Productivity and Profitability of Precision Agriculture Technologies on Peanut Farms

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Abstract

This paper examines farmers' propensity to adopt and the productivity, profitability, and public benefits associated with three common precision agriculture technologies on U.S. peanut farms using a doubly robust treatment-effect estimator. Guidance systems are associated with a 9 percent increase in yield and a 15 percent reduction in both fuel and fertilizer expenditures. Soil maps are associated with a 13 percent increase in yield and a $156 per acre increase in net returns. Variable rate applicators do not have a statistically significant impact on yield, profitability, or input expenditures.

Key Words: Guidance Systems, Peanuts, Precision Agriculture, Soil Maps, Technology Adoption, Variable Rate Applicators. JEL Classifications: Q1

Precision agriculture technologies allow farmers to use site-specific information to improve the efficiency of field operations. As available agricultural technologies change, the success of farms depends on correctly identifying which technologies increase profit. This is especially pertinent in growing industries such as peanut production that need to adapt to changing market environments. The number of peanut acres planted in the United States increased by 64% between 2012 and 2017, compared to just a 16% increase in soybean acres and slight decreases in corn and cotton acres over the same time period. This paper investigates the effects of three common precision agriculture technologies (soil maps, variable rate applicators, and guidance systems) on yield, production costs, profitability, and input use (as a measurement of public benefits) on peanut farms.

A soil map uses soil tests or other tools such as electrical conductivity monitors (Veris machines) to measure soil characteristics throughout the field and records the location using global positioning systems. The map then allows the farmer to understand the spatial variation of the characteristics from one part of the field to another. Common characteristics recorded include PH levels, salinity, soil types, slope, relative elevation, and nitrate levels. Information produced by a soil map can be useful for tailoring inputs on the field to a local level. For example, farmers may use a soil map to identify areas that need more or less lime or fertilizer. The information provided can help farmers prevent over or under applying the input, optimizing input usage. Farmers may also use soil maps to identify areas in the field that have problems such as steep slopes or poor drainage. Addressing drainage problems prevents the crop from being over watered and can, therefore, increase yield. Addressing slope problems may reduce erosion. In some cases, farmers may use soil maps to determine that some parts of the field are too eroded or otherwise too low-quality to be profitable, and take that part of the field out of production (Massey et al. 2008).

A variable rate applicator is a device that allows the tractor operator to vary the amounts of inputs such as fertilizer, pesticides, and seeds to apply across the field from the cab of the tractor. Variable rate applicators can be sensor-based or map-based (Grisso et al. 2011). A sensor-based variable rate applicator takes real-time measurements of soil properties or crop characteristics. The sensors either report the information to the operator who makes the decision of how to adjust the inputs in real time, or they automatically adjust the inputs accordingly. A map-based variable rate applicator uses an electronic map created with previously collected information from soil tests, yield monitors, or irrigation patterns. Data that may contribute to an electronic map include moisture content, soil type, soil texture, topography, and crop yield. An electronic map may simply include the range of the field that is irrigated so that fewer seeds can be planted in the non-irrigated areas. Potential benefits to farmers of variable rate technologies include lower input costs, higher yields, and higher profits (Lambert and Lowenberg-DeBoer 2000). However, empirical studies examining the effects of variable rate technologies in practice have produced mixed results in terms of both yield and profitability. Several studies find that they are profitable only under certain circumstances, such as when used in combination with irrigation or when used on fields with substantial variability in fertility (Griffin et al. 2004; Schimmelpfennig 2016).

