Journal of Agricultural and Resource Economics: Preprint ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.303598

Precision Agriculture Technologies and Farm Profitability

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This paper uses the staggered difference–in–difference model to assess the *ex post* impact of PA technology adoption on whole-farm profitability. The results indicate that PA technologies do not contribute as much to farm profitability when analyzed over a period. PA technologies may increase some operational efficiency, but farmers should not adopt PA, assuming that it will improve farm profitability. The positive contribution of the majority of PA technologies to farm profitability is not yet established.

Key words: difference-in-difference method, ex post impact evaluation, precision agriculture adoption, whole-farm returns

Introduction

The adoption of Precision Agriculture (PA) technologies which began during the mid to late '90s continues to grow (Lowenberg-Deboer, 2000; Kitchen et al., 2002; Popp, Griffin, and Pendergrass, 2002; Fountas et al., 2005; Griffin and Lowenberg-DeBoer, 2005; Lambert, Paudel, and Larsen, 2015; Sonka and Chen, 2015; Griffin and Yeager, 2018). 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 the Global Navigation Satellite System (GNSS, formerly referred to as GPS) georeferenced location information.

With the growing adoption of PA technologies, the question of its impact on farm profitability also becomes relevant. Most of the current literature on the economics of PA technologies has two common features[2]: 1) partial budgeting is the most common analytical framework, and 2) site-specific experimental method is the most common method of data collection. These studies often focus on cost savings due to PA technologies (Smith et al. 2013 and Schimmelpfennig and Ebel 2016). As useful as the studies are, they are specific to a crop and an area, and fail to capture the whole-farm impact, as would a study based on net farm returns. Site-specific studies also fail to capture the indirect benefits that occur due to the integration of multiple technologies that help to improve overall farm management decisions for numerous years[3]. Furthermore, studies based

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Acknowledgments: The author would like to thank Terri Griffin of Kansas State University for providing the KFMA data set, KFMA economists who collected data from KFMA member farmers, Koren Roland from KMAR-105 for data processing, and Emily Carls for data entry. The author acknowledges the support from the College of Agriculture and Human Sciences of Prairie View A&M University to complete this work.

Review coordinated by Dragan Miljkovic.

[2] For the details, see a review of PA profitability literature by Lambert and Lowenberg–Deboer (2000), Griffin et al. (2004), and Tey and Brindal (2012).

[3] 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".

on on-farm trials indicate the potential benefit of the PA conclusions from these studies are more of *ex ante*[4] conclusions.

Studies at the whole farm level using time series data are appropriate to capture the actual impact of PA technologies. Olson and Elisabeth (2003) analyze the impact at the whole-farm level; however, their study is inconclusive in light of the limitation of their work[5]. Schimmelpfennig (2016) uses whole-farm data and estimates net returns, but the coefficient estimates from his model are not directly interpretable. Given this gap in the literature, this paper evaluates the impact of PA technologies on net farm returns using a comprehensive data panel that includes farm-level data from 1980 to 2014, covering 483 farms. Following the staggered difference-in-difference fixed-effect panel data model, we isolate the impact of adopting PA technologies on net farm returns for a particular PA technology as well as the combination of PA technologies.

The next section presents the analytical framework and the empirical model. The third section describes the data. Results are in section four. The final section summarizes and concludes.

Analytical Framework and Empirical Model

Given that the objective of this paper is to estimate the average effect of PA technology adoption on farm profitability, the difference–in–difference (DID) method used in impact evaluations of development interventions is adopted for this study[6]. The basic idea in using DID is to estimate the net difference in net farm returns due to PA adoption by subtracting net farm returns of the non–adopters (control group) from net farm returns of the farms adopting a particular PA (treatment group) technology observed over the same period. The average treatment effect (ATE) of PA adoption is computed as ATE = $(\overline{Y}_{T1} - \overline{Y}_{T0}) - (\overline{Y}_{C1} - \overline{Y}_{C0})$, where $\overline{Y}_{T0}$ and $\overline{Y}_{T1}$ are average net farm returns of the treatment group before and after the adoption of a PA technology and $\overline{Y}_{C0}$ and $\overline{Y}_{C1}$ are for the control group who did not adopt the PA technology. $(\overline{Y}_{T1} - \overline{Y}_{T0})$ represents the change in net farm returns due to the adoption of PA and $(\overline{Y}_{C1} - \overline{Y}_{C0})$ represents the natural change in net farm returns of non–adopters (Janvry and Sadoulet, 2016). The crucial assumption of the DID method is that both treatment and control groups have 'parallel trends,' i.e., in the absence of PA technology, both the treatment and control group would have an identical change in net farm returns.

