The Impact of Precision Agriculture Technologies on Farm Profitability in Kansas

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Abstract: *Even with more than a decade long adoption of the precision agriculture (PA) technologies in the United States, its impact on farm profitability is still not clear. This paper uses farm level data from Kansas Farm Management Association (KFMA) to conduct the ex-post evaluation of PA technologies on farm profitability in Kansas. The analysis of the data using propensity score matching method indicates that there is on an average $60,000 difference in net returns of the farm with at least one PA technology and the net returns of the farm without any PA technology. The results also indicate approximately a linear increase in return with adoption of more PA technology. The conclusion from this paper is specific to the state of Kansas and with availability of national level data, analysis can be extended to draw a more generalized conclusion.*

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Introduction

The adoption of information technologies for agricultural management in the United States can be traced back to mid-80’s (NRC, 1997). However, the adoption of Precision Agriculture (PA) technologies began only during mid to late 90’s and continues to grow over the years (Sonka and Chen, 2015; Lowenberg-Deboer, 2000, Kitchen et al., 2002; Fountas et al., 2005; Griffin and Lowenberg-DeBoer, 2005; Popp et al., 2002; Griffin and Yeager, 2018; Lambert et al., 2015). The National Research Council (NRC, 1997) define PA as “.. a management strategy that uses information technologies to bring data from multiple sources to bear on decisions associated with crop production”. PA technologies include technologies such as yield monitors and yield mapping, grid or zone soil sampling and mapping, automated guidance and section control systems, unmanned aerial vehicles (UAVs) and satellite imageries, and variable rate input application technologies (VRTs). Many of these technologies utilize Global Navigation Satellite Systems (GNSS, formerly referred to as GPS) georeferenced location information since it’s availability for civilian uses around 1994. Although these technologies have been used for more than two decades ago in the United States, the wider adoption occurred during the last decade and it is expected to grow in future. For example, Sonka and Chen (2015) reported that adoption of UAV technology, which is of fairly recent use in agriculture, is expected to grow from 2% in 2015 to 16% of total market area in the mid-west and southern regions of the United States by 2018. The adoption of satellite imagery, grid or zone sampling, yield monitor, and guidance systems which currently stand at 18, 41, 43, and 52 % respectively in the mid-west and southern regions are expected to grow to 64, 59, 54, and 29% respectively by 2018. The adoption of VRT for lime application is expected to grow from 41% to 51% between 2015 and 2018 (Sonka and Chen, 2015).

With growing adoption of PA technologies, the question of its impact on farm profitability also becomes important. The economic analysis of PA technologies conducted so far have predominantly focused on the cost savings due to the technologies. Using the USDA's Agricultural Resource Management Survey data of corn producers, Schimmelpfennig and Ebel (2016) analyzed the cost saving associated with various combination of PA technology adoption. They concluded that for most of the combinations of PA technologies, there are significant cost savings, ranging from $13.45/acre to $25.01/acre, relative to no adoption scenario. Using a partial budgeting framework to analyze data from 500 farms in Kansas, Nebraska, and Colorado, Smith et al. (2013) concluded that PA technologies such as automatic guidance systems and section control increased net farm returns due to cost savings in input application. Olson and Elisabeth (2003) used a two stage econometric model to assess the impact of PA technologies on rate of return to asset (ROA) for Minnesota farmers. Interestingly, contrary to popular belief of positive impact of PA on farm profitability, they concluded significant negative effect of PA on farm ROA. They provided many reasons for this counter-intuitive results: the data used for the analysis was a cross sectional data from one year which failed to capture the small impact of PA, the high variability in the ROA data, the PA technologies being fairly new that it had not matured enough to show its impact at the farm level, and availability of other technology that are as profitable as PA technologies. In a comprehensive review of the literature on profitability of PA technologies, Lambert and Lowenberg-Deboer (2000) concluded that 64% of the total 69 articles[1] using partial budgets as the analytical tool reported positive benefits of PA technologies and 16% reported negative benefits. For example, using a partial budget framework to analyze

