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RESEARCH ARTICLE

Farm Efficiency and Precision Agriculture Technology

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Abstract
Precision agriculture technology (PAT) is often viewed as a potential driver of future efficiency gains in farming. Using within-farm variation from an unbalanced panel of Kansas farms, this study examines the impact of PAT bundles on efficiency in generating gross revenue. On average, we find little evidence that these technologies improve efficiency. However, among less efficient farms, several bundles are linked to notable efficiency gains, underscoring the importance of accounting for farm heterogeneity.

Keywords: Data envelopment analysis; farm efficiency; precision agriculture

JEL classifications: Q16; Q12; Q14

1. Introduction

Precision agriculture technology (PAT) is considered an important economic factor for the future of agricultural efficiency, increasing production or allocating inputs more sustainably (Bullock et al., 2009; Kolady et al., 2021; Tey and Brindal, 2012). Previous studies have examined farmers' adoption decisions[1] and economic outcomes.[2] However, the question of how PATs impact farm financial returns is unclear (Griffin et al., 2018; Lowenberg-DeBoer, 2019). Even at the individual operation level, Farmers themselves often struggle to identify the financial returns of their technology investments. (Thompson et al., 2019). This reality is likely driven by PATs that provide difficult-to-measure indirect effects on production (Griffin et al., 2018; Shockley et al., 2012) and the synergistic effects that arise when technologies are used together (Lambert et al., 2015; Miller et al., 2017). Further adding complexity to the task of identifying the returns to PAT, farmers are likely to have unobservable characteristics that influence both the adoption decision and their financial outcomes (DeLay et al., 2022; McFadden et al., 2022).

This study uses a two-stage data envelopment analysis (DEA) to capture both the direct and indirect effects of PAT on farm efficiency in generating gross revenue. Specifically, instead of examining agricultural production output as in previous studies (e.g. DeLay et al., 2022;

[1]See Bramley (2009); Daberkow and McBride (2003); Erickson et al. (2017); Fernandez-Cornejo et al. (2001); Khanna et al. (1999); Lowenberg-DeBoer and Erickson (2019); Lowenberg-DeBoer (2019); McFadden et al. (2023); Roberts et al. (2004); Thompson et al. (2021).

[2]See Coble et al. (2018); Bullock et al. (1998); Bullock and Bullock (2000); Bullock et al. (2002); Bullock and Lowenberg-DeBoer (2007); Dhoubhadel (2020); Lowenberg-DeBoer (2003); Schimmelpfennig (2016, 2018); Tenkorang and Lowenberg-DeBoer (2008).

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McFadden et al., 2022), we establish cost-minimizing frontiers for farm gross revenue.[3] This modeling choice captures the combined direct effects and indirect effects, like changes in field efficiency (Shockley et al., 2011), convenience increasing farmers' capacity for other management tasks (Daberkow and McBride, 2003; Thompson et al., 2019), and shortening information transfer from principles to non-owner operators (Deininger and Byerlee, 2012). Additionally, we capture the indirect effect of using PATs together, or in a bundle. Farmers often use multiple technologies together (Miller et al., 2019), and the degree to which different technologies may generate financial returns depends on using outside information (Bullock et al., 2009; Swinton and Lowenberg-DeBoer, 1998). Measuring changes in cost efficiency for generating gross revenue allows us to capture the effects of bundling and the complementary effects of information generated and used by different PATs.

This study aims to estimate the within-farm effects of PAT use on farms' efficiency in generating gross revenue. We use an unbalanced panel of Kansas farms and a two-stage DEA, with two-way fixed effects regressions, to account for unobservable characteristics that may influence both PAT adoption and revenue efficiency, such as management ability. Specifically, we compute yearly cost-minimizing frontiers and measure each farm's relative efficiency. Because efficiency scores are bounded between 0 and 1, a two-way fixed effects model estimated with ordinary least squares (OLS) does not fully account for this censoring. However, our objective is to identify within-farm changes associated with PAT adoption, and the inclusion of binary adoption indicators is best suited to the linear fixed effects framework. While nonlinear estimators, such as a Tobit with Mundlak corrections, are often applied to censored outcomes, they can obscure the variation we seek to exploit and substantially reduce statistical power. In our sample, observations at the bounds of 0 and 1 are rare, so the risk of bias from using OLS is limited. Further, McDonald (2009) show that DEA scores are not censored, but fractional, and second stage OLS with White (1980) robust standard errors is a consistent estimator of the second stage effects. Taken together, this modeling choice provides a tractable and interpretable way to assess the within-farm efficiency effects of PAT use.

To our knowledge, this study is the first to use an unbalanced panel and farm efficiency in relation to gross revenue to evaluate the effects of PATs. Previous studies have used a similar empirical approach to analyze returns to PAT (DeLay et al., 2022; McFadden et al., 2022), but frequently use physical output, like yield, obscuring any potential indirect effects of PATs on financial performance. The dataset includes detailed financial information on 570 unique farms and 7,245 observations over the 21 year period from 2002 to 2022. Our empirical approach first establishes the cost-minimizing frontier for farm gross revenue. Then using the annual efficient frontier, we compute each farm's annual relative efficiency. Second, the farms' relative efficiency scores are the dependent variable for two-way fixed effects regressions and the farms' reported bundle of PATs are the independent variables. Hence, the role of year-specific price and weather in farm efficiency is removed. Consequently, our results are estimates of the within-farm change in efficiency related to the farm's collection of PATs. An additional benefit of our DEA analysis is that we are able to compute the effects of PAT on overall, pure technical, scale, and allocative efficiency, further characterizing the role of PAT in farm efficiency. Additionally, we estimate the impacts of PAT on farms at various points on the conditional farm efficiency quantiles to examine how the observable characteristics of farms impact the effect of PATs.

It is important to note that our estimates should be interpreted as the correlation between the farms' reported presence of PATs and measures of farm efficiency. Because PAT is often included in new machinery purchases, our methodology does not exclude the possibility that any changes in efficiency could be attributed to the updated machinery and not the inherent technology. However, given the diversity of our data, the choice to use gross revenue as our output and total

[3]Mugera and Langemeier (2011) use DEA, with farm gross revenue as the output, for their analysis of the relationship between farm size and diversification and efficiency.

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assets (including machinery) as an input in our DEA, and the likely presence of classical measurement error due to weather and price variability, we believe that our results are still conservatively indicative of the role of PATs on the efficiency of Kansas farms. Additionally, our results are inherently time averages, which potentially obscures the any effects of PAT that might accrue over time, as discussed by Lowenberg-DeBoer (2003). Despite these limitations, we believe our results related to PAT use on Kansas farms can help inform farm management decision for a broader range of farm operations.

There are two key findings. First, the majority of examined PAT bundles are not associated with an increase in farm overall efficiency. We examine seventeen different bundles of PAT, and only two – guidance alone and yield monitor and grid soil sampling are associated with an increase. Each of these PATs are associated with an increase in allocating inputs in a more cost-effective manner, but guidance is additionally associated with achieving an optimal farm size. Second, less efficient farms are able to experience efficiency gains relative to their more efficient peers. In contrast to the previously mentioned results, five of the seventeen examined bundles are associated with efficiency increases. Of these bundles, they include multiple technologies, suggesting that less efficient farms may benefit from using multiple PATs together. These findings highlight that returns to PAT are likely nuanced and that further research is needed to understand how new agricultural technology can improve efficiency for heterogeneous operations.

