A Spatio-Temporal Analysis of the Adoption Process of Complementary Precision Agricultural Practices in Kansas

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Abstract

Precision agriculture (PA) is commonly defined as the adoption of new technologies for managing spatial and temporal farming variation for improving overall efficiency and economic return. While the literature on PA technology continues to evolve, many questions still remain unanswered regarding farm-level utilization patterns of PA technologies**.** The purpose of this study is to conduct a spatio-temporal examination of the adoption process of complementary precision agricultural technologies by farmers in Kansas. The PA technologies examined include: yield monitor, precision soil sampling, and variable rate application of inputs. The empirical adoption model for PA technologies follows a multinomial logistic regression framework, given only the observed bundle of PA technologies can be observed for a given farmer at any given time. Using Kansas Farm Management Association (KFMA) data, this study shows the PA adoption patterns of farmers, given different production, financial, socio-demographic, geographic, and soil characteristics. The results indicate that production, financial, and socio-demographic characteristics play a significant role in the adoption decision, whereas geographic and soil characteristics play a negligible role.

Introduction

Farm adoption of precision agriculture (PA) technologies has grown significantly in the past two decades. Precision technologies can be distinguished as being assigned into one of two separate classes: embodied knowledge and information-intensive technology. An embodied knowledge technology (e.g. lightbar, genetically modified seed) refers to a technology in which its value is embodied within the technology and requires no additional, specialized knowledge or time-investment by the user to make full use of. Unlike embodied knowledge technologies, information-intensive technologies (e.g. yield monitor, precision soil sampling) require a significant outlay of time on the part of the individual farmer to be fully utilized. However, these technologies offer farmers valuable, site-specific information that can provide additional insights into optimal farm management strategies and prove useful in decision-making. Applying the knowledge gained by these information-intensive technologies can be useful to operations by increasing production efficiency, either through reallocating and reducing inputs and/or increasing crop yields (the degree to which these gains outweigh the costs of the technology, and in turn the effects of adoption on overall farm profitability is still disputed however).

Though the adoption of information-intensive technologies has historically lagged behind adoption of embodied knowledge technologies, recent studies have shown a rapid uptick in adoption levels over the past several years. Along with increased adoption of individual information-intensive technologies there has been growth in the adoption of multiple technologies. While recent literature has documented the grouping or bundling of information technologies, many question remain unanswered regarding this adoption behavior. The focus of the current study is on examining the characteristics of farms that adopt bundles of information-intensive technologies, and identifying what the specific drivers are in the adoption of different technology bundles.

This study makes use of Kansas Farm Management Association (KFMA) data. Farm members belonging to the KFMA were given a questionnaire, beginning in 2015 on prior and current use of PA technologies. The survey instrument along with farm-level production and financial data, as well as county level soils data were used in the estimation of a multinomial logistic model that relates farm characteristics to adoption of one of six bundles of technology for the year 2014. The technologies examined included yield monitor (with and without GNSS), variable rate fertilizer application, and precision soil sampling. Farms were classified as belonging to one of six states of technology bundle adoption categories – these categories consisted of individual or combinations of the three technologies (along with a ‘none’ bundle – representing no adoption). Following estimation of the model, marginal effects were calculated. The results of this analysis indicated that increases in operator age and farm acreage inversely related to adoption of technology bundles, while increases in machinery investment, value of farm production, and a farm’s crop labor percentage positively impacts adoption.

Literature Review

Adoption patterns of precision agriculture (PA) technology at the state, national, and international level has been discussed in the literature. Griffin and Lowenberg-Deboer (2005) report country level adoption rates based on international consortium of colleagues. At the time of their report, precision agricultural technologies were not ubiquitous and the United States was not the most intensive adopter of yield monitors. At the national level, Schimmelpfennig (2016) analyzed USDA-ARMS data on adoption of technology over time and by crop – showing that yield monitor and variable rate application grew rapidly over the past ten years especially on corn and soybean farms. That study also examined the impacts of technology adoption on farm profitability – a subject that has been the focus of several other prominent studies (Bullock et al. 2002; Olson and Elisabeth 2003; Schimmelpfennig and Ebel 2016). Several state-level adoption studies have been reported.