[1] These articles included both peer reviewed journal articles and non-peer reviewed articles.

data from on farm trials for uniform application of fertilizer and constant planting rate for corn production in central Illinois, Finck (1998) reported a net return increase of $47.01/ha for the use of PA technology. Updating the Lambert and Lowenberg-Deboer (2000) reported, Griffin et al. (2004) reported that of the 87 articles reviewed, 73% reported positive net benefit of PA technologies. Tey and Brindal (2012) conducted yet another rigorous review of the literature of four dozen studies and found that perceived profitability was leading influencer on farmers' decision to adopt in the technology. Using a treatment effect model, Schimmelpfenning (2016) reported that adoption of site-specific soil/yield mapping, guidance system, and VRT increases net returns by 1.8%, 1.5% and 1.1% respectively.

Most of the available literature on economics of PA technologies have two common features: 1) partial budgeting is the most common analytical framework and 2) site specific experimental method is the most common method of data collection. Therefore, the conclusions from these studies are more of a site-specific 'ex-ante' in nature. Moreover, the site-specific studies only capture the direct costs and benefits of PA technologies while failing to capture the indirect benefits that occur due to integration of multiple technologies which helps to improve farm management decisions, not only for a single year but for multiple years. For example, as noted by Lowenberg-Deboer (2000), "…if a producer uses yield maps and soil testing to help diagnose a nematode problem, that knowledge will probably affect rotations and other management on the entire farm not just on the field where nematodes were first found. On-farm trials are not very useful for measuring these benefits". Therefore, to capture the aggregate impact of PA technologies, the analysis should be conducted at the whole farm level. Additionally, the analysis based on on-farm trials indicate the potential benefit of the PA technologies rather than the actual impact of those technologies on farm profitability. To find out the actual impact of PA technologies, it is necessary to analyze the whole farm data. As discussed earlier, Schimmelpfennig and Ebel (2016) used the whole farm data from USDA's Agricultural Resource Management Survey of corn producers, however, they estimate impact of specific PA technologies and their combination on the variable cost of corn production instead of the net returns. The analysis based on a variable cost of production is too specific to the crop considered for the analysis and it fails to capture the whole farm level impact of PA as the net return would do. Although, by analyzing the impact of PA on farm ROA, the Olsen and Elisabeth (2003) study considers the analysis at the whole farm level, their study seems to be inconclusive given the reasons they provided for the contradictory results. Schimmelpfennig (2016) also used whole farm data and estimated net returns, however, the coefficient estimates from his model was not directly interpretable. He, therefore, transformed the estimated coefficients into percentage impacts, the methodology of which was not well explained. Given this gap in the literature, this study will assess the impact of PA technologies at the farm level. Specifically, this study addresses the following research questions:

1. What is the difference in net farm return between farms adopting at least one PA technology versus without any PA technology?
2. What is the difference in net farm return between the farms adopting multiple PA technologies and the farm without any PA technology?
3. Does the adoption of a specific PA technology or combination of specific technologies increase net farm returns?

Analytical Framework

To discern the impact of PA profitability an ex-post facto evaluation of the net returns of farm households with PA technology relative to the net returns of the households without any PA technology is conducted. For this purpose, an analytical framework based on propensity score matching (PSM) is used[2]. PSM method in the case of impact evaluation of PA technologies involves comparing the net returns of the households with PA technologies (treatment group) with a control group of non-participant households, which are similar in a large number of observable characteristics. PSM framework is the appropriate framework for the impact evaluation when the intervention has already occurred and there is no availability of baseline information on the household who are impacted by the intervention. A key assumption of the PSM framework is that the treatment and the control groups are sufficiently similar except for the intervention considered. Then only the conclusions drawn from the comparison of treatment and control group are valid. To make the treatment and control group comparable, first the probability of adopting the PA technologies for both groups is estimated following a discrete model choice model such as probit model as specified below:

1) $p(X) = \Pr(D=1|X) = \Phi(X'\beta)$

where $P(D = 1|X)$ is the probability that PA technology will be adopted by the farm households given the household characteristics, X such as the farm size, age of the farm owner, education level, acreage under major crop etc. D is a qualitative indicator variable that equals to 1 when a PA technology is adopted by the farm household, otherwise it equals

[2] See Janvry and Sadoulet (2016) for details on PSM method.

to zero. Φ is the cumulative distribution function and β is the parameter estimated from the model.