This study provides insights for farmers and PAT manufacturers, retailers. First, for farmers, they can carefully evaluate the ways in which potential technologies may impact their operation, without the pressure to adopt quickly, as their does not appear to be a financial motivation for well-managed farms to adopt PATs. Second, for manufacturers and retailers, our results and the fact that previous literature documents uncertainty around financial returns (Griffin et al., 2018; Lowenberg-DeBoer, 2019; Thompson et al., 2019) suggest that considerable effort should be spent quantifying how farms can benefit from these technologies.

The remainder of this study is organized as follows. In the next section, we discuss our research design, two-stage DEA analysis, which combines DEA analysis, two-way fixed effects OLS estimation, and the unbalanced panel of Kansas farms from the Kansas Farm Management Association (KFMA). We then discuss our results, starting with our analysis at the mean, followed by a discussion of the results estimated at the lowest, median, and highest conditional quartile of farm efficiency. We then conclude, summarizing our results and discussing policy implications and future research.

2. Research design

To examine how PAT impacts farm efficiency, controlling for unobservable characteristics of farm managers, this study employs a two-stage DEA research design. In the first stage, cost frontiers are formed for each production year using DEA. Although recent papers have used stochastic frontier analysis for a similar research aim (i.e. DeLay et al., 2022; McFadden et al., 2023), our analysis uses DEA for three reasons. First, DEA allows for multiple outputs. As we will describe in the Data subsection, our sample of farms contains integrated crop and livestock operations. The presence of these two enterprises may impact a farm's ability to benefit from PAT. For example, guidance may be used to simplify the operator's task when applying manure from a livestock enterprise, but simultaneously performing an operation in a manner that maximizes the fertilizer value, increasing the efficiency for crop production. Second, DEA follows all theoretical considerations that a cost frontier must adhere to: symmetry, quasi-concavity, homogeneity, monotonicity, and differentiability. Third, the established cost frontiers can be used to calculate common efficiency metrics such as overall, pure technical, allocative, and scale efficiency. We use these metrics to characterize the changes in farm efficiency related to PAT use. In our second stage, the mentioned farm efficiency metrics (overall, pure technical, allocative, and scale) are used as dependent

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variables in a farm fixed effects regression. The independent variables are binary indicators for the farms' reported bundle of PATs. As a result, our estimates identify the changes in farms' gross revenue efficiency associated with PATs.

2.1. Stage one: Data envelopment analysis

The input-oriented minimum cost DEA model is represented by the series of linear programming equations below:

$$MC(y_i, x_{im}^*, w_i) = Min \sum_{m=1}^{M} w_{im}^{'} x_{im}^*$$

$$subject\ to:$$

$$\sum_{i=1}^{I} z_i x_{im} \leq x_{qm}^* \forall m = 1, \ldots, M$$

$$\sum_{i=1}^{I} z_i y_{ik} \geq y_{qk} \forall k = 1, \ldots, K$$

$$\sum_{i=1}^{I} z_i = 1 \ (for\ VRS)$$

$$(z_1, \ldots, z_I) \geq 0, \tag{1}$$

where $MC(y_i,x_{im}^*,w_i)$ is the minimum cost to produce the output, w_{im} are the input prices for farm i with respect to input m, x_{qm}^* are the cost-minimizing inputs for farm q with respect to input m, x_{im} are actual inputs used by farm i with respect to input m, z_i measures the weight of each farm when forming the frontier, and y_{ik} is the output k for farm i. All variables are assumed to be strictly positive and z is greater than or equal to zero. This model assumes variable returns to scale technology, which is imposed by constraining all z_i's to sum to one.

Establishing the annual minimum cost frontier provides a standardized efficiency metric for farms. Additionally, inherent in DEA is the ability to calculate various efficiency measures, like overall, pure technical, allocative, and scale efficiency. We use the relative differences in the estimated changes across these efficiency metrics to examine the channels through which PATs impact efficiency.

Overall efficiency is a measure of the optimal cost under constant returns to scale, relative to the actual cost the farm incurred. The formula for overall efficiency is:

$$OE_i = \frac{\sum_{m=1}^{M} w_{im}^{'} x_{im}^{CRS}}{\sum_{m=1}^{M} w_{im}^{'} x_{im}}, \tag{2}$$

where OE_i is the Overall Efficiency for farm i in a given year, $\sum_{m=1}^{M} w_{im}^{'} x_{im}^{CRS}$ is the optimal cost under constant returns to scale for farm i, and $\sum_{m=1}^{M} w_{im}^{'} x_{im}$ is the actual cost incurred by farm i. Overall efficiency ranges from zero to one.

Scale efficiency is a measure of the optimal scale under constant returns to scale, relative to the actual cost the farm incurred. The formula for scale efficiency is:

$$SE_i = \frac{\sum_{m=1}^{M} w_{im}^{'} x_{im}^*}{\sum_{m=1}^{M} w_{im}^{'} x_{im}^{CRS}}, \tag{3}$$

where SE_i is the Scale Efficiency for farm i in a given year, $\sum_{m=1}^{M} w_{im}^{'} x_{im}^*$ is the optimal cost under variable returns to scale for farm i, and $\sum_{m=1}^{M} w_{im}^{'} x_{im}^{CRS}$ is the minimum cost for farm i under

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constant returns to scale. Scale efficiency scores range from zero to one and are a measure of the optimum scale of the firm. A scale efficiency of 1 indicates the firm is at constant returns to scale, a score less than 1 indicates the farm is not at the optimal scale.

In addition to (1), we estimate pure technical efficiency with the following series of linear programming equations:

$$Min\ \lambda_i$$

$$subject\ to:$$

$$\sum_{i=1}^{I} z_i x_{im} \leq \lambda_i x_{im}\ for\ m = 1, \ldots, M$$

$$\sum_{i=1}^{I} z_i y_{ik} \geq y_{qk}\ for\ k = 1, \ldots, K$$

$$\sum_{i=1}^{I} z_k = 1\ (for\ VRS)$$

$$(z_1, \ldots, z_I) \geq 0, \tag{4}$$

where λ_i is the measure of pure technical efficiency for the model. Pure technical efficiency is a measure of how far off the cost frontier a firm is or how efficiently a firm takes inputs and converts them into outputs.

Allocative efficiency is a measure of the optimal input mix for the farm. It measures the distance between the optimal input mix and the input mix the farm actually used. The formula for allocative efficiency is:

$$AE_i = \frac{\sum_{m=1}^{M} w_{im} x_{im}^*}{\sum_{m=1}^{M} w_{im} \lambda_i x_{im}}, \tag{5}$$

where AE_i is the allocative efficiency for farm i, $\sum_{m=1}^{M} w_{im} x_{im}^*$ is the optimal cost under variable returns to scale for farm i, and $\sum_{m=1}^{M} w_{im} \lambda_i x_{im}$ is the actual cost incurred multiplied by pure technical efficiency (λ_i) for farm i. Allocative efficiency ranges from zero to one.

