WGP states over the four-year study period, as defined by Equation (13) and estimated based on Equation (12), was 0.56 (Table 4). The mean TE score of 0.56 was slightly lower than the average efficiency of 0.59 that Mugera and Langemeier (2011) found for Kansas crop and livestock farms between 1993 and 2007 but is much lower than findings from other studies which ranged between 0.60 and 0.93 as reported in Table 1 (Chavas & Aliber, 1993; Featherstone et al., 1997; Olson & Vu, 2009; Rowland et al., 1998).

A Wilcoxon test was used for testing mean difference of efficiency across state with the null hypothesis of no difference in mean TE scores. Results of the Wilcoxon tests failed to accept the null hypothesis indicating that TE scores were significantly different (P < 0.05) among states. Technical efficiency scores ranged from a high of 0.76 in Kansas farms to a low of 0.38 in Wyoming farms (Table 4). The wide range of TE scores across state

Variables	BC95	Modified Pitt-Lee	Alvarez et al.
Constant	0.74 ***	7.17**	0.25 **
Age	0.00	0.00	0.01
Education	0.01	-0.04	0.04 ***
Family tenure	0.00	0.00	0.00 *
Gov't. payments	1.05 ***	-4.56	1.27 ***
Insurance payments	0.36 ***	2.57	0.43 ***
Off-farm income	0.06 **	0.20	0.10 *
Yes			
Livestock	-0.02	-0.28	-0.05
Yes			
Use of insecticide	-0.07 **	-1.13 *	-0.17 ***
Yes			
Power machines	-0.01	0.06	-0.01
Implements	0.01	-0.01	-0.00
Hiring Custom services	0.02	2.51	0.08
Cash-rented land	0.02	0.30	0.05
Crop share rate	0.06 *	0.12	0.11 **
Crop diversity	0.00	0.02	0.03
Some diversity	-0.02	-0.13	0.03
Full diversity			
Farm size	0.43 ***	-2.66 **	-0.48 ***
Small	-0.78 **	-3.94 ***	-1.21 **
Medium	-105.95 *	-6.80 **	-11.43 *
Large			
Tillage	-0.01 **	0.78	0.05
Minimum till	-0.09	-0.59	-0.04
Conventional till			
Year	0.03 ***		0.28 ***
2003	0.03 ***		0.23 ***
2004	0.02 ***		0.27 ***
2005			
State	-0.01 *	-2.67	-0.20 *
Kansas	-0.00 ***	0.38	0.01 *
Nebraska	-0.00	-1.32	0.04
Oklahoma	-0.02	-0.33	-0.10
Texas	0.01	1.19	0.13
Wyoming			
Log likelihood value	147	40	134
No. of Obs.		544	

Table 5. Three different inefficiency effect models for finding significant factors affecting TE.

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counties likely resulted from differences in climate, cropping patterns, and the other factors discussed below.

Figure 1(b) shows the distribution of the TE. The kernel density was spread relatively widely, but there were two peaks, one around the mean, and a second near 1.0. The peak near 1.0 indicates that there was a cluster of highly efficient producers that could serve as a benchmark for the less efficient producers clustered around the mean of 0.56. Overall, the TE measure indicates that producers in the WGP have been moderately successful in organizing and implementing their farming operations. This is an encouraging result because winter wheat, the dominant crop in the region, has a significant gap between planting and harvest (typically 9 months), making it one of the more challenging crops to produce. Adverse weather and pests can harm crops, and markets can turn volatile during the extended nine-month growing season.

5.4. Demographic and economic factors affecting TE

A one-step regression approach that simultaneously estimated TE and inefficiency effects was used to determine whether the demographic and economic factors characterizing farms could significantly explain TE (Equation 15). This part of the regression model provided a good fit to the data as several regression variables were significant and each had signs as expected: government payments, insurance payments, off-farm income, insecticide use, crop share rate, farm size, tillage, year effect and the intercept term also affected the inefficiency score (Table 5).

Government payments had a significant positive effect (1.05) on technical inefficiency, indicating that additional government payments *ceteris paribus* decreased TE (Table 5). In each year of the survey (2002–2005), government payments to producers included both direct and counter cyclical payments. Direct payments serve as a safety net providing an alternative revenue safety net and counter cyclical payments serve as a price safety net. Producers hence received government payments when crop prices or revenues were lower than those associated with a base year, which was typically established based on prior averages of prices dating back as far as 5 years. Government payments can cause a moral hazard problem because revenue is protected through crop price stabilization, thus reducing the incentive to optimally manage crop productivity and subsequently reducing revenue. Our results are consistent with Kumbhakar (2002), and Latruffe et al. (2017), who also identified a negative relationship between government payments and TE.