A guidance system (also known as a parallel swathing system) helps farmers plant crops in parallel rows by using a monitor that displays real-time directional feedback to the tractor operator. The system records the location of initial rows using a GPS system and a microprocessor. The tractor operator can then use the GPS-connected monitor to guide subsequent pesticide applications, fertilizer applications, and harvests to follow the same row. Potential benefits to farmers include more efficient use of fertilizers and chemicals from accurate placement, faster and easier row creation, fewer skips and overlaps between rows, and fewer missed or damaged pods. As a result, guidance systems may increase yields (Taylor et al. 2008; Bergtold et al. 2009), reduce fuel and chemical utilization (Batte and Ehsani 2006), reduce soil compaction (Watson and Lowenberg-DeBoer 2003), and increase profits (Griffin 2009; Schimmelpfennig 2016). The potential benefit for peanut farms is particularly high because peanuts develop underground, so they are not visible once planted. Without a GPS guidance system, farmers must rely on a skilled tractor operator to run the tractor over the same row locations that the peanuts were initially planted in. A deviation of a few centimeters results in some peanuts being damaged or left in the ground at harvest. Recently, new peanut varieties make aligning the placement of the planting equipment with the placement of the harvest equipment even more difficult because they have more green-vine biomass that makes the original row placement more difficult to see. (Ortiz et al. 2013; Balkcom et al. 2010).

In addition to the potential private benefits of these technologies for the farmer, there may be public benefits in the form of reduced fertilizer and pesticide runoff and reduced greenhouse gas emissions from fuel usage. Allowing the farmer to tailor inputs to specific places where they are needed may reduce the overall input usage on the farm.

Previous studies regarding the yield and profitability associated with precision agriculture technology in crop production have used simulations (Thrikawala et al., 1999; Batte and Ehsani 2006), small scale-experiments (Watson and Lowenberg-DeBoer 2003; Griffin et al. 2005; Ortiz et al. 2013; and Bergtold et al. 2009), survey data on other crops (Schimmelpfennig, 2016; and Schimmelpfennig and Ebel, 2016), or literature review (Griffin and Lowenberg-DeBoer, 2005;

Tey and Brindal, 2012). This article adds to the literature by using field-level data from a representative survey of farmers to investigate the effects of three precision agriculture technologies on profitability, yield, and fertilizer, fuel, and chemical use of peanut farms. Analysis with these data has three advantages relative to the existing literature: 1) the profitability of agricultural technologies may vary from farm to farm, so individual experiments may not be representative; 2) experimental settings tend to be more controlled than commercial farm settings; survey data provide insight on how the technology benefits farmers who do not have researchers guiding them through the adoption process; and 3) despite the growing acreage of peanuts in recent years, the current literature examining the impact of precision agriculture on peanut production is limited.

Data

The Agricultural Resource Management Survey (ARMS) is a nationally representative annual cross sectional survey of U.S. farmers conducted by the U.S. Department of Agriculture. Phase I of the survey screens farms from a nationwide list frame, selecting a sample of farms representing all commodities and farm sizes from the 48 contiguous states for the ARMS Phase 3 "whole farm" survey of production, finances, and operator attributes. Farms from that sample are further screened for production of a target field crop, and a subsample of producers of that crop are selected for the ARMS Phase 2 "commodity enterprise" survey of field-level production practices and input use. Information from each phase is used to develop estimates of costs and returns for the target commodities. In 2013, the target field crops were peanuts and rice. In phase 2 of the survey in 2013, 7.3 percent of all peanut farms in the United States were surveyed (2012 Census of Agriculture). That sample is drawn from the 6 largest peanut states, and represents 93 percent of nationwide planted peanut acres. States with the highest levels of peanut production were selected for the 2013 survey: Alabama, Georgia, Florida, North Carolina, South Carolina, and Texas. The survey provides weights for each observation to represent a specific number of farms in the general peanut farm population. A total of 482 farms were included in phase 2 of the ARMS peanut survey in 2013. Adjusting for population weight, 35% of farms used GPS guidance systems, 14% used soil maps and 14% used variable rate applicators (Table 1 and Figure 1). Other precision agriculture technologies that were included in the survey had lower adoption rates: 2% of operations used yield monitors, 3% produced a yield map with the information from the yield monitors, and 1% used satellite or airplane photographs or images.