2.2. Stage two: farm fixed effects regression

We use the four efficiency measures, (overall, pure technical, scale, and allocative efficiency) from the previously mentioned DEA and the within-farm variation in bundles of PAT to identify the effects on efficiency using the following equation:

$$\text{Efficiency}_{it} = \alpha + \beta 1\ \text{Bundle}'_{it} + \delta_i + \tau_t + \varepsilon_{it}, \tag{6}$$

where Bundle'_{it} is a vector of dummy variables corresponding to PATs bundles for farm i in time t, δ_i is the farm fixed effect, and τ_t is the year fixed effect. We define Efficiency_{it} with the output from the previous described DEA. Specifically, we are interested in overall efficiency, pure technical efficiency, scale efficiency, and allocative efficiency. Equation (6) is estimated using OLS so that fixed effects may be used to control for time invariant farm characteristics. Robust standard errors are used when estimating this model. This approach does not take into account the possible censorship of the DEA efficiency measures at 0 or 1. However, McDonald (2009) argues that tobit models are inappropriate to analyze the efficiency scores from DEA models as they are generated from a fractional process, not a censoring process. Additionally, within our data, the censorship issue is minimal in most of the years across the four efficiency measures (see Figure 2).

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Our aim is that β captures the within-farm effect of each combination of PATs on farm efficiency. Our DEA efficiency measures are generated separately for each year, controlling for stochastic elements which are common to the year, like weather and prices. Furthermore, τ_t controls for any additional year-specific variation common among farms, yet not captured in the DEA analysis. There is a potential that a farm may experience an idiosyncratic shock that would be reflected in their efficiency, such as region specific weather and prices. However, there is no reason to believe that this idiosyncratic shock follows a pattern over several periods. Thus, although we do not address the potential classic measurement error, we believe that our estimates of β are conservative.

Bundle'_{it} is defined by dummy variables for important PAT and the interactions of these technologies. We include yield monitors, guidance (both lightbar and automated), section control, grid soil sampling, variable rate fertilizer, and variable rate seeding. Each of these technologies are represented with a dummy variable, which takes the value of one if the farm reports using this technology and zero otherwise. The full complement of interaction possibilities with technology is included. For example, we estimate the effect of guidance alone, guidance bundled with each other technology as a pair, guidance bundled with every combination of three technologies, guidance bundled with every combination of four technologies, guidance bundled with every combination of five technologies, and the full bundle of all six technologies. Hence, Bundle'_{it} is a vector of 56 potential bundles of PATs.

2.3. Data

We use an unbalanced panel of Kansas farms from the KFMA to examine the degree to which the use of PAT influences farm efficiency between 2002 and 2022. The panel consists of 7,245 observations from 570 unique farms. Farms that are part of the KFMA data opt-in by becoming members of the management association. In general these types of farm management datasets represent "larger farms" and a higher percentage of crop vs. livestock operations (H. Kuethe et al., 2014). The reporting farms average almost 13 years within the panel. This data has been used by several studies that examine the economics of PAT. For example, a subset of current data was used by Miller et al. (2019) to estimate the propensity to adopt precision agriculture as bundles. Additionally, Ofori et al. (2020) use a subsample of the same data to analyze the time to adoption of Kansas farms. Most pertinent to our study, Dhoubhadel (2020) use a subsample of the same data to show that PAT technologies are not associated with long-term impacts on farm profitability.

Farmers participating in KFMA report both production and financial characteristics. We use their financial metrics for our DEA analysis. We define the farms' output as the gross revenue generated by crop production and livestock production. We define farm inputs as the dollar amounts spent on land, labor, capital, and other variable expenses. All expenses are on an accrual basis. Other variable expenses represent the value of all crop and livestock expenses for the year. Capital is the beginning inventory of all capital assets used on the farm. Labor is the annual dollar amount recorded for labor along with any unpaid operator and/or family labor expense. Unpaid operator and/or family labor is an imputed measure based on the average family living expense over the past three years for the state of Kansas. Land expense is the cash rental expense plus the opportunity cost of the owned land which was calculated using USDA NASS county-level cash rental rates (U.S. Department of Agriculture, National Agriculture Statistics Service, 2024). We retain any farms that reported positive input and output values for analysis.

Table 1 reports the annual means for our two outputs and the four inputs on the represented KFMA farms. The mean livestock receipts show that the average farm in our sample generates less than 20% of their revenue from livestock. Our sample contains many integrated crop and livestock farms, further validating our choice to model two outputs with DEA. The role of variability in weather and prices is exhibited in the mean outputs. There is a steady growth in the value of

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Table 1. Mean of outputs and inputs for data envelop analysis for farms of KFMA 2002 to 2022 (*in US dollars*)

Year	Output			Input		
	Crop	Livestock	Land	Labor	Capital	Expense
2002	202,677	38,765	30,988	38,911	717,949	224,208
2003	242,837	48,989	33,690	39,099	728,983	236,980
2004	268,003	66,745	35,259	42,130	773,000	266,728
2005	280,827	70,166	37,099	43,209	956,985	307,222
2006	296,914	66,951	38,109	42,529	991,173	323,803
2007	406,809	67,577	42,421	62,853	1,020,979	363,560
2008	532,399	62,884	48,274	66,887	1,132,338	442,540
2009	490,144	46,623	49,718	68,737	1,311,398	435,251
2010	517,406	60,174	52,142	72,271	1,592,405	471,025
2011	582,083	103,709	56,355	77,688	1,791,796	540,485
2012	641,927	81,986	63,152	80,387	1,875,481	562,001
2013	639,987	76,178	67,105	86,806	2,109,950	576,880
2014	542,479	100,904	65,888	92,495	2,203,582	581,335
2015	483,368	65,105	68,466	95,948	2,717,015	594,548
2016	542,111	62,406	71,864	98,919	2,628,822	587,313
2017	548,023	83,785	74,731	101,044	2,644,734	614,553
2018	614,290	77,635	75,062	102,672	2,641,775	633,462
2019	668,110	69,875	81,028	109,232	2,853,573	678,877
2020	745,607	76,427	84,583	121,420	3,061,528	688,591
2021	940,818	156,466	83,735	124,334	3,054,990	779,005
2022	835,710	111,555	86,243	122,066	3,247,445	845,140

Source: KFMA 2002 to 2022.

production, as we would expect, but years like 2009, 2014, 2015, and 2022 show an annual decrease in average crop receipts, and 2006, 2008, 2009, 2012, 2013, 2015, 2016, 2018, 2019, and 2022 show an annual decrease in average livestock receipts. Similar trends exist for the four inputs, land, labor, capital, and other variable expenses.