Insurance payments also had a significant, positive effect on inefficiency (0.36) indicating higher crop insurance payments decreased TE (Table 4). A likely explanation is the moral hazard associated with crop insurance that provides guaranteed payments when crops fail and reduces incentives to employ improved production practices that would better protect crops. Crop insurance can artificially reduce the financial risk for producers to a point where they even employ cropping strategies that seek insurance payments rather than minimizing exposure to actuarial risk from yield and price uncertainty. This result was different from that of Agahi et al. (2008) who found a positive relationship between crop insurance and TE in the Middle East region among dryland wheat farmers. This difference could be explained by differences in the study regions in terms of their policy and marketing conditions.

Off-farm income had a significant (P < 0.05) positive effect (0.06) on technical inefficiency, indicating that producers who receive a large proportion of their income from off-farm activities may have less incentive to increase TE (Table 5). Our results are similar to those of Langemeier and Bradford (2005), who found a positive relationship between efficiency and time devoted to farming. This outcome was expected because producers who concentrate only on farming are able to dedicate more time to their farm and better positioned to optimize their operations and achieve a higher TE. This result also suggests that full-time producers likely gain additional knowledge and experience that translate over time into improved management and greater levels of TE.

Insecticide use had a significant (P < 0.05) and negative effect (-0.07) on technical inefficiency. This was an expected effect because the WGP area has a variety of insect pests that can economically damage crops, including aphids, mites, armyworms, caterpillars, cutworms, grasshoppers, etc. The results suggest that the producers in the WGP who applied insecticides did so in a timely manner and generated greater output compared to those who did not use insecticide as intensively.

Producers who rent land on a crop share their production with landowners. A typical crop share arrangement for dryland wheat is that landowners typically provide one-third of seed and fertilizer to the leasing producer and in return receive one-third of the crop production. This type of crop sharing had a significant and negative effect (0.06) on technical efficiency (Table 5). There has been a recent trend towards cash renting rather than crop sharing, but cash renting did not have a significant effect on TE. The results suggest that, while there are efforts to provide equity in land-rental contracts, the use of direct cash payments is advantageous to both parties because it does not have a negative effect on TE. The use of crop sharing as a rental agreement likely reduces the incentive for the producer to optimally manage the fields, resulting in a lower TE. These results also indicate that renting and increases farm size, thus exceeding the optimal size given the management level and capital resources available. This is consistent with Giannakas et al. (2001), who reported that short-term lease agreements and a lack of incentives to maintain suitable agronomic conditions in the long-term results in land rental having a negative effect on TE. Crop sharing is also likely to result in a less equitable sharing of the risk, with the producers bearing more of the risk, leading to a less intensive use of inputs and resources, thus reducing TE.

Farm size also contributed to TE but with mixed effects. For example, small farms were more technically efficient than very small farms, and medium farms more technically efficient than both very small and small farms (Table 5). However, large farms were not efficient compared to very small farms. This is consistent with our RTS results that found farms with DRTS. These results suggest that there are TE gains that can be achieved and maintained in moving from very small- to medium-sized but farms falling into the large category were less able to optimally manage their inputs and resources, thus operating at lower TE levels (Table 5). This farm size-scale relationship is consistent with Byrnes et al. (1987) and Mugera and Langemeier (2011) both of whom found small farms in Illinois and Kansas more scale efficient than larger sized farms

Our findings on size and scale are in partial agreement with previous research that identified a consistently positive relationship between farm size and technical efficiency (Featherstone et al., 1997; Mugera & Langemeier, 2011; Olson & Vu, 2009; Paul et al., 2004). Efficiency gains can be explained by pecuniary economies of scale. Machinery

generates a comparative advantage in per acre production costs for larger farms and, over the long term, the accumulation of landholdings, as seen in the increased farm size of U.S. corn producers over the past several decades (Paul et al., 2004). Farms with larger landholdings spread the fixed costs of assets over more acres than their smaller counterparts, reducing their unit fixed costs. Compared to their smaller counterparts, larger farms also have greater access to resources such as financial capital and are better to handle risk. Family labor also tends to be better used with greater demand and shorter periods of slack labor.

Conventionally tilled farms were more efficient than no-tilled farm (Table 5). Despite this, WGP producers continue to use no-till. The greater efficiency of conventional tillage is likely explained by the dominant soil structure in the WGP. Combined with the low rainfall, producers often till their land four or five times prior to planting. Year effect shows that efficiency is different from year to year. The significance of year was likely explained by the changes in the weather and pest outbreaks from one year to the next. Age, education, family operating year, livestock ownership, the number of machines, hiring custom services, the lease rate, and diversity did not have any significant effects on TE.