The results from state-level studies mirror those done at the national level in particular by Schimmelpfennig. In Arkansas, Popp et al. (2002) assessed the early adopters of the technology in two different years – a similar study was conducted by Castle (2016) in Nebraska. In Kansas, Griffin et al. (2016) and Miller et al. (2017) show historic adoption trends and the recent surge in growth of information intensive technology, including yield monitor, variable rate application of fertilizer and seed, and precision soil sampling.

There is also a sizeable literature examining characteristics of farms that adopt PA technologies. For instance, Daberkow and McBride's (2003) study used a two-stage logistic regression model to show the impacts of computer literacy and farm size on the probability of PA adoption. A wider review of the literature is provided by Tey and Brindal (2012). The literature on the grouping or 'bundling' of technologies is limited. Lambert et al (2015) made use of Multiple Indicator Multiple Causation regression analysis to determine the bundling behavior of cotton farms in the southeastern U.S. They found that large acreage, irrigated farms that practiced crop rotation were more likely than their peers to adopt in bundles rather than piecemeal. The current study differs from the study by Lambert et al. both methodologically and in scope. This paper uses a more direct, multinomial logit approach to model the dynamics of adoption decision making. Also, the subject of this paper's analysis, it could be argued, provides a more varied perspective of adoption, as the farms under investigation grow a variety of crops and are, due to the nature of spatial variation of crop production across Kansas, much more representative of wider trends nationally.

Conceptual Model

A modeling approach based on a multivariate logit or multivariate probit framework is best suited to answering the underlying question of farmer decision making, as farms are faced with the adoption of multiple PA technology bundles. This study adopted a multinomial logit model. The multinomial logit model is a utility model with alternative choices which are assumed to be mutually exclusive. This model is used to estimate the probability that a farmer will choose from different alternative technology groups or 'bundles', assuming that the farmer chooses the alternative that maximize his utility from the set of alternatives. The utility function for the farmer can be specified as follows:

$$\mathrm{V}_{ij} = \mathrm{X}_{ij}\beta + \varepsilon_{ij} \tag{1}$$

where V_{ij} is the utility for farmer i choosing technology bundle j, $\mathrm{X}_{ij}\beta$ is the observed components, ε_{ij} is the unobserved component of the utility function, and X_{ij} is the vector of covariate variables which are assumed to be linear (McFadden 1974). Farmer i will choose technology bundle j subject to the following constraints:

$$\mathrm{V}_{ij} \geq \mathrm{V}_{ik} \qquad for\ \forall\ j \neq k \tag{2}$$

$$\mathrm{X}_{ij}\beta + \varepsilon_{ij} \ \geq\ \mathrm{X}_{ik}\beta + \varepsilon_{ik} \tag{3}$$

The probability of farmer i choosing technology bundle j can be defined as a follows:

$$P_{ij} = \frac{e^{\mathrm{V}_{ij}}}{\sum_{j=1}^{J} e^{\mathrm{V}_{ij}}} \tag{4}$$

The coefficients resulting from the multinomial logistic regression model are difficult to interpret directly. Marginal effects are the appropriate measurement to use when capturing the impact of a relative change in the probability (or conditional mean) of a particular choice. Following Bergtold and Onukwugha (2014), the marginal effects for continuous explanatory variables are calculated as a follows:

$$\frac{\partial P(V_{i=j}|X_i=x_i)}{\partial x_k} = \frac{\partial \mathrm{h}_j(\mathrm{X}_i;\beta)}{\partial x_k} = \mathrm{h}_j(\mathrm{X}_i;\beta) = \left[\frac{\partial \eta_j(\mathrm{X}_i;\beta_j)}{\partial x_k} - \sum_{s\neq m}\frac{\partial \eta_s(\mathrm{X}_i;\beta_s)}{\partial x_k}\ \mathrm{h}_s(\mathrm{X}_i;\beta)\right] \quad (5)$$

For binary variables, the marginal effect is just relative change in probability when the value of the explanatory variable changes from ‘0’ to ‘1’.

