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Acta Agriculturae Scandinavica, Section B — Soil & Plant Science

ISSN: 0906-4710 (Print) 1651-1913 (Online) Journal homepage: https://www.tandfonline.com/loi/sagb20

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To cite this article: Tseganesh Wubale Tamirat, Søren Marcus Pedersen & Kim Martin Lind (2018) Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany, Acta Agriculturae Scandinavica, Section B — Soil & Plant Science, 68:4, 349-357, DOI: 10.1080/09064710.2017.1402949

To link to this article: https://doi.org/10.1080/09064710.2017.1402949

Published online: 15 Nov 2017.

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ACTA AGRICULTURAE SCANDINAVICA, SECTION B — SOIL & PLANT SCIENCE, 2018
VOL. 68, NO. 4, 349–357
https://doi.org/10.1080/09064710.2017.1402949

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Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany

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ABSTRACT

Precision Agriculture (PA) has been advocated as a promising technology and management philosophy that provides multidimensional benefits for producers and consumers while being environmentally friendly. In Europe, private stakeholders (farm advisors, farm equipment producers, decision support providers, farmers) and research institutions have been trying to develop, test and demonstrate adoption of precision agriculture solutions with governments financing big projects in these areas. Despite these efforts, adoption is still lagging behind expectations.

Whether farmers adopt PA or not is likely to be influenced by several factors. This study intends to identify the main socio-economic determinants of adoption of precision agriculture in Denmark and Germany employing a binary logit model on a cross-section survey data. The results show that farm size, farmer age and demonstration and networking events like attending workshops and exhibitions significantly influence farmers' adoption decision.

ARTICLE HISTORY
Received 16 November 2016
Accepted 3 November 2017

KEYWORDS
Auto-guidance; GPS; logit; odds ratio; perception; precision technologies

Introduction

Precision Agriculture (PA) is believed to provide multifaceted benefits of improving performance, production, and economic and environmental quality in the face of increasing demand for agricultural produce and pressing environmental challenges (Zarco-Tejada et al. 2014). Nevertheless, adoption of PA is still far behind expectations partly due to limitations in quantifying and demonstrating its economic value, lack of detailed knowledge on crop production functions and difficulties in identifying optimal management zones (Mintert et al. 2015).

PA adoption in Europe is regarded as lower than expected mainly due to high investment costs for equipment (Reichardt and Jürgens 2009) and high learning costs due to complexities of the systems (Kutter et al. 2011). In fact, it is difficult to find reasonable statistics from literature on PA adoption partly due to varying definitions as to what constitutes PA. An account of PA adoption, challenges and perspectives in Germany is provided in Busse et al. (2014); Reichardt and Jürgens (2009); Kutter et al. (2011) and Reichardt et al. (2009). Some of the studies in the case of Denmark are Pedersen et al. (2004) and Jensen et al. (2012). Jensen et al. (2012) provided simulation results on the likely farm level and national socio-economic and environmental effects of PA and controlled traffic farming in Denmark and provided projections of considerable economic and environmental benefits.

Studies on the adoption of precision technologies often employ logit model with the objective of explaining adoption behaviour of individuals (Daberkow and McBride 2003). Comparison of results from literature is difficult due to differing definitions of the adoption variable, methodology employed and sample size issues. In this paper, PA adoption is defined by use of 'GPS assisted farm management' and/or 'auto-guidance'. Vehicle guidance systems including auto-guidance are reported to be the most widely adopted PA technologies owing to their direct and visible economic benefits for farmers (Tey and Brindal 2012).

Paudel et al. (2011) reported positive influence of farm size and farm income on the probability of technology adoption. Cluster analysis of survey data from Denmark, Germany and Finland indicated that farm size and farmers' interest in farm planning and knowledge sharing have a significant bearing on adoption of auto-guidance (Pedersen et al. 2015). In a study based on farm surveys in Denmark and the US Eastern corn Belt, it was reported that farmers' years of experience, age and acreage did not influence management practices of Danish farmers in the sample even if they had adopted some form of PA (Fountas et al. 2005). Paudel

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et al. (2011) also found that younger, better educated farmers adopt precision technology quickly once those technologies are available. According to Paxton et al. (2011), the extent of PA adoption at a farm level is influenced by within-field yield variability, farmers' education, age and computer literacy where young, educated farmers and those using computers for management decisions are reported to adopt a higher number of precision agriculture technologies.

The discussion concerning the adoption of agricultural technologies in general and precision agriculture in particular is so far focused on analyzing the relatively low adoption of farmers. There is a need to empirically assess what factors play an important role in farmers' decision to adopt PA. This is the intended aim and contribution of this study. The objective of this study is to empirically identify the main farm and operator related factors behind the adoption of PA technologies by analyzing survey data from Denmark and Germany.

Materials and methods

Data and variable definition

The study uses survey data of 260 farmers collected in 2008 from Denmark and Germany[1] on the adoption of PA practices and technologies. The majority (about 71%) of the sample respondents are from Denmark. Detailed description of the content and administration of the survey is presented in Lawson et al. (2011) who provided descriptive analysis of the survey data (samples from Finland included in their study).