6. Conclusions and implications

The mean TE score of 0.56 estimated for WGP farms is consistent with results from Mugera and Langemeier (2011) which found an average TE of 0.59 for Kansas wheat farms, though both imply low management performance compared to Western Canadian producers TE score of 0.76 during the same time period. Farm management in the WGP is even less impressive when compared to findings from a variety of enterprises including corn, soybean, dairy and beef cattle whose TE scores typically range from 0.70 to 0.90 (Table 1). This is an important finding since it suggests WGP producers are not utilizing capital and technology to its fullest extent or even to the level of other producers. One possible explanation is that wheat technology and practices have a steeper learning curve and are more difficult to implement than those other enterprises. Whether or not this is the case, extension efforts should concentrate on transferring successful techniques from other regions to improve WGP efficiency. Best farmer workshops, training efforts, and collaboration among farms can successfully transfer skills and techniques from efficient to inefficient farms.

Regional disparity in efficiency could also be caused by technology gaps between wheat and other crops such as corn and soybean. Small grain crops such as wheat and sorghum have had substantially less investment over the past few decades and have lagged in productivity gains to corn, cotton, and soybean. This is in part caused by investment bias that is usually found in government funded sectors such as agriculture where funding is disproportionally earmarked towards more productive and hence politically favored crops such as corn and specialty crops. Overall equity must also be considered to assure that regions such as the WGP are not placed at a long-term disadvantage. This will require policy makers and planners to allocate funding not solely on rates of return but to also factor in regional equity.

Positive factors affecting TE were insecticide use, farm size, and tillage system. The positive effect of insecticide use on TE suggests that extension efforts should encourage, if not already do so, the timely and proper application of insecticides. This includes routine scouting of fields, the development of economic thresholds, and applying recommended

quantities once pest counts exceed threshold levels. Applying insecticides has been reported to reduce crop yield loss from 20% to 60%. Survey results indicate 79% of the farms applied insecticides during the study period suggesting that most producers spray on a regular basis but extension efforts should continue to monitor the optimal application. Although effect of applying insecticide is different in different region due to different weather, optimal timing and targeting the correct insects when applying insecticides increase total revenue with better crop protection.

Across all six states, farms were on average producing with decreasing RTS, indicating that the farms in this area are too large compared to better-configured farms identified as operating under constant RTS. Decreasing RTS implies farms per acre production costs are higher than farms producing in CRTS or IRTS. Care, however, must be taken when analyzing farm scale since farm size is fixed in the short run and even when changed has major implications. Reducing farm size to reduce per acre costs is not a recommended policy action since it is likely to have unintended consequences on net farm income likely to jeopardize household welfare. Rather, lower production costs are better achieved through ameliorating existing inefficiencies including those identified by this study identified such as fertilizer use and government payments.

In addition, conventional tillage performed better than no-till operation in the WGP. Because of protecting soil erosion and reducing labor cost, no-till has been popular in this region. However, our results show conventional tillage generates higher crop yields than no-till. Future research is required to developing improved no-till techniques such as providing lower cost of no-till equipment, better herbicides to control weed problems, and alternative crops and crop rotations to replace the wheat monoculture.

The weak relationship between TE and government payments suggests that policymakers should reconsider how government payments and crop insurance can be structured. According to the model results, to increase TE, government payments should be bundled with incentive packages that enhance farm productivity, perhaps by encouraging environmentally friendly farming practices, which would reduce negative externalities while improving long-run sustainability. Existing U.S. farm programs encourage producers to be self-motivated and develop conservation plans that best conform to their unique farming situation rather than implementing a one-size fits all approach. The EQIP program for example partners agents from the NRCS to work one-on-one with producers to develop a conservation plan to conserve resources such as soil and water to reduce farm's environmental footprint (Lichtenberg, 2014). Results from efficiency studies could be used as input to EQIP plans to implement improved practices such as no-till that can simultaneously increase TE while safeguarding natural resources.

Results from this study suggest several sources of inefficiency that such extension work can target. Given the inefficient use of fertilizer highlighted in this study, it is likely that farms are using field-level fertilizer application rates that cannot account for field variability and plant growth. Soil testing could be an important factor that tells producers how much and which fertilizers they might use.

Age, education, family tenure, off-farm income, power machines, implements hiring custom services, crop share rate, having livestock (cattle ranching) and crop diversity did not have any effect on TE. The non-significance of livestock is an unexpected result and a potential source of future research for extension efforts. Prior research has most often found a positive effect of crop–livestock interaction on farm efficiency due to the complementary

aspects of producing both enterprises. Most notably, in the WGP dual-purpose wheat, wherein cattle graze on early season wheat has been generally considered as having positive benefits. Crop diversity was also expected to have had an effect on TE as the use of cover crops and crop rotation has been considered to provide agronomic benefits to wheat through reduced pest and weed protection and improved soil moisture. Future research will need to assess how beneficial dual-purpose wheat and crop diversity are for WGP producers.