Data

For the empirical estimation, cross-sectional production, financial, and demographic farm-level data on Kansas farms for 2014 was obtained from the Kansas Farm Management Association (KFMA) database. Current and prior PA adoption data were appended to the existing KFMA databank. As of April 2017, there were 359 farms present in both the existing KFMA database and PA technology data for the year 2014. This study also incorporated SSURGO soils data aggregated to the county-level – including soil slope and slope composition variables.

The choice sets of information-intensive technologies examined included: yield monitor (YM) (both with and without GNSS), variable rate application of fertilizer (VRF), and precision soil sampling (PSS). These technologies were adopted either individually or jointly as bundles. The bundle categories included: ‘None’, ‘YM’, ‘PSS’, ‘YM & PSS’, ‘VRF & PSS’, and YM, VRF & PSS’. The other two possible bundles, ‘VRF’ and ‘YM & PSS’, had too few a number of observations, and therefore were excluded for the empirical analysis. Observations for these two bundles were dropped from the dataset. The number of farms adopting the six remaining different technology bundles is shown in Table 1.

For the empirical estimation of the model, different farm and farmer characteristics are used as independent, explanatory variables. Descriptive statistics of the farm variables used in this study are shown in Table 2. The selection of explanatory variables was made based on prior literature. Variables such as age of farmer, farm size, acreage, and investments, geographic location, and soil characteristics have been used in both the literature specific to precision agriculture (Daberkow and McBridge 2003; Jenkins et al. 2011; Watcharaanantapong et al. 2013) and in the literature on other forms (e.g. conservation tillage) of adoption of farm practices (Gould et al. 1989; Lambert et al. 2007). Farms in the KFMA databank are, on average, medium to large in size, are operated by farmers advanced in age, and have significant machinery investment costs.

Variables are defined as follows. Total acres operated represents a measurement of farm size. The crop machinery investment variable represents the average of beginning and ending basis values for motor vehicles, listed property, machinery and equipment used for crop production. Ending debt to asset ratio equals current debt divided by the value of all assets. Value of farm production is gross farm income equal to value of farm production plus accrual feed purchased. Characteristics that measure slope of the land, percentage of sand, and percentage of silt are also included. These soil variables represent average county soil characteristics (note that this data is constant across time and varies only across counties, so that farmers from the same county share the same soil characteristics). Regional dummies are also used to account for spatial heterogeneity in technology adoption across Kansas. These binary variables represent region-specific fixed effects and are based on the six KFMA Associations. Five dummies, for the northeast, southeast, north central, south central, and western regions of Kansas, were used (KFMA also defines northwestern and southwestern regions, but these regions were combined because the data used has only limited observations for northwestern Kansas).

Results

The multinomial logistic regression model was estimated in STATA. The results of the estimation are omitted because of their limited interpretability. The pseudo R^2 is 0.25 indicating that the model explains variability in adoption patterns. Following estimation, marginal effects for each explanatory variable were calculated following the derivation in equation (5). A summary of the marginal effects is reported in Table 3. In general, the marginal effects analysis results indicated that per unit increases in the demographic, production, and financial level variables have a significant impact on the probability of adopting PA technology bundles.