This study intends to empirically identify the most important farm and operator attributes determining adoption focusing on socio-economic attributes of farmers/farm managers (age, education, farmer experience, farm structure, and relative importance of farming as a share of income, etc.), availability of and access to reliable information about PA**,** and farmers' perceptions about future profitability and importance of precision agriculture. The following variables are identified as variables of interest in the dataset analyzed.

Country (*Country*): Denmark and Germany coded as 1 and 2 respectively.

Education (Education): Education level of the farmer defined as primary school (0), short education such as agricultural college or technical school (1) and longer education after high school including University education) (2).

Farmer's age (*Age*): In the survey, age is defined as a range variable[2] but in the analysis it was regrouped into two classes: 'young' (below 50) and 'old' above 50 years and assigned values of 1 and 2 respectively.

Land area (*Landarea*): approximate total land area in hectares with three categories: small (<250 ha), medium (250–750 ha) and large (>750 ha) labelled respectively as 1, 2, and 3.

Income from tilled crops (*Tilled*): the percentage share of income coming from tilled crops out of total farm income.

Employed staff (L_employed): the number of permanent staff including the farmer.

Seasonal labor (L_seasonal): seasonal labour for field work.

Time for paperwork, planning, and farm related visits: the amount of yearly average time in hours that a farm manager and his employees spend at farm office working with computer (***Toffice***) and outside-office on farm related visits (***Tout***).

PA related information availability (*Info*): whether a farmer believes information available on precision agriculture is adequate ('Yes' is labelled as '1', 'No' as '0', and '2' as 'do not know or no answer'). 'Don't know' here would mean 'I am in doubt to say *Yes* or *No*'. It is good to have this response category because uncertainty is to be expected in situations like this involving subjective judgement. The doubt may most likely be due to lack of exposure to the phenomenon.

Participation in workshops and exhibitions (Workshop): dummy variable with value of 0 if a respondent reported zero hours and 1 if a positive number is reported.

Farmer's Perception (*Perception*): farmer's perception about the benefit of precision agriculture as approximated by his/her reported belief about the potential of PA to improve crop yield (whether he/she expects the use of precision farming to increase crop yield on his/her farm) and whether he/she encourages[3] other farmers to use PA practices). Both variables were recorded with three data values: 1 for yes, 0 for no and 2 for 'do not know or no answer'.

Adoption of Precision Agriculture (Adoption): defined by the use of precision agriculture in open field with the help of GPS (excluding auto guidance) and/or use of auto-guidance. The distribution of observations according to their adoption response is as follows: 10 use only GPS-assisted PA, 22 only auto-guidance, 18 both, and 210 neither of the two. Adoption of PA (the response variable in the regression analysis) is constructed as a dichotomous variable (0, 1) from answers to these two questions. If the answer for either of the questions is yes (1), then Adoption is set to a value of 1; else it takes the value of '0'. Defined this way from the analyzed sample of 260 observations, the number of observations in each category is as follows: *'0'* = 210 and *'1'* = 50.

While defining the 'Adoption' variable, some ambiguity was encountered for the case where a respondent answers 'No' for the use of either 'PA with GPS' or 'auto-guidance' but did not answer the question for the other. This group of samples is here referred to as 'unclear adoption' category to mean that it is not clear as to whether respondents in this category use some PA. Even though this group accounts for the majority of the sample size (62%), it is not clear from the data as to whether such a respondent has adopted any PA system as defined in this study. The authors argue that such respondents most likely have not adopted the technology to which they have not responded as it is behaviourally straightforward to say 'yes' if they had adopted the system. For the main part of the analysis, this group is treated as non-adopter.

Empirical model and estimation method

With dependent variables of a non-continuous nature (e.g. adoption or non-adoption of a technology), discrete choice models are employed, the commonly used estimation algorithms being probit and logit (Tey and Brindal 2012). The difference between probit and logit basically lies in their distributional assumption of the error terms, i.e. standard normal versus standard logistic distribution. In large samples, the two methods provide comparable results; however, probit estimation is complicated due to the stringent assumption of normal distribution of the error terms while logit tries to smooth the distribution assumption by means of logarithmic transformation.

Based on normality test results, this study employed the logit model with an ex-post approach in the sense that the focus is on actual adoption or non-adoption instead of the intention to adopt. Given that the response variable *Adoption* is a dichotomous response variable (1 = adoption, 0 = non-adoption), the bivariate logit model specified below is applied.

$$P(\text{Adoption} = j) = \log\left(\frac{\text{Adoption} = 1}{\text{Adoption} = 0}\right) = \alpha_j + \beta_1 * \text{Age} + \beta_2 * \text{Landarea} + \beta_3 * \text{Toffice} + \beta_4 * \text{Tout} + \beta_5 * \text{L\_employed} + \beta_6 * \text{L\_seasonal} + \beta_7 * \text{Info} + \beta_8 * \text{Perception} + \beta_9 * \text{Workshop} + \beta_{10} * \text{Cou\_no} + \varepsilon_{ij}$$