In addition to financial and production records, KFMA also collects information on the use of PAT. Farms voluntarily report this information starting in 2015. The farmer discloses whether they use a specific PAT, the year of first use, and the year of last use or when whether they discontinue the use. In 2015, farms reported their PAT use going back to 2002. As a result, we construct a backward looking representation of the farms' use of PAT starting in 2002. We focus our analysis on the use of yield monitor, guidance, section control, grid soil sampling, variable rate fertilizing, and variable rate seeding. Figure 1 plots the growth of reported use of PAT in the KFMA subsample. These trends are similar to the patterns reported by USDA (McFadden et al., 2022) and Purdue University and CropLife magazine (Erickson et al., 2017).

Table 2 shows the frequency with which each technology bundle occurs in the data. Thirty percent of the farm observations indicate that they did not use any of the technologies during the duration of the study. For clarity, this result could represent a farm that has never used PATs or a farm with PATs in recent years and none in the early years of our analysis. The most common

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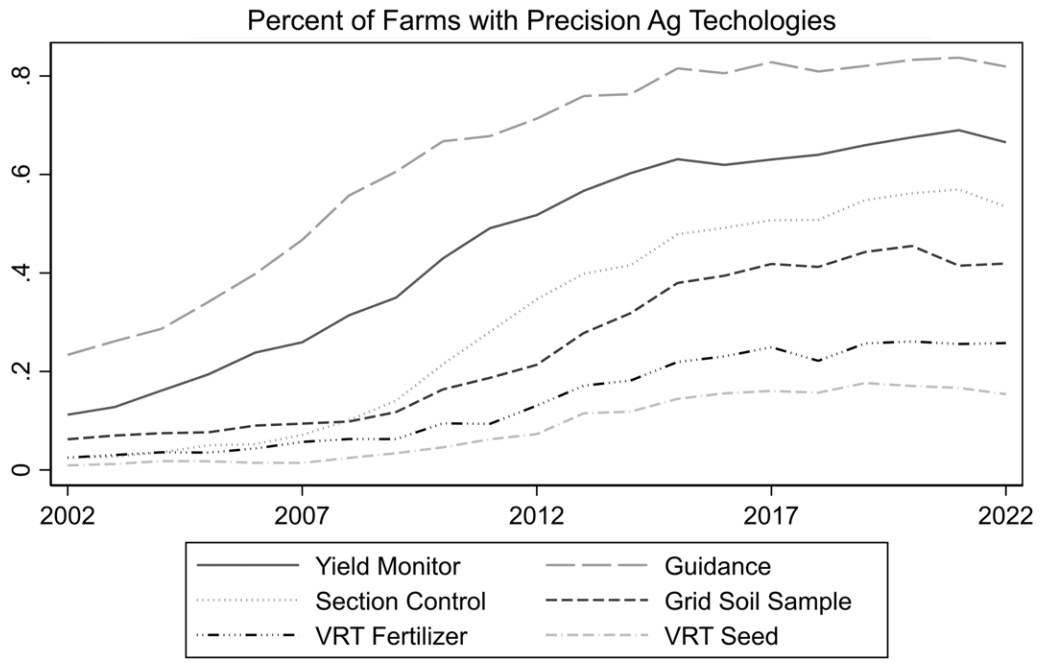


Figure 1. Precision agriculture usage on farms in the Kansas farm management data 2002 to 2022.

technology reported was the use of guidance, with 16.2% of the farm observations indicating that during a given year, guidance was the only technology they had used. We believe that the prevalence of common bundles of technology is suggestive of the perceived gains of technology (Thompson et al., 2019) and a common adoption path (Miller et al., 2017). We choose to limit our analysis to bundles of PAT that account for at least 0.5% of the observations. As a result, Grid Soil Sampling (GRID) is the bundle with the fewest observations included in our analysis.

3. Results

3.1. DEA

Figure 2 reports box and whisker plots of the estimated efficiency scores from our DEA analysis for each year. The top right panel plots the pure technical efficiency as computed by (4) for each year in our data. The top left panel plots the overall efficiency computed by (2). In our sample, the median farms exhibited overall efficiency of 0.2 to 0.35 during our time period. In contrast to the overall efficiency, the median farm in each year exhibited pure technical efficiency between 0.6 and 0.8. The bottom left panel plots the scale efficiency as computed by (3). The scale efficiency exhibits more variation by year, relative to the other efficiency metrics. Lastly, the bottom right panel plots the allocative efficiency as computed by (5). The estimated allocative efficiency of the median farm in each year is in the range of 0.3 to 0.6.

Although the efficiency scores are bounded in [0,1], Figure 2 demonstrates that the distribution of our estimated scores is concentrated well within the interior of this range, with only a negligible share of farms at the boundary. This mitigates the typical concern that censoring at 0 or 1 dominates the regression and biases the results. As Greene (2018) notes, the bias of OLS under censoring is attenuating and proportional to the mass at the boundary. Given the interior concentration of our scores, any attenuation bias is expected to be minimal. Further, our regressors are binary indicators that vary within farms over time. In this setting, the two-way fixed

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Table 2. Precision agriculture technology bundle frequency in KFMA 2002 to 2022. Bundles highlighted in light gray are used in our analysis

	Frequency	Percent	Cumulative
NONE	2,188	30.20%	30.20%
GDNC	1,174	16.20%	46.40%
YM × GDNC	772	10.66%	57.06%
YM × GDNC × SC_CNTL	617	8.52%	65.58%
YM × GDNC × SC_CNTL × GRID	376	5.19%	70.77%
YM × GDNC × SC_CNTL × GRID × VRT_FRT	280	3.86%	74.63%
YM × GDNC × SC_CNTL × GRID× VRT_FRT × VRT_SD	279	3.85%	78.48%
YM	263	3.63%	82.11%
GDNC × SC_CNTL	178	2.46%	84.57%
GDNC × GRID	139	1.92%	86.49%
YM × GDNC × GRID	137	1.89%	88.38%
YM × GDNC × SC_CNTL × GRID × VRT_SD	88	1.21%	89.59%
GDNC × GRID × VRT_FRT	74	1.02%	90.61%
YM × GDNC × GRID × VRT_FRT	74	1.02%	91.64%
YM × GDNC × SC_CNTL × VRT_FRT	68	0.94%	92.57%
YM × GDNC × SC_CNTL × VRT_SD	66	0.91%	93.49%
YM × GRID	49	0.68%	94.16%
GRID	41	0.57%	94.73%
GDNC × SC_CNTL × GRID × VRT_FRT	32	0.44%	95.17%
YM × GDNC × SC_CNTL × VRT_FRT × VRT_SD	32	0.44%	95.61%
YM × GRID × VRT_FRT	31	0.43%	96.04%
YM × SC_CNTL × GRID	29	0.40%	96.44%
GDNC × SC_CNTL × GRID	27	0.37%	96.81%
GDNC × SC_CNTL × VRT_SD	23	0.32%	97.13%
YM × GDNC × VRT_SD	23	0.32%	97.45%
GRID × VRT_FRT	22	0.30%	97.75%
YM × GDNC × GRID × VRT_FRT × VRT_SD	20	0.28%	98.03%
YM × GDNC × GRID × VRT_SD	20	0.28%	98.30%
YM × GDNC × VRT_FRT × VRT_SD	20	0.28%	98.58%
SC_CNTL	17	0.23%	98.81%
GDNC × SC_CNTL × GRID × VRT_FRT × VRT_SD	15	0.21%	99.02%
YM × GDNC × VRT_FRT	14	0.19%	99.21%
GDNC × SC_CNTL × VRT_SD × VRT_FRT	11	0.15%	99.37%
YM × VRT_FRT	11	0.15%	99.52%