Using the estimated coefficients from equation (1), the probability of adopting PA technology for each member in the treatment and the control groups is calculated, which is termed as the propensity score. Once the propensity score is calculated for each member in the treatment and control groups, they are matched based on their propensity score value, i.e. member *i* and *j* in the treatment and control groups are a matched pair if $\mathrm{p}(X_i) \approx \mathrm{p}(X_j)$. We employ two propensity score matching methods: 1) Nearest Neighborhood (NN) matching method 2) Kernel Matching (KM) method. The NN method compares the observations in the treatment group (i.e. farms with PA technology) with the nearest comparable propensity score observations in the control group (i.e. farms without PA technology). The NN method strives to matches observation *i* in the treatment group to observation *j* in the control group by minimizing$\|p_{i-}p_j\|$, where *p* is the propensity score. In case of KM method, observations in treatment group are compared with the weighted average of several observations in control group with weights varying inversely with the distance between the treatment and control observations propensity scores. As stated by Katchova (2013), the weights are estimated as $w(i,j) = \frac{K\left[\frac{p_{j-}p_i}{h}\right]}{\sum_{j=1}^{n} K\left[\frac{p_{j-}p_i}{h}\right]}$ where *h* is the kernel bandwidth parameter.

As the matched pair are identified, the difference in net returns between the matched pair is interpreted as the estimated difference due to the PA adoption. The estimated difference in net returns for each matched pair is then averaged to obtained the average impact of the PA technology on the profitability of farm households; i.e. we are estimating average treatment effect on treated . A simple t-test is then conducted to determine if the average difference in net returns is statistically significant.

Data

This paper uses farm level data maintained by the Kansas Farm Management Association (KFMA). The KFMA database includes detailed information on many farm characteristics (e.g. farm size, types of crops planted, livestock production, land tenure status, irrigation status etc.), financial information (e.g. net farm income, gross farm income, non-farm income, total assets and liabilities, various financial ratios such as the debt to asset ratio etc.) and the information on the type of PA technologies adopted by the member farms (Stabel et al., 2018). The database includes time series information of farms from 1972 to the present. The KFMA have been analyzed for financial and farm management studies as well as technology adoption. Recent financial studies include Stabel et al. (2018) who evaluated the likelihood of transitioning between financial vulnerability categories. Regarding adoption of technology, Griffin et al. (2017) applied similar methodology as Stabel et al. to determine the most common path a farm takes from no precision technology to a complete bundle of technology. Given their methodology, Griffin et al. (2017) was unable to ascertain the relative profitability of precision agricultural technologies. This study contributes to the knowledgebase by extending analyses of the data used by Griffin et al. (2017) to address their limitations.

Given that the adoption year of individual PA technology differed, i.e. adoption year was not uniform among farms, such that some farms adopting technology as early as the late 90s and others adopting only more recently, use of time series data for analysis was not feasible and hence a cross section data for 2014 was used. Based on the KFMA database, we included variables such as county ID, farm size, total cropland, main crop land acers, proportion of own land, main crop yield, debt to asset ratio, insurance expense of the farms and operator's age to estimate the propensity scores of the treatment and control farms. After cleaning for missing data in the original database for 2014, altogether 372 farms remained in the analysis. These farms included farms with no PA technology as well as farms that had adopted one or more PA technology by 2014. Altogether six PA technologies, namely yield monitor with GNSS (YMGPS), automated guidance with GNSS (AGGPS), section control with GNSS (SCGPS), grid soil sampling (GSS), variable rate fertilizer (VRF), and variable rate seed (VRS) application technologies were included in this analysis.