Consider the marginal effect for age. A one-year increase in the age of the operator increases by 0.75% the likelihood of adopting no technology, and decreases by 0.27% the likelihood of adopting the complete bundle of YM, VRF & PSS. This conforms to results found elsewhere (Lambert et al. 2015). Similarly, a per unit increase in the number of farm acres also increased the likelihood of adopting no technology (i.e. the 'none' bundle). This indicates that as farms expand they are less likely to adopt any technology bundle. This result makes sense given that farms have two strategies by which they can expand production: either through physical expansion (increasing the acreage of the farm) or through intensification (increasing the productivity of land already under production). As a significant part of the attraction of information intensive PA technologies comes from their intensification property (making cropland more productive) it follows then that farmers engaged in physical expansion of acreage are less likely to adopt PA technologies.

Also unsurprising is the marginal effect of machinery investment on the probability of adoption of technology bundles. A per unit increase in farm investment in machinery raises the probability of adopting bundles with multiple technologies (YM & PSS, VRF & PSS, and YM, VRF & PSS). For some time now, farm equipment has often come equipped with PA technology capabilities (e.g. YM on new combines). It is therefore likely that investment in machinery and investment in precision agriculture technology is highly positively correlated. Farms that invest in machinery are often investing directly or indirectly in PA technologies. This explains both the sign and the level of significance on the marginal effects of machinery investment on adoption of technology bundles. In recent years, when farmers purchase new or even used equipment, PA technology may be a standard part of that equipment.

Similarly, the marginal effects of crop labor percentage and the total value of farm production on the probability of adoption of PA technology bundles (that include one or more technology) are, with one exception, positive. A one percent increase in the crop labor percentage increases the probability of adopting a PA technology bundle (other than the "none" bundle) as does a one-unit increase in the value of farm production. The result on the marginal effect of the total value of farm production on technology adoption supports previous literature. Schimmelpfennig (2016) reported higher rates of adoption of YM, VR, and PSS on farms that had relatively higher crop values.

It is also important to examine the marginal effects that were found to be insignificant. The marginal effect on the debt to asset ratio is insignificant, indicating that increases in debts relative to assets played at most a marginal role in the likelihood of adopting PA technology. And compared to the demographic, production, and financial characteristic marginal effects, the majority of the soils and geographic-specific marginal effects were insignificant. For the marginal effects of soil this reveals that unit increase in the slope, percentage of sand, and percentage of silt has no effect on the probability of technology adoption. For the marginal effects of the region fixed effects variables, this indicates that farm location within any particular KFMA region does not have any discernable effect on adoption of PA technologies. This outcome was surprising as the information intensive technologies being investigated were thought to be more valuable to farms that operate in areas where the productivity of land is low – and this level of productivity is assumed to fluctuate across geographic space. The estimated marginal effects of soils contradict this point of view.

Conclusion

The multinomial logit model was used to examine the adoption of six technology bundles (including a 'none' bundle) by farmers based on a variety of farm-related explanatory variables. Production, financial, demographic, and soil characteristics were regressed on the probability of adopting each technology bundle. The choice sets of technologies examined included: yield monitor (YM), variable rate application of inputs (VR), and precision soil sampling (PSS). KFMA farm-level data, along with the KFMA PA technology adoption data, and county-level soils data were used in estimating the multinomial logit model.

Results of this analysis show that demographic, production, and financial variables play a key role in farm adoption of technology bundles. Marginal effects for both age and acreage on the probability of adopting technology bundles (other than the 'none' bundle) were negative indicating that larger farms with older operators were less likely to adopt. In contrast, the marginal effects on the crop labor percentage, machinery investment, and value of farm production variables were positive, indicating that farms with higher crop labor percentages, higher investments in machinery, and higher value of farm production are more likely to adopt technology bundles. Soil and regional marginal effects indicated that these variables play a negligible role in the adoption decision-making process. For future study, we suggest estimating this model for multiple years. As adoption of the information intensive technologies has increased sharply (rather than steadily), it is expected that the factors influencing adoption have also changed over time. Incorporating new variables into the model (e.g. crop-specific and tillage practice variables) also have the potential to yield further insight into farms' adoption decision making process.