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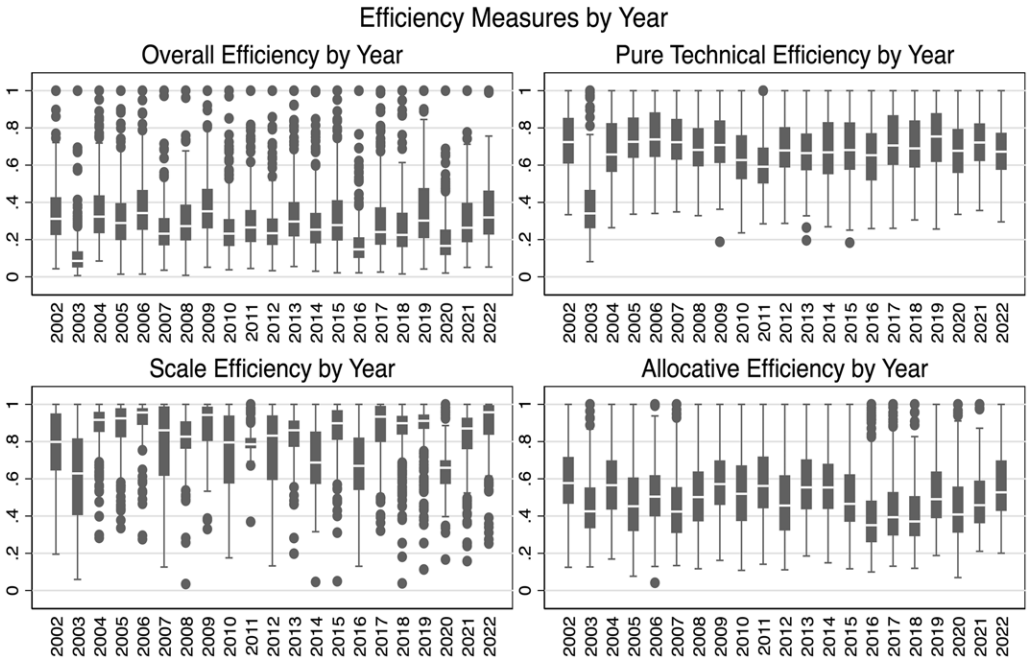


Figure 2. Box and whisker plot for estimated farm efficiency in minimizing the cost of generating gross revenue from KFMA farms from 2002 to 2022.

effects OLS estimator has a natural interpretation as the within-farm mean difference in efficiency associated with switching a binary variable from zero to one, holding the shared year effects constant. This interpretation does not rely on distributional assumptions about the dependent variable, making two-way fixed effects a practical and transparent modeling choice for our specific aim. Lastly, as mentioned previously, McDonald (2009) show OLS with White (1980) robust standard errors is a consistent second stage estimator for two-stage DEA analysis.

3.2. Two-way fixed effects

Table 3 reports the two-way fixed effects OLS estimates of the within-farm effects of reported use of PATs on farm efficiency. For brevity, we display coefficients only for the technology bundles highlighted in Table 2; the full set of year fixed effect estimates is reported in Appendix Table A1. The columns of Table 3 correspond to the dependent variable: pure technical efficiency, overall efficiency, scale efficiency, and allocative efficiency. Each coefficient reflects the estimated within-farm change in efficiency when the corresponding technology or bundle is reported in use, relative to periods when the same farm reports no PATs. For example, farms reporting guidance exhibit a 2.2 percentage point higher overall efficiency (column 2) compared to periods when the same farm reports no PATs.

Although several technologies and bundles show coefficients different from zero, the main conclusion of our estimates is that PATs are not an important driver of farm efficiency. Of the seventeen technologies and bundles, only two – guidance (GDNC) and the yield monitor and grid soil sampling bundle (YM × GRID) – have coefficients statistically different from zero at the 1 percent level. Guidance is associated with a 2.2 percentage point increase in overall efficiency, while yield monitor and grid soil sampling are associated with a 3.9 percentage point increase.

These findings are interesting due to the distinction between embodied knowledge technologies and information-intensive technologies discussed by Griffin et al. (2017) and Miller et al. (2019).

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Table 3. Two-way fixed effects estimates of the effects of precision agriculture technology on within Kansas farm efficiency 2002 to 2022

	Pure technical	Overall	Scale	Allocative
GRID	0.028	0.041	0.058*	0.022
	(0.037)	(0.035)	(0.031)	(0.038)
GDNC	0.002	0.022***	0.018**	0.027***
	(0.010)	(0.007)	(0.009)	(0.010)
GDNC × GRID	−0.018	0.019	0.032*	0.016
	(0.020)	(0.015)	(0.018)	(0.019)
GDNC × GRID × VRF	−0.038	−0.018	0.006	0.006
	(0.026)	(0.022)	(0.019)	(0.031)
GDNC × SC	−0.024	−0.003	0.031**	0.010
	(0.019)	(0.015)	(0.016)	(0.018)
YM	0.003	0.006	0.016	−0.015
	(0.015)	(0.016)	(0.014)	(0.019)
YM × GRID	0.006	0.039***	−0.006	0.077***
	(0.032)	(0.013)	(0.038)	(0.020)
YM × GDNC	−0.015	0.011	0.009	0.025**
	(0.013)	(0.010)	(0.010)	(0.012)
YM × GDNC × GRID	−0.034	−0.003	0.031*	0.007
	(0.026)	(0.017)	(0.017)	(0.021)
YM × GDNC × GRID × VRF	−0.014	0.003	0.010	0.013
	(0.026)	(0.027)	(0.019)	(0.029)
YM × GDNC × SC	0.003	0.019	0.014	0.030*
	(0.014)	(0.012)	(0.012)	(0.017)
YM × GDNC × SC × VRS	−0.007	0.021	0.042**	0.028
	(0.030)	(0.017)	(0.018)	(0.028)
YM × GDNC × SC × VRF	0.048*	−0.012	0.009	−0.015
	(0.025)	(0.026)	(0.033)	(0.038)
YM × GDNC × SC × GRID	0.027	0.016	0.011	0.016
	(0.019)	(0.016)	(0.016)	(0.022)
YM × GDNC × SC × GRID × VRS	0.069***	0.045*	0.036	0.018
	(0.021)	(0.025)	(0.025)	(0.040)
YM × GDNC × SC × GRID × VRF	0.035*	0.024	0.013	0.028
	(0.020)	(0.016)	(0.017)	(0.021)
YM × GDNC × SC × GRID × VRF × VRS	0.026	0.028	0.012	0.052**
	(0.027)	(0.019)	(0.020)	(0.023)
Constant	0.743***	0.348***	0.785***	0.594***
	(0.009)	(0.008)	(0.008)	(0.008)

(*Continued*)

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Table 3. (*Continued*)

	Pure technical	Overall	Scale	Allocative
Obs.	6863	6863	6863	6863
Farm and Year Fixed Effects	YES	YES	YES	YES
R^2	0.256	0.337	0.310	0.230

Huber-White heteroskedastic robust standard errors, clustered at the panel level, in parentheses.
* $p < 0.10$, ** $p < 0.05$, * * * $p < 0.010$.
Each coefficient is relative to the farm having no reported Precision Agriculture Technology.