A slight modification is needed when the time of the entry of the units in the treatment group is not identical. The DID framework assumes that all the farms adopting a particular PA technology do so at the same time. However, in reality, this is not the case. Farms adopt PA at different times. To account for this difference in timing of adoption, a modified version of DID called the DID with a staggered entry of units is used[7]. The assumption of "parallel trend' is also valid in the case of staggered entry DID. The assumption is violated in this case if the adoption of PA technology is correlated with the trend in net farm return. For example, if the farms that adopt PA technologies are markedly different from the farms that do not adopt PA, and these differences are correlated with their net return. The other scenario where the assumption is violated is when there is an unusual period just before the adoption of PA technologies that triggers adoption/non-adoption of PA technologies, i.e., presence of the so–called 'Ashenfelter's dip.'

[4] Since results from farm trials are yet to be validated at farmers' field located in various regions, the inferences drawn from these studies are 'potential impacts' rather than the actual realization and hence *ex ante* in nature.

[5] Olson and Elisabeth (2003) point out that the data used in their analysis was cross sectional from one year that failed to capture the small impact of PA. Moreover, they contend that PA technologies being new at the time of their study, their analysis failed to show its impact at the farm level.

[6] See Janvry and Sadoulet (2016) for a good account on the DID method.

[7] See Galiani, Gertler, and Schargrodsky (2005) and Jansen (2007) for applications of the staggered entry DID framework.

To empirically estimate the DID with a staggered entry, we adopt a standard fixed effect panel data DID model. The fixed effect panel model controls not only the time–invariant unobservable individual characteristics of the farms that might be correlated with the adoption of PA technologies but also allows the observable time–variant variables that affect PA adoption. The inclusion of both time–invariant and time–variant variables in the model help to isolate the true impact of PA technologies on net farm income. The fixed effect DID model is specified as:

(1) $$Y_{it} = \alpha + \beta \boldsymbol{X}_{it} + \lambda_i + \gamma_t + \delta_j PA_{ij} + \epsilon_{it}$$

where Y_{it} is net farm return per acre of farm *i* in year *t*. $\boldsymbol{X}_{it}$ is the vector of time–varying observable characteristics of the farms such as farm size, proportion of cropland, proportion of owned land, main crop yield, debt to asset ratio, insurance payments to the farms, and operator's age that can affect adoption of PA technologies[8]. λ_i is the fixed effect unique to each farm, and γ_t is the time effect that is common to all farms. PA_{ij} is the indicator variable that takes the value of 1 for the years when the farm *i* operates with a PA technology *j*, zero otherwise. ϵ_{it} is an independently distributed error term. The estimate of δ_j is the DID estimate, i.e., the average change in net farm returns per acre attributable to PA technology *j* as shown in the derivation below:

For control farms

(2) $$Y_{c0} = \alpha + \beta + \lambda_c + \gamma_0$$

(3) $$Y_{c1} = \alpha + \beta + \lambda_c + \gamma_1$$

(4) $$Y_{c1} - Y_{c0} = \gamma_1 - \gamma_0$$

For treatment farms

(5) $$Y_{T0} = \alpha + \beta + \lambda_T + \gamma_0$$

(6) $$Y_{T1} = \alpha + \beta + \lambda_T + \gamma_1 + \delta_j$$

(7) $$Y_{T1} - Y_{T0} = \gamma_1 - \gamma_0 + \delta_j$$

(8) $$\text{ATE} = (Y_{T1} - Y_{T0}) - (Y_{c1} - Y_{c0}) = \delta_j$$

While it is not possible to test the assumption of parallel trends for the entire period, it is possible to test if the trends were 'parallel' in periods before PA adoption. For this purpose, first, we test if the pre–treatment trends in net returns of the farms are correlated with the order of adoption of PA. This test is implemented by slightly modifying equation (1) as follows:

(9) $$Y_{it} - Y_{it-1} = \alpha + \beta \boldsymbol{X}_{it} + \lambda_i + \gamma_t + \sigma Entry_i + \epsilon_{it},$$

where $Entry_i$ is a binary variable equal to one for all years before the adoption of a PA technology and zero for the years after adoption by farm *i*.

To test if the adoption of PA technology is not correlated with net farm return immediately before the adoption of the technology, the following model is estimated.

(10) $$Y_{it} = \alpha + \beta \boldsymbol{X}_{it} + \lambda_i + \gamma_t + \delta_j PA_{ij} + \phi ImPd_{it} + \epsilon_{it}$$

where $ImPd_{it}$ is an indicator variable equal to one for the year immediately before the farm *i* adopted a PA technology and zero for the other years.

[8] See Tey and Brindal (2012) and Torrez et al. (2016) for details on factors influencing PA adoption.

Data

The farm–level data used to estimate the model is maintained by the Kansas Farm Management Association (KFMA). The data includes information on several 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 information on the type of PA technologies adopted by member farms (Stabel, Griffin, and Ibendahl, 2018). The database includes time–series information on farms from 1972 to 2014. For some of the farms, the data was not available for the initial years of the sample period, so our sample covers 1980–2014 and 483 farms. The sample includes farms without any PA technology as well as farms that had adopted one or more PA technologies by 2014. Altogether four PA technologies are considered for analysis: yield monitor with GNSS, automated guidance with GNSS, section control with GNSS, and grid soil sampling[9].

Results

Table 1 shows the summary statistics of the farm characteristics and the number of PA technologies adopted. The characteristics include net farm return per acre[10], farm size, proportion of cropland, proportion of own land, major crop yield, debt to asset ratio, insurance payments to the farm, and operator's age.

The descriptive statistics on average net farm returns indicate that without matching the farms on their characteristics, the farms without any PA technologies have the lowest average net returns compared to the farms with one or more PA technologies. The variability of net returns of non–adopting farms is also relatively higher than those farms with two or more technologies. Farms with PA technologies have greater average farm size, proportion of cropland, major crop yield, debt–to–asset ratio, and insurance payments than the farms without any PA technology, but they have a lesser proportion of owned land and their operators are younger. These observed differences in net returns are based on a simple comparison of farms adopting PA technologies and no PA technologies, without controlling for the farms' observable characteristics that influence the adoption decisions. As a result, the observed differences in net return may not hold when farms are compared by their observable characteristics. The question is whether the observed difference in net farm returns is statistically significant when farms are similar in the observable characteristics listed in Table 1.

Before implementing the DID model to estimate the contribution of PA technologies to net farm returns, the assumptions of the DID method must be validated. As mentioned earlier, it is necessary that the pre–treatment trends in net returns of the farms are not correlated with the order of adoption of PA, and adoption of the PA technology is not correlated with the net farm return immediately before the adoption of the technology. The results of these tests are presented below.

Pre–Treatment Trend and Immediate Period Performance Tests

Table 2 presents results on the pre–treatment trend test, as specified in equation (9). The coefficient on the entry variable is not statistically significant, confirming that the trend on net farm returns before the adoption of PA technology is comparable for both treatment and control farms.

[9] Although KFAMA also collects data on adoption of variable rate technologies, we have not analyzed the impact of these technologies, as few farms had adopted these technologies during the sample period.
[10] Referred as net return from this point forward

Table 3 presents the estimates from the model specified in equation (10). Because the coefficient on the variable immediate period is not statistically significant, it verifies that the immediate period before the adoption of any PA technology has not influenced PA adoption.