References

Bergtold, J.S. and E. Onukwugha. 2014. "The Probabilistic Reduction Approach to Specifying Multinomial Logistic Regression Models in Health Outcomes Research." *Journal of Applied Statistics*, Vol. 41(10).

Bullock, D.S., J. Lowenberg-DeBoer, S.M. Swinton. 2002. "Adding Value to Spatially Managed Inputs by Understanding Site-Specific Yield Response." *Agricultural Economics*, Vol. 27.

Daberkow, S.G. and W.D. McBride. 2003. "Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture Technologies in the US." *Precision Agriculture*, Vol. 4.

Gould, B.W. S.E. Saupe, and R.M. Klemme. 1989. "Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion." *Land Economics*, Vol. 65(2).

Griffin, Terry, and J. Lowenberg-DeBoer. 2005. Worldwide Adoption and Profitability of Precision Agriculture: Implications for Brazil. *Revista de Politica Agricola*, 14(4):20-37. http://bit.ly/Zj3D7x

Griffin, T. W., Miller, N. J., Torrez, C., Ciampitti, I., & Sharda, A. 2016. "Precision Agriculture Technology Adoption and Obsolescence." Kansas State University Department of Agricultural Economics Extension Publication. KFMA Research Article. KSU-AgEcon-TG-2016. Retrieved from: https://www.agmanager.info/sites/default/files/pdf/TechnologyAdoption.pdf

Jenkins, A., M. Velandia, D.M. Lambert, R.K. Roberts, J.A. Larson, B.C. English, and S.W. Martin. 2011. "Factors Influencing the Selection of Precision Farming Information Sources by Cotton Producers." *Agricultural and Resource Economics Review*, Vol. 40(2).

Lambert, D.M., P. Sullivan, R. Claassen, and L. Foreman. 2005. "Profiles of US Farm Households Adopting Conservation-Compatible Practices." *Land Use Policy*, Vol. 24.

Lambert, D.M., K.P. Paudel, and J.A. Larson. 2015. "Bundled Adoption of Precision Agriculture Technologies by Cotton Producers." *Journal of Agricultural and Resource Economics*, Vol. 40(2).

McFadden, D. 1974. "The Measurement of Urban Travel Demand." *Journal of Public Economics*, Vol. 3.

Miller, N. J., Griffin, T. W., Bergtold, J., Ciampitti, I. A., & Sharda, A. 2017. Farmers' Adoption Path of Precision Agriculture Technology. *European Conference on Precision Agriculture 2017*. Forthcoming.

Olson, K., P. Elisabeth. 2003. "An Economics Assessment of the Whole-Farm Impact of Precision Agriculture. *Annual Meeting of the American Agricultural Economics Association*. Montreal, Canada. Jul 27-30, 2003. Retrieved from: http://ageconsearch.umn.edu/bitstream/22119/1/sp03ol01.pdf

Popp, J. **Griffin, T.W.,** and Pendergrass, E. 2002. How Cooperation May Lead to Consensus Assessing the Realities and Perceptions of Precision Farming in Your State. *Journal of the American Society of Farm Managers and Rural Appraisers* 65(1):26-31. http://bit.ly/1smabOp

Schimmelpfennig, D. 2016. "Farm Profits and Adoption of Precision Agriculture." Economic Research Report Number 217. United States Department of Agriculture, Economic Research Service.

Schimmelpfennig, D. and R. Ebel. 2016. Sequential Adoption and Cost Savings from Precision Agriculture. *Journal of Agricultural and Resource Economics*, Vol. 41(1).

Tey, Y.S. and M. Brindal. 2012. "Factors Influencing the Adoption of Precision Agricultural Technologies: A Review for Policy Implications." *Precision Agriculture*, Vol. 13.