Guidance, which generates value without additional external information, represents an embodied technology, while yield monitors and grid soil sampling inherently provide information that must be incorporated into decision-making to generate value. In our results, one embodied technology (guidance) and one information-intensive bundle (YM × GRID) are associated with efficiency gains. Thus, we cannot conclude that either category is systematically more effective.

Looking more closely at guidance, the overall efficiency gains appear to stem from improvements in both scale efficiency and allocative efficiency. Gains in scale efficiency may reflect reduced overlap and better utilization of machinery, an effect often emphasized in the PAT literature (Griffin et al., 2018). Increases in allocative efficiency suggest improved site-specific use of inputs. In contrast, the gains from the yield monitor and grid soil sampling bundle are concentrated in allocative efficiency, with farms reporting this bundle exhibiting a 7.7 percentage point increase. This result aligns with the expectation that information-intensive technologies improve the cost-effectiveness of input use through site-specific management.

While other technologies and bundles are not associated with changes in overall efficiency, several are linked to improvements in specific efficiency components. For pure technical efficiency, the bundle of yield monitor, guidance, section control, grid soil sampling, and variable rate seeding is associated with a 6.9 percentage point increase, suggesting greater output with given inputs. For scale efficiency, the bundles of guidance and section control (+3.1 percentage points) and yield monitor, guidance, section control, and variable rate seeding (+4.2 percentage points) show significant gains, likely reflecting improved capacity to utilize machinery at optimal scale. For allocative efficiency, yield monitor with guidance (+2.5 percentage points) and the larger bundle of yield monitor, guidance, section control, grid soil sampling, variable rate seeding, and fertilizer (+5.2 percentage points) are both associated with improvements in cost-effective input use.

Table 3 reports the estimated average within-farm change in efficiency associated with reported use of PATs, relative to periods with no PATs. Because farms may differ in their capacity to realize efficiency gains, we also estimate equation (6) using quantile regression. Quantile regression, a generalization of median regression, minimizes absolute error and allows us to examine the conditional effects of PAT use at different points of the efficiency distribution. We estimate the model at the lower quartile, median, and upper quartile of overall farm efficiency.

Table 4 reports the least absolute deviation two-way fixed effects estimates of the within-farm change in overall efficiency associated with PAT use. The first column corresponds to the least efficient 25 percent of farms, the second to the median, and the third to the most efficient 25 percent. As with the OLS estimates, coefficients reflect the change in efficiency associated with reporting a given technology or bundle, relative to no PATs.

The results suggest that less efficient farms experience the greatest gains from PATs. For farms in the lowest quartile, five of the seventeen technology bundles are associated with statistically significant gains:

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Table 4. Two-way fixed effects least absolute difference estimates of the effects of precision agriculture technology adoption on Kansas farm efficiency 2002 to 2022 (Overall efficiency)

	0.25 quartile	Median	0.75 quartile
GRID	0.020	0.038	0.061
	(0.050)	(0.049)	(0.085)
GDNC	0.021***	0.022***	0.024*
	(0.008)	(0.008)	(0.014)
GDNC × GRID	0.021	0.019	0.017
	(0.019)	(0.019)	(0.032)
GDNC × GRID × VRF	−0.005	−0.016	−0.030
	(0.023)	(0.023)	(0.039)
GDNC × SC	−0.001	−0.003	−0.005
	(0.016)	(0.015)	(0.026)
YM	0.011	0.006	0.001
	(0.015)	(0.015)	(0.025)
YM × GRID	0.059**	0.042	0.021
	(0.027)	(0.027)	(0.046)
YM × GDNC	0.013	0.012	0.010
	(0.010)	(0.010)	(0.018)
YM × GDNC × GRID	0.009	−0.002	−0.014
	(0.020)	(0.019)	(0.033)
YM × GDNC × GRID × VRF	0.012	0.004	−0.006
	(0.022)	(0.022)	(0.037)
YM × GDNC × SC	0.020*	0.019*	0.018
	(0.012)	(0.012)	(0.020)
YM × GDNC × SC × VRS	0.035	0.023	0.008
	(0.025)	(0.024)	(0.042)
YM × GDNC × SC × VRF	0.015	−0.008	−0.036
	(0.028)	(0.027)	(0.047)
YM × GDNC × SC × GRID	0.032**	0.018	0.002
	(0.016)	(0.016)	(0.027)
YM × GDNC × SC × GRID × VRS	0.050*	0.045*	0.040
	(0.027)	(0.027)	(0.046)
YM × GDNC × SC × GRID × VRF	0.031**	0.025	0.017
	(0.016)	(0.016)	(0.027)
YM × GDNC × SC × GRID × VRF × VRS	0.042**	0.030	0.015
	(0.020)	(0.020)	(0.034)

(*Continued*)

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Table 4. (*Continued*)

	0.25 quartile	Median	0.75 quartile
Obs.	6863	6863	6863
Farm fixed effects	Yes	yes	yes
Year fixed effects	Yes	yes	yes

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

- Guidance (GDNC),
- Yield monitor × grid soil sampling (YM × GRID),
- Yield monitor × guidance × section control × grid soil sampling (YM × GDNC × SC × GRID),
- Yield monitor × guidance × section control × grid soil sampling × variable rate fertilizer (YM × GDNC × SC × GRID × VRF), and
- Yield monitor × guidance × section control × grid soil sampling × variable rate fertilizer × variable rate seeding (YM × GDNC × SC × GRID × VRF × VRS).

Estimated gains range from 2.1 percentage points for guidance to 5.9 percentage points for YM × GRID. Guidance and yield monitors appear in four of the five significant bundles, underscoring their central role in driving efficiency improvements.

Near the median of the distribution, only guidance is associated with overall efficiency gains, and no technologies are associated with gains in the most efficient quartile. Together with the OLS results in Table 3, these findings suggest that the efficiency benefits of PATs accrue primarily to less efficient farms. Moreover, the quantile regression indicates that the largest gains for these farms often arise from using multiple technologies in combination. Five bundles are associated with efficiency gains that are at least weakly significant, and all include at least five technologies. Our analysis does not allow us to isolate which specific technology drives these gains, but the evidence suggests synergies among technologies play an important role for less efficient farms.

An important caveat to our analysis concerns the learning curve associated with PAT adoption. Farmers may not realize efficiency gains immediately; in the early years, adoption could be characterized by adjustment costs and incomplete utilization of the technology. Over time, as farmers accumulate experience and develop the skills needed to manage information-intensive tools, the potential efficiency benefits are more likely to be realized. Our analysis does not capture this dynamic process, but the results nonetheless provide an important first step in contextualizing the role of PATs in agricultural production.