Results

Three sets of analysis were conducted. In the first set, farms without any PA technology were compared with farms with only one technology, two technologies, and three or more technologies. Table 1 shows the summary statistics of the farms that were matched on various farm characteristics for estimating the propensity scores. The farm characteristic variables used are net farm income (ninc), county ID (countyid), farm size (fmsz), crop land acres (crland), proportion of own land (prownland), major crop acres (mcrpacr), major crop yield (mcrpyd), debt to asset ratio (dbassra), insurance expenses (insexp), and operator's age (age).

The statistics on net income indicates that the farms with one or more technologies have greater average net income than the farms without any PA technology. The farms with two technologies or those with three or more technologies have more than double average net income compared to the farms without any PA technology (Table 1). These observed differences in net returns are based on simple comparison of net returns of the farms adopting PA technologies with those without any PA technologies without matching the farms in terms of observable characteristics that determine the adoption of PA technology. Therefore, the farms with PA technologies have bigger farm size, greater cropland, more major crop acres and yield, higher debt-to-asset ratio and higher insurance expense but they have lesser proportion of own land and their operators are younger in age (Table 1). The pertinent question for this paper is whether the observed difference in net farm income is statistically significant when farms are matched in terms observable characteristics listed above.

Table 2 shows the average treatment effect of using PA technologies on net farm income for farms with only one PA technology, two technologies and three or more technologies. The results indicate that there is a significant difference in net farm income of those farms using PA technologies compared to the farms not using any technology. The results using NN method indicate that there is about $65,025, $120,000 and $190,000 difference in net income of the farms using one, two, and three or more PA technologies compared to the farms without any technology. The results from KM method are consistent with NN method but slightly lower with $57,584, $99,609 and $182,000 difference in net farm incomes.

The second set of analysis involved examining if presence of a particular PA technology, whether in isolation or in combination with other technologies, help to improve net farm income. Table 3 provides results from this set of analysis. For all technologies, there is a statistically significant difference in net farm incomes of the farms adopting a particular technology and those farms without any technology. The greatest difference in net farm income is observed for variable rate seed and fertilizer technologies with income difference ranging from $211,000 to $236,000 for farms with VRF and $219,000 to

$227,000 with VRS. Farms with yield monitors with GNSS also have significantly higher difference in net income ranging from $185,000 to $213,000. The farms with technologies such as auto guidance with GNSS, section control with GNSS and grid soil sampling have statistically significant income difference range of ($104,000 to 160,000), ($170,000 to $201,000) and ($159,000 to $168,000).

Table 4 presents the results of third set of analysis, which tested if there is a significant difference in net farm income between the farms with a particular combination of three technologies with the farms without any PA technology. Altogether, ten combination of technologies are analyzed and all combination of technologies analyzed have significant difference in net farm income compared to the net income of the farms without any PA technology. The largest difference in net income between the farms with no PA technology and with a particular combination of three technology is observed for the combination of YMSCVRF (yield monitor with GNSS, section control with GNSS and variable rate fertilizer). For YMSCVRF the difference in net income ranged from $312,000 to $315,000 and the smallest difference in net income is observed for the combination YMSCVRS (yield monitor with GNSS, section control with GNSS and variable rate seed) with the rage of $201,000 to $313,000 compared to the farms with no PA technology. All the combinations of technologies have net income difference above $200,000 compared to the farms without any PA technology, which is a very significant difference.

Summary and Conclusions

This paper examined the adoption of different PA technologies, and specifically the difference in profitability associated with bundles of those technologies. Using propensity score matching method, the paper examined the difference in net returns of the farms with and without PA technologies for various scenarios of PA adoption. On an average, we found a difference of about $60,000 in net returns between the farms without any PA technology and the farms with at least one PA technology. This difference in net return increases almost at a constant rate with the addition of more PA technologies. The results from this paper aligns with the conclusions of some of the previous researches on profitability of PA technologies and confirms that precision agriculture are profitable in the state of Kansas. Insights gained here are from our unique database of Kansas and hence, there is a potential to apply the analytical framework utilized in this paper to a nation level data set and draw a more generalized conclusion in regards to profitability of precision agriculture.