Staggered Entry DID Model Results

Table 4 shows the average treatment effect of using PA technologies on net farm return for farms with only one PA technology, two technologies, and three or more technologies without distinguishing the type of PA technologies[11]. The estimates are negative, raising the possibility of negative returns with PA technology adoption in all three cases. However, the estimates are not statistically significant, indicating no significant difference in net farm returns of farms using PA technologies compared to farms not using any technology[12].

Tables 5 and 6 compare estimates from Table 4 with estimates from two alternative model specifications. The alternative specifications considered are 1) inclusion of interaction between PA technologies, and 2) inclusion of timing of the adoption of PA technologies variables in the original model specifications of Table 4. Table 5 compares estimates from the model in Table 4 for two PA technologies (replicated in column 1 of Table 5) to the estimates from models with the inclusion of interaction terms of various technologies (column 2 of Table 5) and timing of adoption of a PA technology (column 3 of Table 5). Table 6 presents a similar comparison for three or more technologies model estimates. In the case of two PA technologies models, the coefficient estimate on the contribution of two PA technologies to net returns changes from -$15.23 to $9.16 with the inclusion of technological interaction terms and to -$11.37 with the addition of timing of PA adoption variables to the original model specification (Table 5). For three or more technologies models, modifications in the original model result in a positive contribution of $7.39 with technological interaction terms and $1.50 with adoption time terms compared to -$0.722 contribution to net returns in the original specification (Table 6). Although alternative model specifications indicate the possibility of some positive contribution of PA technologies, those contributions are not statistically different from zero in both two technologies and three or more technologies models. Therefore, the initial result that there is no significant difference in net returns of those farms using PA technologies compared to the farms not using any technology is valid with alternative model specifications as well.

In Tables 4, 5 and 6, the models estimate the contribution of PA technology by lumping together multiple PA technologies without identifying any particular technology. As those results obtained in Tables 4, 5 and 6 do not distinguish the contribution of a specific PA technology; a positive contribution of a PA technology may be masked by the negative contribution of another PA technology. Therefore, it is necessary to isolate the contribution of each of the four PA technologies considered for the analysis. Table 7 presents the result from another fixed–effect

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[11] The estimates for one PA technology model are obtained by dropping all farms that had two or more technologies from the data set. Hence, the coefficient estimate on one PA technology reflects the difference in net return per acre for farms with one PA and the farms without any PA technology. The estimates for two PA technology models are obtained by dropping farms with one and three or more technologies, and the estimates for three or more PA model are obtained by dropping farms with one or two technologies from the data set.

[12] The independent variables in the model that account for PA adoption decision such as farm size, percent crop area, percent land owned, major crop yield, D/A ratio, and operator age might be correlated. To test for multicollinearity in the model, we estimated Variance Inflation Factor (VIF) for one technology model, and we found that the VIFs for all of the above variables are close to 1.25 and mean VIF for the model is 1.27. The pairwise correlation coefficients are also below 0.10 among almost all of those variables. Hence, multicollinearity of the adoption variables is not an issue in the model.

model[13] that separates the contribution of a specific PA technology to net farm returns[14]. The results show that bigger farms and a higher proportion of crop acres contribute negatively, and a greater proportion of owned land, a higher yield of the major crop, and the operator's age add positively to net farm returns. Variables such as debt–to–asset ratio and insurance payments of the farms contribute positively to the net returns but are not statistically different from zero. Inclusion of all of these farm characteristics variables in the fixed effect model is necessary, as they affect not only net farm returns but also the adoption of PA technologies by farms. The coefficient on yield monitor with GNSS technologies indicates that there can be some positive contribution of this technology to net farm returns, but the coefficient is not statistically significant. The contribution of auto steer with GNSS technology is also statistically insignificant, though the technology may contribute negatively to net returns. Results from Table 7 show that the adoption of section control with GNSS technology can significantly decrease net farm returns per acre by $139.4. Interestingly, the adoption of grid soil sampling technology adds about $53.32 per acre compared to the farm without this technology. These results highlight the differential impact of PA technologies on farm profitability.