4. Conclusion

Economists are perplexed by farmers' pattern of PAT adoption, potentially due to difficulty in quantifying financial returns. This study uses within-farm variation to identify the effect of PATs on farm efficiency. The results suggest that the use of PATs are not broadly associated with gains in efficiency. However, farms reporting using guidance alone or yield monitors and grid soil sampling are estimated to increase overall efficiency relative to periods when they did not report using PATs. In further analysis, we find that less efficient farms are associated with gains from an expanded set PATs and that gains are associated with PAT bundles of multiple technologies. Our results suggest that financial returns to PATs are still difficult to identify. This fact may be an important driver of the adoption puzzle.

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Although this study incorporates various aspects of farm management, there are some limitations. First, although the KFMA data allow for an evaluation of within-farm variation, the counterfactual farm without PATs and one with all potential bundles is unlikely. These technologies are likely to be adopted sequentially, layering benefits in subsequent periods. A future analysis could use individual farm data to evaluate the learning process and the efficiency gains of PATs. Second, our methodology is based on the assumption that weather-related variation and marketing effects are random. Although these assumptions are valid, this modeling choice introduces classical measurement error and the implied attenuation bias. As a result, our estimated relationships are likely muted. Future studies may be able to use a more comprehensive set of financial, digital production, and weather records to identify the desired effects. Third, we use DEA to produce the dependent variable, but PAT is an inherent input. Future studies could create a variable related to PATs that could be used in the DEA. Despite these limitations, we believe that our estimates are an important contribution to the literature.

An additional challenge for this study is the fact that the PAT landscape is ever evolving. This study uses PATs that have existed for decades. As a result, the definition of technology bundles excludes potential interaction effects with information synthesizing technologies such as farm management software or data analytics service providers. In addition, these bundles are likely to represent heterogeneous effects for farms of various scope and scale. As farm management datasets continue to incorporate the potential to observe technology engagement, economists will be better able to identify the factors related to heterogeneous effects. Furthermore, McFadden et al. (2023) details the interplay of the broader definition of digital agriculture. Future studies could work to understand how farmers use digital agriculture technologies alongside established PATs.

This study has implications for farmers. First, farms and specifically efficient farms may not benefit financially from adopting PATs. If a farmer experiences utility gains from the adoption of PATs, as described in DeLay et al. (2022), then we may see further adoption. Second, inefficient farms should consider the adoption of PATs. In contrast to the findings for efficient farms, inefficient farms are likely to experience additional gains from technology adoption.

The findings of this study have implications for equipment manufacturers and policy makers. Equipment manufacturers should focus on identifying inefficient farms and develop PAT platforms for this group. These producers experience a disproportionate increase in efficiency and, as a result, may be motivated consumers. In addition, policymakers, especially those focused on environmental impact, should also be interested in this inefficient group. PAT will allow this group to use their inputs more efficiently. Collectively our results suggest that these two stakeholder groups will benefit by exploring how farm efficiency heterogeneity impacts their goals.

Data availability statement. The farm management database used in this research from Kansas Farm Management Association is available upon request.

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Appendix A

Table A1. Two-way fixed effects estimates of the effects of precision agriculture technology on within Kansas farm efficiency 2002 to 2022

	(PTE)	(Overall)	(Scale)	(Allocative)
GRID	0.028	0.041	0.058*	0.022
	(0.033)	(0.025)	(0.035)	(0.031)
GDNC	0.002	0.022***	0.018**	0.027***
	(0.007)	(0.005)	(0.007)	(0.006)
GDNC × GRID	−0.018	0.019	0.032*	0.016
	(0.016)	(0.012)	(0.017)	(0.015)
GDNC × GRID × VRF	−0.038*	−0.018	0.006	0.006
	(0.021)	(0.016)	(0.022)	(0.020)
GDNC × SC	−0.024*	−0.003	0.031**	0.010
	(0.014)	(0.011)	(0.015)	(0.013)
YM	0.003	0.006	0.016	−0.015
	(0.012)	(0.010)	(0.013)	(0.012)
YM × GRID	0.006	0.039**	−0.006	0.077***
	(0.025)	(0.019)	(0.026)	(0.023)
YM × GDNC	−0.015	0.011*	0.009	0.025***
	(0.009)	(0.007)	(0.009)	(0.008)
YM × GDNC × GRID	−0.034**	−0.003	0.031*	0.007
	(0.017)	(0.013)	(0.018)	(0.016)
YM × GDNC × GRID × VRF	−0.014	0.003	0.010	0.013
	(0.022)	(0.017)	(0.023)	(0.021)
YM × GDNC × SC	0.003	0.019**	0.014	0.030***
	(0.011)	(0.008)	(0.011)	(0.010)
YM × GDNC × SC × VRS	−0.007	0.021	0.042*	0.028
	(0.022)	(0.017)	(0.024)	(0.021)
YM × GDNC × SC × VRF	0.048**	−0.012	0.009	−0.015
	(0.024)	(0.019)	(0.026)	(0.023)
YM × GDNC × SC × GRID	0.027**	0.016	0.011	0.016
	(0.013)	(0.010)	(0.014)	(0.012)
YM × GDNC × SC × GRID × VRS	0.069***	0.045***	0.036	0.018
	(0.022)	(0.017)	(0.023)	(0.021)
YM × GDNC × SC × GRID × VRF	0.035**	0.024**	0.013	0.028**
	(0.014)	(0.011)	(0.015)	(0.013)
YM × GDNC × SC × GRID × VRF × VRS	0.026	0.028**	0.012	0.052***
	(0.017)	(0.013)	(0.018)	(0.016)

(*Continued*)

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Table A1. (*Continued*)

Year = 2002 *omitted*				
Year = 2003	−0.324***	−0.220***	−0.184***	−0.125***
	(0.010)	(0.008)	(0.011)	(0.009)
Year = 2004	−0.038***	0.008	0.093***	−0.024**
	(0.010)	(0.008)	(0.011)	(0.009)
Year = 2005	0.017*	−0.027***	0.094***	−0.116***
	(0.010)	(0.008)	(0.011)	(0.009)
Year = 2006	0.028***	0.031***	0.133***	−0.068***
	(0.010)	(0.008)	(0.011)	(0.009)
Year = 2007	−0.001	−0.092***	0.008	−0.147***
	(0.010)	(0.008)	(0.011)	(0.009)
Year = 2008	−0.031***	−0.049***	0.035***	−0.085***
	(0.010)	(0.008)	(0.011)	(0.009)
Year = 2009	−0.012	0.027***	0.090***	−0.013
	(0.010)	(0.008)	(0.011)	(0.009)
Year = 2010	−0.082***	−0.096***	−0.036***	−0.063***
	(0.010)	(0.008)	(0.011)	(0.010)
Year = 2011	−0.123***	−0.066***	−0.001	−0.028***
	(0.010)	(0.008)	(0.011)	(0.010)
Year = 2012	−0.038***	−0.101***	−0.036***	−0.114***
	(0.011)	(0.008)	(0.011)	(0.010)
Year = 2013	−0.065***	−0.023***	0.040***	−0.029***
	(0.011)	(0.008)	(0.012)	(0.010)
Year = 2014	−0.056***	−0.083***	−0.092***	−0.043***
	(0.011)	(0.008)	(0.012)	(0.010)
Year = 2015	−0.048***	−0.044***	0.067***	−0.105***
	(0.011)	(0.009)	(0.012)	(0.011)
Year = 2016	−0.095***	−0.201***	−0.142***	−0.218***
	(0.011)	(0.009)	(0.012)	(0.011)
Year = 2017	−0.031***	−0.090***	0.072***	−0.193***
	(0.012)	(0.009)	(0.012)	(0.011)
Year = 2018	−0.043***	−0.115***	0.042***	−0.210***
	(0.012)	(0.009)	(0.012)	(0.011)
Year = 2019	−0.024**	−0.029***	0.067***	−0.111***
	(0.012)	(0.009)	(0.012)	(0.011)
Year = 2020	−0.087***	−0.187***	−0.155***	−0.192***
	(0.012)	(0.009)	(0.013)	(0.011)
Year = 2021	−0.048***	−0.092***	0.012	−0.152***