Empirical Approach

Investigation of the causal effects of precision agriculture technologies requires considering the fact that farms that adopt them may differ systematically from farms that do not. Treatment effects models estimate the effect a treatment (in this case, technology) has on an outcome. The average treatment effect is the average difference between the predicted outcome variable if all observations were to be treated and the predicted outcome variable if all observations were to be untreated in the pooled sample of both the treated and untreated observations. Treatment effects models usually use estimated probabilities of treatment, also known as propensity scores, to determine which observations are more likely to be treated. Most economics papers estimate the treatment effect using matching estimators such as nearest-neighbor matching or caliper matching.

This article uses augmented inverse probability weighting (AIPW), a treatment effects model proposed by Robins and Rotinski (1995) and refined by Rubin and van der Laan (2008). AIPW is doubly robust in the sense that in order for the estimate of the average treatment effect to be consistent, only the propensity score equation or the outcomes regression equation must be specified correctly, but not both (Robins and Rotnitzky 1995; Imbens and Wooldridge 2009).

Glynn and Quinn (2009) compared the AIPW estimator to three alternative estimators: ordinary least squares, propensity score matching, and inverse probability weighting with no regression component. They found that the AIPW performed at least as well as other estimators when the model was correctly specified. It outperformed the other estimators when the model was partially mis-specified.

The AIPW model requires calculating the inverse probability weights of each observation. An inverse probability weight is the reciprocal of the propensity score for treated observations and the reciprocal of one minus the propensity score for untreated observations. Weighting observations in this way ensures that untreated observations that were predicted to have a high probability of treatment based on covariates are given larger weights because they are more similar to the treated observations and vice versa (Imbens and Wooldridge, 2009; StataCorp, 2014). Next, the AIPW model separates the outcome regression models into one regression of only treated observations and one regression of only untreated observations and yields two sets of predicted outcomes for each observation based on the two treatment levels. The weighted means of the predicted outcomes of each treatment group are then calculated using the inverse probability weights.

The three binary treatments considered in this article are adoption of soil maps, adoption of guidance systems, and adoption of variable rate applicators. The outcome variables considered in this article are yield per acre, net returns per acre, net operating returns per acre, fertilizer expenditures per acre, chemical expenditures per acre, and fuel expenditures per acre. All the outcome variables are on the field level, and therefore relate only to peanut production. If a farm produced other commodities, the costs and returns for those commodities are not included. Net returns are the gross value of production less expenses for the annualized cost of the land, paid and unpaid labor, capital, and other inputs. Net operating returns are revenue less variable input expenses such as seed, fertilizer, chemicals, and interest on operating capital. Hired labor is considered as allocated overhead and therefore is included in net total returns but not included in net operating returns. Since producers often adopt multiple technologies together (Schimmelpfennig and Ebel, 2016; Lambert et al., 2015), the propensity to adopt each of the three treatments is estimated jointly. The regressions for each outcome variable (yield, net operating returns, net total returns, chemical use, fertilizer use, and fuel use) are estimated separately.

First, a probit model is estimated to determine the drivers of adoption for each of the three precision agriculture technologies, and is then used to calculate the propensity score for each observation:

$$(1)\ \Pr(Adopt\ Technology) = \Phi(\beta_0 + \boldsymbol{\beta X} + \rho_i),$$

where **X** represents a vector of farmer and field characteristics. The probit equation for the propensity-score generation should include characteristics that influence the likelihood of treatment (adoption of the precision agriculture technologies) and exclude characteristics that may be influenced by the treatment assignment (Rosenbaum and Rubin 1983; Austin 2011; Stuart 2010). Covariates include the state where the farm is located, the age and age squared of the primary operator, the number of peanut acres on the farm and the number of peanut acres squared, the debt to asset ratio of the farm, a dummy variable for whether the primary operator holds a four-year college degree, a dummy variable for whether farming is the operator's primary occupation, and a dummy variable for whether the education level, age, primary work, and debt to asset ratio of the farm are missing. The education level, age, and debt to asset ratio of the farm are collected in the final stage of the survey, so operations that did not complete this phase are missing all four data elements. Although the debt to asset ratio may be slightly affected by precision agriculture adoption, the impact of these technologies on debt to asset ratio is likely to be quite low. Total debt is usually driven by larger purchases such as land or buildings, and total assets accumulate over many years while production decisions change from year to year.[1] Missing values for age, education, other primary work, and debt to asset ratio are assigned a zero in the analysis.