The estimates presented in Table 7 also nest the estimates for a combination of multiple technologies. For example, a combination of yield monitor with a grid soil sampling technology results in a positive contribution to net return of about $53 per acre, but the combination of yield monitor with section control negatively affects net returns. Given that section control has a large magnitude of negative contribution compared to other technologies, any combination involving section control technology is likely to have a net negative contribution towards net return. The negative coefficient on section control indicates that it may require several years of use before the farmers can recover the substantial investment in the technology[15].

Summary and Conclusions

This paper examines the difference in profitability associated with adoption of various PA technologies. Using the staggered entry DID method, the paper estimates the difference in net returns per acre of farms with and without PA technologies for different PA technologies. Farms using Grid Soil Sampling technology have net returns higher than farms with no PA technology by an average of $53 per acre. Contrastingly, the adoption of Section Control with GNSS is found to negatively contribute to net farm return by about $139 per acre. The contributions of the other two technologies – i.e., yield monitor with GNSS and auto steer with GNSS– are not statistically different from zero.

The findings indicate that random adoption of PA technologies would not be fruitful as the contribution of various PA technologies to the farm level profitability varies. Adoption of any combination of technologies that include grid soil sampling is likely to contribute positively to net farm returns. In contrast, combinations with auto steer and section control are expected to reduce net farm returns, possibly due to the high investment cost of the technologies.

[13] A Hausman test was conducted to test if a random effect model is appropriate instead of a fixed–effect model. The test result failed to rule out correlation between farm/unit specific error and the regressors included in the model. Therefore, a fixed–effect model is adopted for the analysis. Further, following the result from a heteroscedasticity test for a fixed–effect model, robust standard errors are used. An LM test was conducted to check serial correlation in the data, and the test ruled out serial correlation.

[14] The sample used for this specific analysis consisted of only those farms without any PA technology and with one particular technology. All farms with multiple technologies were dropped from the original sample. Hence, the coefficient estimate for a particular PA technology in Table 7 represents the difference in net returns for the farms with a particular PA technology and the farms with no PA technology.

[15] Velandia, M. et al. (2013) reports about $16,464 cost for installing an automated section control on an existing planter.

The takeaway is that although PA technologies may be cost–saving investments[16], they do not contribute as much to farm profitability when analyzed over a period. PA technologies may increase some operational efficiency, but farmers should not adopt PA, assuming that it will improve farm profitability. The positive contribution of the majority of PA technologies to farm profitability is not yet established.

Insights gained from this analysis are unique to the database of Kansas. A suggestion for future research is to apply the analytical framework in this paper to national data. Incorporation of national data in the analysis would allow drawing a more general picture of the relationship between whole–farm profitability and adoption of PA technologies.

[First submitted October 2019; accepted for publication April 2020.]

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Table 1. Comparison of the Summary Statistics of Farms with Alternative Combinations of PA Technologies

	No PA Technology			One PA Technology			Two PA Technologies			Three or More PA Technologies		
Variables	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Net returns per acre	2,624	57.45	129.02	1,688	67.71	204.58	1,529	61.13	75.98	3,658	75.14	93.87
Farm size	2,624	1434.81	1119.96	1,688	1857.53	1233.54	1,529	1815.90	1297.76	3,658	2220.66	1507.00
Percent crop area	2,624	62.99	24.33	1,688	69.50	23.99	1,529	77.03	27.24	3,658	79.41	21.67
Percent land owned	2,624	36.00	29.03	1,688	28.73	24.97	1,529	29.08	27.64	3,658	29.07	26.54
Major crop yield	1,224	97.09	80.40	857	99.25	45.36	944	100.64	46.12	2,631	103.19	43.16
Debt–to–asset ratio	1,253	0.30	0.28	795	0.30	0.27	778	0.35	0.64	1,880	0.34	0.34
Insurance payments	1,253	15307.89	37647.89	795	20313.51	37781.99	778	29384.63	56275.24	1,880	43923.35	94383.62
Age of the operator	2,623	51.32	11.37	1,688	50.33	12.27	1,529	50.71	11.60	3,657	47.70	11.87

Table 2. Testing the Association between Pre–Program Trend and Order of Entry

Independent Variables	**Estimates**
Farm size	–0.00614
	(0.007)
Percent of crop area	–0.0806
	(0.196)
Percent of land owned	–0.0440
	(0.200)
Major crop yield	0.650***
	(0.0999)
Debt–to–asset ratio	31.96
	(23.92)
Insurance payments	0.000129***
	(4.77e–05)
Age of the operator	0.412
	(0.494)
Entry	–0.984
	(6.012)
Constant	–83.28**
	(41.61)
Observations	3,200
Number of farms	379
R–squared	0.062

Robust standard errors in the parentheses
*** p<0.01, ** p<0.05, * p<0.1
Due to space limitation, the coefficients on farm fixed–effect and year effects are not presented here.