(*Continued*)

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Table A1. (*Continued*)

	(0.012)	(0.010)	(0.013)	(0.012)
Year = 2022	−0.090***	−0.039***	0.087***	−0.079***
	(0.012)	(0.010)	(0.013)	(0.012)
Constant	0.743***	0.348***	0.785***	0.594***
	(0.007)	(0.006)	(0.008)	(0.007)
Obs.	6863	6863	6863	6863
Farm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
R^2	0.256	0.337	0.310	0.230

Huber-White heteroskedastic robust standard errors, clustered at the panel level, in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Each coefficient is relative to the farm having no reported Precision Agriculture Technology

Table A2. Two-way fixed effects least absolute difference estimates of the effects of precision agriculture technology on within Kansas farm efficiency 2002 to 2022 (Overall Efficiency)

	0.25 quartile	Median	0.75 quartile
NONE *omitted*			
GRID	0.020	0.038	0.061
	(0.050)	(0.049)	(0.085)
GDNC	0.021***	0.022***	0.024*
	(0.008)	(0.008)	(0.014)
GDNC × GRID	0.021	0.019	0.017
	(0.019)	(0.019)	(0.032)
GDNC × GRID × VRF	−0.005	−0.016	−0.030
	(0.023)	(0.023)	(0.039)
GDNC × SC	−0.001	−0.003	−0.005
	(0.016)	(0.015)	(0.026)
YM	0.011	0.006	0.001
	(0.015)	(0.015)	(0.025)
YM × GRID	0.059**	0.042	0.021
	(0.027)	(0.027)	(0.046)
YM × GDNC	0.013	0.012	0.010
	(0.010)	(0.010)	(0.018)
YM × GDNC × GRID	0.009	−0.002	−0.014
	(0.020)	(0.019)	(0.033)
YM × GDNC × GRID × VRF	0.012	0.004	−0.006
	(0.022)	(0.022)	(0.037)

(*Continued*)

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Table A2. (*Continued*)

	0.25 quartile	Median	0.75 quartile
YM × GDNC × SC	0.020*	0.019*	0.018
	(0.012)	(0.012)	(0.020)
YM × GDNC × SC × VRS	0.035	0.023	0.008
	(0.025)	(0.024)	(0.042)
YM × GDNC × SC × VRF	0.015	−0.008	−0.036
	(0.028)	(0.027)	(0.047)
YM × GDNC × SC × GRID	0.032**	0.018	0.002
	(0.016)	(0.016)	(0.027)
YM × GDNC × SC × GRID × VRS	0.050*	0.045*	0.040
	(0.027)	(0.027)	(0.046)
YM × GDNC × SC × GRID × VRF	0.031**	0.025	0.017
	(0.016)	(0.016)	(0.027)
YM × GDNC × SC × GRID × VRF × VRS	0.042**	0.030	0.015
	(0.020)	(0.020)	(0.034)
Year = 2002 *omitted*			
Year = 2003	−0.218***	−0.219***	−0.222***
	(0.015)	(0.015)	(0.025)
Year = 2004	0.029**	0.010	−0.012
	(0.013)	(0.013)	(0.023)
Year = 2005	−0.014	−0.025*	−0.038
	(0.014)	(0.014)	(0.024)
Year = 2006	0.045***	0.032**	0.017
	(0.014)	(0.014)	(0.024)
Year = 2007	−0.055***	−0.088***	−0.126***
	(0.013)	(0.013)	(0.021)
Year = 2008	−0.019	−0.046***	−0.077***
	(0.013)	(0.013)	(0.022)
Year = 2009	0.047***	0.029**	0.008
	(0.014)	(0.013)	(0.023)
Year = 2010	−0.057***	−0.091***	−0.132***
	(0.013)	(0.013)	(0.022)
Year = 2011	−0.031**	−0.062***	−0.098***
	(0.013)	(0.013)	(0.022)
Year = 2012	−0.064***	−0.096***	−0.134***
	(0.013)	(0.013)	(0.022)
Year = 2013	0.006	−0.019	−0.050**

(*Continued*)

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Table A2. (*Continued*)

	0.25 quartile	Median	0.75 quartile
	(0.014)	(0.014)	(0.023)
Year = 2014	−0.055***	−0.079***	−0.108***
	(0.014)	(0.014)	(0.024)
Year = 2015	−0.017	−0.041***	−0.069***
	(0.014)	(0.014)	(0.024)
Year = 2016	−0.161***	−0.195***	−0.237***
	(0.014)	(0.014)	(0.023)
Year = 2017	−0.050***	−0.085***	−0.127***
	(0.014)	(0.014)	(0.024)
Year = 2018	−0.068***	−0.109***	−0.157***
	(0.014)	(0.014)	(0.023)
Year = 2019	−0.005	−0.026*	−0.052**
	(0.015)	(0.015)	(0.025)
Year = 2020	−0.144***	−0.182***	−0.227***
	(0.014)	(0.014)	(0.024)
Year = 2021	−0.052***	−0.087***	−0.129***
	(0.015)	(0.015)	(0.025)
Year = 2022	−0.011	−0.036**	−0.064**
	(0.016)	(0.016)	(0.027)
Obs.	6863	6863	6863
Farm fixed effects	yes	yes	yes
Year fixed effects	yes	yes	yes

Standard errors in parentheses.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

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Table A3. KFMA precision agriculture technology data collection (*in US dollars*)

Precision agriculture technology	Usage	Start year	End year
Combine yield monitor (w/out GPS)	Used	2011	2015
Combine yield monitor (w/GPS)	Used	2016	
GPS lightbar guidance	Used	2007	2010
GPS automated guidance	Used	2011	
GPS automated section control	Used	2013	
Grid soil sampling	Never Used		
Imagery	Never Used		
Telematics	Never Used		
Variable rate N, P, K, lime with auto Ctlr	Never Used		
Variable rate seeding	Never Used		
Cotton harvester yield monitor (w/out GPS)	Never Used		
Cotton harvester yield monitor (w/GPS)	Never Used		
Turn compensation sprayer	Never Used		
Turn compensation planter	Never Used		

Source: KFMA 2002–2022

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