Previous studies suggest that operator demographics tend to correlate with agricultural technology adoption; younger and more educated farmers are more likely to adopt new technologies (Feder et al., 1985; Roberts et al., 2004; Daberkow and McBride 2003; Lichtenberg et al. 2013). Adoption may increase with farm size. Spreading fixed costs over greater output decreases per-unit costs of the technology (Daberkow and McBride 2003; Schimmelpfennig and Ebel, 2016). Farms with lower debt to asset ratios may be more likely to adopt new technologies because they have lower credit constraints (Tey and Brindal 2012). The state variables reflect regional differences in production conditions and input prices, which may influence adoption. The propensity score equations do not include management practices such as tillage, irrigation, and peanut variety because the choice of technology may affect the use of such management practices.

[1] As a robustness check, we repeated this analysis without debt to asset ratios in the selection equations and found similar results.

We then separate the observations into treated and untreated groups, and for each group, we regress each of the field-level outcome variables (yield, net returns, and fertilizer, fuel, and chemical expenditures) on field, farm, and operator characteristics weighting each observation by the inverse probability weights calculated from the probit equations (1). Characteristics included in the outcome regressions include state, operator age, operator age squared, a dummy variable for whether the operator holds a four-year college degree, number of peanut acres, dummy variables for peanut variety, and whether the farmer uses (1) soil tests, (2) irrigation, and (3) no-tillage farming. The state may affect productivity or profitability due to variation in weather patterns or input prices. State dummy variables include Alabama, Georgia, Florida, North Carolina, South Carolina, and Texas, with Alabama as the base. Age may be positively correlated with productivity due to increased experience, but decline later in life (Tauer, 1995). Education may similarly increase a farmer's managerial ability. Farm size may increase profitability or decrease cost due to increased economies of scale. Soil tests help farmers make field-level input decisions, and may increase productivity by providing more information. This is an important element to control for because precision agriculture technologies add value by allowing farmers to precisely apply inputs in a spatially variable manner. Irrigation may increase average yields, and when water is available at low cost, it may also increase profit (Abou Kheira 2009). No-till farming can reduce the required amount of labor, irrigation water, fertilizer, field operations, and other inputs and decrease overall costs. However, it may also reduce average yield (Ogle et al. 2012). Peanut variety includes dummy variables for Runner peanuts, Virginia peanuts, Valencia peanuts, and Spanish peanuts as a base. Different varieties may use different levels of input and produce different yields.

Augmented Inverse Probability Weighting (AIPW)

The AIPW estimator was proposed by Robins and Rotinski (1995) and refined by Rubin and van der Laan (2008). The AIPW estimator separates the sample into a treated regression and an untreated regression, where each regression is weighted only by the farm population weight w_i:

(2) $Y_i = \alpha_0 + \mathbf{X\Omega} + \varepsilon_{i,}$ weighted by w_i

t_i=0, 1

where Y_i is the outcome variable (yield, net returns, fertilizer expenditures, chemical expenditures, or fuel expenditures) for field i, **X** is a vector of field characteristics, and t is the treatment level for each field. The estimate for the average treatment effect is

$$(4)\widehat{ATE}_{AIPW} = \frac{1}{\sum w_i}\sum_{i=1}^{n} w_i\{\left[\frac{t_iY_i}{\hat{\pi}(\boldsymbol{Z}_i)} - \frac{(1-t_i)Y_i}{(1-\hat{\pi}(\boldsymbol{Z}_i))}\right] - \frac{t_i-\hat{\pi}(\boldsymbol{Z}_i)}{\hat{\pi}(\boldsymbol{Z}_i)(1-\hat{\pi}(\boldsymbol{Z}_i))} *$$