Watcharaanantapong, P., R.K. Roberts, D.M. Lambert, J.A. Larson, M. Velandia, B.C. English, R.M. Rejesus, C. Wang. 2014. "Timing of Precision Agriculture Technology Adoption in US Cotton Production." *Precision Agriculture*, Vol. 15.

Table 1: 2014 Farm Adoption of PA Technology Bundles

Bundle	Number of Farms
None	211
Yield Monitor (YM)	38
Precision Soil Sampling (PSS)	27
YM & PSS	34
Variable Rate Fertilizer (VRF) & PSS	15
YM, VRF & PSS	34

n = 359

Table 2: Explanatory Variable Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Operator Age	359	58.97	11.26	23	87
Total Acres Operated	359	2158.02	1754.08	154	11422.80
Crop Machinery Investment ($)	359	429084.30	423311.60	0	2912940
Debt to Asset Ratio	359	0.25	0.24	0	1.59
Value of Farm Production ($)	359	604458	572137.60	9676.01	4972300
Slope	359	2.55	0.97	1.21	6.26
Sand (%)	359	14.74	9.54	5.30	55.21
Silt (%)	359	50.31	6.88	23.21	66.62

Table 3: Marginal Effects

	None	YM	PSS	YM & PSS	VRF & PSS	YM, PSS & VRF
Age	0.0075*** (0.0021)	-0.0021 (0.0014)	-0.0017 (0.0013)	-0.00077 (0.0013)	-0.00032 (0.0011)	-0.0027** (0.0013)
Acres	6.94E-05** (2.85E-05)	1.49E-06 (1.94E-05)	-1.4E-05 (0.000016)	-4.9E-05** (1.99E-05)	4.29E-06 (7.96E-06)	-1.2E-05 (1.27E-05)
Machinery	-1.72E-07 (1.21E-07)	5.24E-08 (6.62E-08)	-2.14E-07** (9.91E-08)	1.06E-07* (5.45E-08)	7.43E-08** (3.52E-08)	1.54E-07*** (4.12E-08)
Crop Labor	-0.40*** (0.16)	0.22* (0.126478)	0.10 (0.09053)	0.14 (0.11)	-0.13** (0.056)	0.065 (0.099)
Debt to Asset	-0.014 (0.11)	0.061 (0.062533)	-0.080 (0.072063)	0.052 (0.064)	-0.068 (0.059)	0.049 (0.061)
Value Farm Production	-3.46E-07*** (1.18E-07)	6.44E-10 (7.59E-08)	1.42E-07** (6.20E-08)	1.46E-07*** (5.24E-08)	-1.17E-08 (3.50E-08)	6.84E-08* (3.78E-08)
Slope	-0.0065 (0.035)	-0.0277 (0.025)	0.021 (0.021)	0.021 (0.019)	-0.0063 (0.027)	-0.0016 (0.018)
Sand	0.0061 (0.0072)	-0.003 (0.0051)	-0.0034 (0.0034)	-0.0044 (0.0058)	-0.0017 (0.0036)	0.0064 (0.0056)
Silt	-0.0012 (0.011)	0.0016 (0.0068)	-0.00605 (0.0047)	-0.011 (0.0091)	-0.00037 (0.0061)	0.017* (0.0093)
Region 1	0.10 (0.11)	0.027 (0.063)	0.14*** (0.047)	-0.012 (0.098)	-0.0094 (0.064)	-0.25 (0.12)
Region 2	-0.12 (0.11)	-0.070 (0.084)	0.088 (0.067)	0.010 (0.073)	0.084* (0.046)	0.0095 (0.060)
Region 4	0.37 (54.44)	-0.015 (7.88)	0.027 (6.72)	0.076 (9.07)	-0.55 (91.94)	0.096 (13.83)
Region 5	2.26 (200.46)	0.502 (45.17)	-0.73 (230.32)	-0.70 (185.26)	-0.39 (123.95)	-0.94 (135.58)

Significance: *** = .01, ** = .05, * = 0.1

Figure 1: Study Area Regions