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Table1: Comparison of the summary statistics of farms without any PA technology, with one technology, two technology and three or more technologies

	No PA Technology			One PA Technology			Two PA Technology			Three or More PA Technologies		
Variables	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.
ninc	114	70712.81	113035.2	73	109859	170484.3	60	155821.7	225626.4	123	180106.1	285062.3
countyid	114	441.8333	203.2444	73	344.3151	199.4851	60	406.35	215.0007	123	480.4634	190.8205
fmsz	114	1539.939	1111.88	73	2348.162	2221.245	60	2197.285	1435.529	123	2705.509	1971.567
crland	114	933.7614	693.6365	73	1417.686	1114.07	60	1663.453	1108.325	123	2051.406	1279.311
prownland	114	45.71729	31.17507	73	39.51441	26.9904	60	31.77279	25.74176	123	30.2097	25.81831
mcrpacr	114	114.4132	138.8758	73	194.0781	265.7233	60	328.5433	396.4403	123	576.3569	478.1528
mcrpyd	114	80.10035	69.4582	73	84.17964	72.80375	60	104.525	55.45009	123	126.2165	51.19243
dbassra	114	0.208702	0.217345	73	0.230808	0.229204	60	0.26415	0.24693	123	0.269179	0.224541
insexp	114	11782.06	20826.99	73	28752.57	38533.42	60	38881.77	113303.3	123	27946.72	62172.73
age	114	62.35965	9.857504	73	60.27397	9.633939	60	58.26667	12.94953	123	54.21951	12.63519

Table 2: Average difference in net returns of farms with at least one, two, and three or more PA technologies

	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method
No of treated*	73	73	60	60	123	123
No of control*	43	100	30	105	37	104
ATT	65025.25	57584.46	120000	99609.71	190000	182000
Standard Error	34793.19	31877.62	44370.90	41048.74	55466.41	51637.38
t-Stat	1.869	1.806	2.707	2.427	3.422	3.530

*The numbers of treated and controls refer to actual matches for each methods

Table 3: Average difference in net returns of farms with at least a particular PA technology

	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method
No of treated*	118	118	219	219	136	136	117	117	65	65	74	74
No of control*	28	105	56	112	38	113	38	113	24	105	24	103
ATT	213000	185000	160000	104000	201000	170000	168000	159000	227000	219000	236000	211000
Standard Error	68017.85	71175.97	513.06	40538.71	47670.72	56504.57	76843.90	63760.96	85006.78	67098.61	66813.52	47949.65
t-Stat	3.132	2.597	3.108	2.445	4.207	3.002	2.191	2.497	2.665	3.259	3.539	4.392

*The numbers of treated and controls refer to actual matches for each methods

Table 4: Average difference in net returns of farms with at least a particular combination of three PA technology

	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method
No of treated*	61	61	37	37	37	37	38	38	37	37	37	37
No of control*	12	71	8	23	8	23	11	35	11	35	12	53
ATT	248000	240000	315000	312000	201000	313000	307000	293000	314000	301000	262000	244000
Standard Error	135000	108000	105000	105000	47670.72	8837.57	98710.32	105000	95745.23	90568.52	101000	81814.27
t-Stat	1.831	2.220	3.002	2.973	4.207	3.528	3.109	2.793	3.283	3.32	2.589	2.980

*The numbers of treated and controls refer to actual matches for each methods

Table 4 (continue..): Average difference in net returns of farms with at least a particular combination of three PA technology

	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method	NN Matching Method	Kernel Matching Method
No of treated*	38	38	37	37	43	43	54	54
No of control*	9	20	9	20	12	35	20	104
ATT	290000	304000	297000	311000	303000	306000	257000	235000
Standard Error	76985.26	76740.87	90804.07	93151.43	74912.01	80813.61	56401.63	61236.03
t-Stat	3.773	3.960	3.276	3.341	4.051	3.788	4.554	3.842

*The numbers of treated and controls refer to actual matches for each methods

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