$$\left[(1-\hat{\pi}(\boldsymbol{Z}_i))\hat{E}(Y_i|t_i = 1, \boldsymbol{X}_i, \boldsymbol{Z}_i) + \hat{\pi}(\boldsymbol{Z}_i)\hat{E}(Y_i|t_i = 0, \boldsymbol{X}_i, \boldsymbol{Z}_i)\right]\}$$

where $\boldsymbol{Z}_i$ is a vector of variables that affect either the treatment category or the outcome variable, $\hat{\pi}(\boldsymbol{Z}_i)$ is the propensity score for treatment, and t_i is the treatment assignment. $\hat{E}(Y_i|t_i = 1, \boldsymbol{X}_i, \boldsymbol{Z}_i)$ is the predicted outcome from regression (3) using the coefficients from the treated group and $\hat{E}(Y_i|t_i = 0, \boldsymbol{X}_i, \boldsymbol{Z}_i)$ is the predicted outcome from regression (3) using the coefficients from the untreated group.

Results

Adoption

Several factors predicted the adoption of precision agriculture technologies. The number of acres in peanut production was positively associated with the propensity to adopt all three technologies (soil maps: p=0.0003; guidance systems: p=0.0001; variable rate applicator: p=0.07) (Table 1). The effect of additional acres diminished for larger farms with the coefficient of acres squared negative for all three technologies. The covariates for the state in which the farm was located were jointly significant predictors of adoption for variable rate technologies (p=.042) and soil maps (p=.047), but not for guidance systems. Both soil maps and variable rate technologies were most likely to be adopted in South Carolina and least likely to be adopted in Texas. A four-year college degree was positively associated with guidance system adoption, but with borderline statistical significance (p=.06). College degrees were not significantly associated with soil map or variable rate technology adoption. Other factors, including the age of the primary operator, were not statistically significant at the α=0.05 level for any of the three technologies.

Yield

The estimates of the population average treatment effects for the precision agriculture technologies on yield were large and positive for guidance systems and soil maps but not statistically significant for variable rate applicators (Table 2). The estimate for the average treatment effect of guidance systems was an increased yield of 335 pounds per acre (p=.04). Soil maps were also associated with a large increase in yield, with an estimated average treatment effect of 581 pound per acre (p=0.02). Since the outcome equations controlled for whether the farmer used soil tests for nutrients on the field, any yield effect of soil map is not likely to be solely the result of the farmer making better informed nutrient-management decisions for the field as a whole. Rather, the result is more likely to be driven either by more spatially specific management decisions such as identifying areas that have drainage issues or applying different levels of fertilizer to different parts of the field.

Profit

The estimates for the treatment effect of soil maps on net total returns and net operating returns were large with an estimated per acre increase of $156 per acre in the net operating returns (p=0.47) and $180 per acre in net total returns (p=0.049). Since the estimated average treatment effects for fertilizer and chemical expenditures on soil maps are almost zero, and estimates on the average treatment effect of soil maps for fuel expenditures are small compared to the estimates for the average treatment effect on net returns, the increase in net returns is likely driven by the increase in yield. The National Agricultural Statistical Service reports that the national average price of peanuts was $0.27 per pound in 2013. Based on the estimate of the effect of soil maps on yield, this would correspond to an increase in revenue of ($0.27*580.6)= $156.76. Additionally, field information presents farmers with opportunities to increase profits separately from its effects on inputs and yield. In particular, farmers may use the information to negotiate crop leases or to monitor crop moisture content.

Public Benefits

The benefits of soil maps and variable rate technologies were largely private, with the estimated treatment effects on fertilizer, chemical, and fuel use statistically insignificant for both models. Guidance systems, however, were associated with a 15 percent reduction in fertilizer expenditures and a 15 percent reduction in fuel expenditures. These findings are consistent with findings from Batte and Ehsani (2006). Since guidance systems allow tractor operators to align their vehicles with existing rows, they can reduce their fertilizer usage by placing fertilizer only over rows rather than everywhere on the field. Aligning precisely with existing rows also allows tractor operators to reduce the number of passes over a field, which may explain the reduction of fuel costs. The lower level of fertilizer expenditures may imply a lower amount of nutrient runoff and the lower level of fuel expenditures implies a lower level of greenhouse gas emissions from machinery.