Table 3. Testing the Association between Entry into the Program and the Immediate Period before Entry

Independent Variables	**Estimates**
Farm size	–0.00658
	(0.00532)
Percent of crop area	–0.474***
	(0.179)
Percent of land owned	0.512**
	(0.204)
Major crop yield	0.542***
	(0.0676)
Debt–to–asset ratio	14.89*
	(7.995)
Insurance payments	2.55e–05
	(3.15e–05)
Age of the operator	1.108***
	(0.380)
One tech	2.013
	(6.975)
Immediate period	4.609
	(6.428)
Constant	–44.96
	(29.63)
Observations	3,380
Number of farms	394
R–squared	0.151

Robust standard errors in the parentheses
*** p<0.01, ** p<0.05, * p<0.1
Due to space limitation, the coefficients on farm fixed–effect and year effects are not presented here.

Table 4. Impact on Net Returns per Acre with Alternative Combinations of PA Technologies

Independent Variables	**One Technology Estimates (1)**	**Two Technologies Estimates (2)**	**Three or More Technologies Estimates (3)**
Farm size	–0.0190***	0.00314	–0.0153***
	(0.00388)	(0.0107)	(0.00357)
Percent of crop area	–1.075***	–0.270	–0.912***
	(0.389)	(0.350)	(0.308)
Percent of land owned	0.824*	0.450	0.602**
	(0.452)	(0.378)	(0.257)
Major crop yield	0.483***	0.532***	0.564***
	(0.125)	(0.113)	(0.0875)
Debt–to–asset ratio	21.31	34.01**	12.24
	(30.64)	(16.90)	(7.552)
Insurance payments	5.97e–05	–4.74e–05	5.98e–05*
	(9.46e–05)	(5.90e–05)	(3.53e–05)
Age of the operator	1.664***	0.133	0.946*
	(0.520)	(0.726)	(0.488)
One PA technology	–4.717		
	(12.92)		
Two PA technologies		–15.23	
		(11.17)	
Three or more PA technologies			–0.722
			(10.09)
Constant	–26.26	–42.17	14.22
	(47.89)	(52.58)	(37.68)
Observations	1,175	1,255	2,334
Number of farms	146	145	269
R–squared	0.165	0.173	0.152

Robust standard errors in the parentheses
*** p<0.01, ** p<0.05, * p<0.1
Due to space limitation, the coefficients on farm fixed–effect and year effects are not presented here.

Table 5. Comparison of Two Technologies Model Estimates under Three Specifications

Independent Variables	**Two Technologies Estimates (1)**	**Two Technologies Estimates with Interaction Terms (2)**	**Two Technologies Estimates with Adoption Time Terms (3)**
Farm size	0.00314	0.00270	–0.00109
	(0.0107)	(0.0109)	(0.00494)
Percent of crop area	–0.270	–0.313	–0.426**
	(0.350)	(0.367)	(0.193)
Percent of land owned	0.450	0.486	0.499**
	(0.378)	(0.392)	(0.253)
Major crop yield	0.532***	0.541***	0.517***
	(0.113)	(0.115)	(0.103)
Debt–to–asset ratio	34.01**	33.23*	12.52
	(16.90)	(17.25)	(16.01)
Insurance payments	–4.74e–05	–4.58e–05	–6.21e–05
	(5.90e–05)	(5.94e–05)	(5.85e–05)
Age of the operator	0.133	0.219	–0.887
	(0.726)	(0.723)	(0.611)
Two PA technologies	–15.23	9.163	–11.37
	(11.17)	(54.88)	(11.61)
Yield monitor*auto steer		–26.53	
		(56.86)	
Yield monitor*grid soil sampling		–74.49	
		(56.20)	
Auto steer*section control		–26.43	
		(56.57)	
Auto steer*grid soil sampling		–28.95	
		(55.06)	
Section control*grid soil sampling		130.9**	
		(55.42)	
Adoption time of yield monitor			58.50
			(35.58)
Adoption time of auto steer			18.65
			(17.21)
Adoption time of section control			–13.35
			(18.60)
Adoption time of grid soil sampling			–8.092
			(30.46)
Constant	–42.17	–44.60	34.33
	(52.58)	(52.99)	(43.05)
Observations	1,255	1,255	1,255
Number of farms	145	145	145
R–squared	0.173	0.179	0.173