Future research will be needed to identify additional factors related to optimal farm management. Future research could include farm surveys that investigate a wider range of farm manager characteristics and financial variables such as the debt–asset ratio, returns to assets, and capital borrowing that. Producers' access to extension information services could also provide additional explanatory power.

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Appendix A

sante) ea regioni		
Crop	No. of Obs.	Planted Acres
Alfalfa	94	216
Barley	10	128
Canola	5	181
Corn	103	322
Cotton	57	376
Millet (Hay)	53	188
Millet (Proso)	107	587
Oats	21	151
Oats (Hay)	20	154
Red top cane (Hay)	7	79
Sorghum (Forage)	25	290
Sorghum (Grain)	238	448
Sorghum Sudan	89	118
Soybeans	57	275
Sunflowers (Conf)	23	666
Sunflowers (Oil)	85	361
Winter wheat	561	1,341

Table A1. Planted acres and number of farms by crop in the surveyed region.

Crops with fewer than five observations are not presented. Source: Survey for this study.

Table A2. Comparison of findings from USDA estimates of wheat cost and returns for the USDA prairie gateway region, 2002–2005, to average findings from the study survey for states included in both estimates.

		USDA Cost of Production Estimates ^a				Sur	vey ^b		
ltem	Units	2002	2003	2004	2005	2002	2003	2004	2005
Revenue: wheat grain	\$/acre	65.49	100.23	101.32	98.27	54.64	104.73	88.48	94.96
Revenue: straw/grazing	\$/acre	2.78	2.54	6.72	7.33	11.37	11.78	10.95	11.17
Total gross revenue	\$/acre	68.27	102.77	108.04	105.60	66.01	116.51	99.43	106.13
Seed cost	\$/acre	4.53	5.25	5.42	5.70	7.75	7.79	7.81	7.78
Fertilizer cost	\$/acre	14.18	18.54	19.84	23.24	18.41	21.55	25.20	24.59
Chemicals cost	\$/acre	3.15	3.16	3.75	3.81	5.22	4.75	5.73	5.96
Custom operations	\$/acre	6.61	8.05	6.24	6.29	5.74	7.51	7.20	7.85
Hired labor cost	\$/acre	2.06	2.15	2.27	2.34	2.70	3.03	2.94	2.66
Wheat yield	bu/acre	22.2	35.2	29.2	31.7	20.3	34.0	31.2	32.7
Wheat acres	Acres	347	347	443	443	1,314	1,447	1,298	1,463

^aEstimates produced by the USDA cost of production surveys. The Prairie Gateway Region includes parts of Colorado, Oklahoma, and Texas.

^bEstimates produced by the current study.

Table A3. Summary statistic	s for the data	used to calculate	efficiency (\$/proc	lucer/vear).

Variables	No. of Obs.	Mean	Standard Deviation	Max.	Min.
Revenue	564	240,614	207,593	1,748,716	3,157
Machinery	564	50,379	50,113	460,117	1,787
Seeds	564	15,645	15,002	114,513	420
Fertilizer	564	33,982	39,848	263,601	0
Chemicals	564	22,163	41,275	457,999	0
Labor	564	6,255	5,012	43,434	0
Miscellaneous	564	20,869	22,621	274,929	342
Land	564	62,501	55,634	438,843	2,920

Variables	Definition	Mean	Standard Deviation
Age	Operator age (years)	49.40	10.67
Education	Operator formal education (years)	14.70	1.59
Family tenure	Years of operation by the farm family	72.03	33.00
Gov't payments	Prop. of gov. payments to total revenue	0.14	0.08
Insurance payments	Prop. of insurance payments to total revenue	0.12	0.19
Off-farm income	No = 0, yes = 1	0.72	0.45
Livestock	No = 0, yes = 1	0.79	0.41
Use of insecticide	No = 0, yes = 1	0.80	0.36
Power machines	Number of power machines, including tractors	4.70	2.36
Implements	Number of unpowered implements	11.50	5.10
Hiring custom services	% of field operations conducted by hired custom operators	0.16	0.18
Cash-rented land	% of farm land cash leased to total cropped land	0.16	0.23
Crop share rate	% of farm land crop share leased to total cropped land	0.42	0.33
Crop diversity	Wheat-only = 0, some diversity = 1, full diversity = 2	1.00	0.70
Farm size	Very small = 0, small = 1, medium = 2, large = 3	1.20	0.90
Tillage	No till = 0, minimum till = 1, conventional till = 2	1.20	0.68
No. of Obs.	544ª		

Table A4. Summary statistics for the variables used for finding significant factors affecting efficiency.

^aMissing data from a total of 564 observations excluded.



Figure A1. Locations and number of surveyed farms.