Conclusion

Precision agriculture technologies have garnered much attention and increased rates of adoption across regions and crops. Much of the initial promise of precision agriculture technologies has been sown using field experiments and computer simulations, but evidence of profitability when the technologies are actually used in the field has been mixed. Using two doubly robust inverse-probability estimators and data from the Agricultural Resource Management Survey, this article presents evidence that soil maps provide private benefits to farmers and that guidance systems provide both private and public benefits. Our estimates suggest that guidance systems are associated with an increase in yield and soil maps are associated with an increase in both yield and profitability. However, we do not find any evidence of an effect of variable rate applicators for either factor. We also find that guidance systems are associated with a decrease in fuel and fertilizer expenditures. In light of these findings, guidance systems may prove to be a significant element in efforts to reduce greenhouse gas emissions and nutrient runoff.

With soil map users experiencing higher levels of net returns and guidance system users experiencing higher yields, more farms are likely to adopt both technologies in the future. This is particularly true for large farms, which have a higher propensity to adopt than small farms and can benefit more from precision agriculture technologies in part because there is likely to be more variability across the farm. Farms that use precision agriculture technologies frequently use multiple technologies in conjunction with one another. Further research is needed to determine how these technologies complement or substitute for one another, and how farmers can evaluate the effects of interacting technologies on their production outcomes.

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Tables

Table 1: Multivariate Probit Model for Propensity to Adopt Precision Agriculture Technologies

	Soil Map	Guidance System	Variable Rate Applicator
Florida	0.03 (0.37)	-0.05 (0.30)	-0.06 (0.48)
Georgia	0.10 (0.20)	0.37** (0.17)	-0.44** (0.21)
North Carolina	0.41* (0.24)	0.06 (0.24)	0.14 (0.24)
South Carolina	0.58** (0.27)	0.32 (0.24)	0.26 (0.24)
Texas	-0.44 (0.30)	0.12 (0.20)	-0.46* (0.24)
Acres (10s)	1.62*** (0.45)	1.59*** (0.41)	1.18* (0.64)
Acres Squared	-0.49** (0.19)	-0.47** (0.17)	-0.37* (0.22)
Debt to Asset Ratio	2.49 (1.76)	0.11 (1.19)	2.41 (1.81)
Debt to Asset Ratio Squared	-4.82* (2.92)	-0.95 (1.52)	-5.02 (3.41)
Age	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)
Age Squared	-0.0002 (0.0003)	-0.0003 (0.0002)	-0.0003 (0.0002)
College Degree	0.08 (0.21)	0.36* (0.19)	0.05 (0.21)
Age, Debt to Asset Ratio, Education, and Primary Work Missing	0.04 (0.46)	0.07 (0.54)	0.26 (0.60)
Other Primary Work	0.27 (0.55)	-0.35 (0.46)	0.83* (0.48)
Constant	-1.69*** (0.47)	-1.18** (0.54)	-1.50*** (0.58)

N=482

* p<0.1, ** p<0.05, *** p<0.01

Standard errors in parentheses

Table 2: Treatment Effects of Precision Agriculture Technologies

	Soil Maps	Guidance Systems	Variable Rate Applicators
Fuel Expenditures	-5.1 (5.0)	-6.3** (2.5)	1.0 (7.5)
Chemical Expenditures	-9.0 (22.8)	16.1 (9.8)	-22.7 (32.3)
Fertilizer Expenditures	-6.9 (10.3)	-15.3** (7.3)	7.4 (11.6)
Net Operating Returns	155.8** (78.6)	63.0 (51.8)	37.2 (86.2)
Net Total Returns	180.4** (92.0)	82.0 (62.6)	59.8 (102.8)
Yield per Acre	580.6** (250.0)	334.7** (163.3)	-82.6 (364.9)

N=482

* p<0.1, ** p<0.05, *** p<0.01

Standard errors in parentheses

Figures

Figure 1: Precision Agriculture Adoption in Peanut Farms