Robust standard errors in the parentheses
*** p<0.01, ** p<0.05, * p<0.1
Due to space limitation, the coefficients on farm fixed–effect and year effects are not presented here.

Table 6. Comparison of Three Technologies Model Estimates under Three Specifications

Independent Variables	**Three or More Technologies Estimates (1)**	**Three or More Technologies Estimates with Interaction terms (2)**	**Three or More Technologies Estimates with Adoption Time Terms (3)**
Farm size	–0.0153***	–0.0153***	–0.00568***
	(0.00357)	(0.00358)	(0.00210)
Percent of crop area	–0.912***	–0.910***	–0.543***
	(0.308)	(0.314)	(0.197)
Percent of land owned	0.602**	0.589**	0.540***
	(0.257)	(0.258)	(0.186)
Major crop yield	0.564***	0.563***	0.528***
	(0.0875)	(0.0873)	(0.0819)
Debt–to–asset ratio	12.24	12.76	–7.192
	(7.552)	(7.791)	(6.957)
Insurance payments	5.98e–05*	6.21e–05*	3.75e–05
	(3.53e–05)	(3.52e–05)	(3.42e–05)
Age of the operator	0.946*	1.005**	–0.471
	(0.488)	(0.497)	(0.357)
Three or more pa technologies	–0.722	7.390	1.505
	(10.09)	(9.342)	(9.677)
Yield monitor*auto steer*section control		–11.96	
		(15.97)	
Yield monitor* auto steer*grid soil sampling		–4.199	
		(12.38)	
Yield monitor *section control*grid soil sampling		33.49*	
		(17.03)	
Auto steer*section control*grid soil sampling		–27.91**	
		(12.07)	
Adoption time of yield monitor			0.556
			(8.355)
Adoption time of auto steer			–0.518
			(6.589)
Adoption time of section control			–8.594
			(8.407)
Adoption time of grid soil sampling			–7.478
			(10.46)
Constant	14.22	11.42	46.89*
	(37.68)	(37.97)	(26.34)
Observations	2,334	2,334	2,334
Number of farms	269	269	269
R–squared	0.152	0.153	0.150

Robust standard errors in the parentheses
*** p<0.01, ** p<0.05, * p<0.1
Due to space limitation, the coefficients on farm fixed–effect and year effects are not presented here.

Table 7. Impact of a Particular PA Technology on Net Return per Acre

Independent Variables	**Estimates**
Farm size	–0.0191***
	(0.00386)
Percent of crop area	–1.042***
	(0.389)
Percent of land owned	0.838*
	(0.454)
Major crop yield	0.484***
	(0.126)
Debt–to–asset ratio	19.00
	(30.95)
Insurance payments	5.68e–05
	(9.48e–05)
Age of the operator	1.671***
	(0.524)
Yield monitor with GNSS	0.303
	(17.46)
Auto steer with GNSS	–13.22
	(14.38)
Section control with GNSS	–139.4***
	(16.77)
Grid soil sampling	53.32**
	(25.03)
Constant	–28.45
	(48.25)
Observations	1,175
Number of farms	146
R–squared	0.171

Robust standard errors in the parentheses
*** p<0.01, ** p<0.05, * p<0.1
Due to space limitation, the coefficients on farm fixed–effect and year effects are not presented here.