Where α_j is a constant and β_j is a vector of regression coefficients, and the explanatory variables are as defined in the data section. For a response variable of j categories, *j–1* parameters are estimated because one serves as a reference group relative to which estimated coefficients are interpreted. Direct interpretation of estimated coefficients is problematic given that a marginal effect of each respective variable in the model depends not only on the level of the variable of interest but also all other explanatory variables in the model. An alternative way is interpreting the odds ratio which is the ratio of odds of a variable at two different values, in this case the ratio of the probability of PA adoption divided by the probability of non-adoption (the reference group in the estimation is Adoption = 0). Depending on the definition of the dependent variable (Adoption), two regressions labelled as 'Model 1' where the 'unclear adoption'[4] sub-sample is treated as non-adopter and 'Model 2' where this group is excluded are carried out. The sample size of the two models is 260 and 100, respectively.

In this study, it is hypothesised that young age of farmers, longer education, large farms, positive expectation about the economic potential of PA, considerable share of tilled crops in farm income, spending considerable time working with computers, attending workshops and exhibitions, positive perception about availability of PA related information increase the propensity to adopt PA.

Results

Descriptive statistics

The data used in this study is a cross section survey of 260 observations from Denmark (184) and Germany (76). Summary statistics of relevant numeric variables included in the analysis is presented in Table A1 in the appendix. An important observation to mention here is the wide dispersion in land area in the sample ranging between less than 20 and greater than 1250 hectares where many of the large farms in the sample are located in Germany. The size of employed staff generally follows farm size distribution. It was also observed that on average farmers spend considerable time (484 hours per year) at farm office for farm planning and learning new procedures; and also for off-field visits and farm related networking (73 hours per year).

Income from tilled crops during 2008 accounted for at least half of total farm income for no less than 68% of the respondents. As for farmers' education, 24.6% have only high-school education, 43.5% have attended short courses most probably targeted vocational training, while the rest 32% reported longer education. From the Danish sample, 50% of the respondents have vocational training while the rest equally divided into primary education and higher education. The case is different for the German sample where close to half of the farmers have attained higher education and about 23% have only primary education.

Respondents who reported of adopting one or both of the PA systems considered in this study constitute 19.2% from the aggregate sample (7.3% are German and 11.9% are Danish respondents). Despite the relatively small representation in the sample, adoption rate is higher for the German sample (40.8%) compared to the Danish sample (10.3%). The majority of adopters are in the age range of 40–50 years.

Regression results

This section presents results from a binary logit regression done using logistic procedure in SAS 9.2. Unless specified, the reported results refer to 'Model 1' where the 'unclear adoption' category is treated as non-adopter. Given the construction of the model, estimated parameters are interpreted as the value for adopter category (Adoption = 1) as compared to the base category of non-adoption (Adoption = '0'). For quick reference, label and description of categorical variables and their respective reference groups used in the regression model are presented in Table 1.

Multicollinearity diagnosis was performed using 'vif', 'collin' and 'tol' functions in proc reg.[5] The test resulted with maximum condition index of 17.592, smallest eigenvalues of 0.0865 and 0.0233, and low variance inflation factors the maximum being 1.20059. All the three indicators[6] suggest that multicollinearity is not as such a concern in our model. A set of tests were performed to assess the goodness of the fit for the regression model (results presented in Table A3 in the appendix). The null hypothesis of joint insignificance of explanatory variables was rejected by Likelihood Ratio, Score and Wald tests. Similarly**, AIC** (Akaike Information Criterion) and **SC** (Schwarz Criterion) test results preferred the model with covariates. SAS output also provides statistics on the individual statistical significance of explanatory variables as presented in Table A4. The fit of the model appears to be better when the 'unclear adoption' category is excluded from the analysis.

Estimated parameters for categorical explanatory variables are to be interpreted relative to their respective reference group. For example, the estimated coefficient associated with Info = 1 and Adoption = 1 denotes the probability (propensity) of a farmer who perceives that information about precision agriculture is publicly available to adopt PA as compared to another that thinks otherwise about information availability, keeping all other things similar.

The number of seasonal field labourers (L_seasonal), the amount of out of office time for farm related visits (Tout) and percentage share of income from tilled crops out of farm income (Tilled) were initially included in the regression as explanatory variables but found to be insignificant. The information criteria (AIC and SC) suggest excluding the variables and hence they are left out of the final analysis. Table 2 presents results from Model 1 where the unclear adoption sample is treated as non-adopter. Comparison of regression results from the two models is provided in Table A5 in the appendix. With the exception of the intercept term and the Country variable, the exclusion of the unclear sample maintains the direction of influence of covariates.

Keeping other things unchanged, being a young age farmer increases the log odds of adoption of PA technology by *0.742* as compared to the reference group of old age. The likelihood of adoption is higher for the German farmers relative to their Danish counterparts as reflected by estimated log odd value of 1.223. Exclusion of the 'unclear adoption' sample pronounced the effect of farmer age but reversed the direction of influence for the Country variable (see Table A5 in the appendix).

Operating a small farm is found to significantly reduce the probability of adopting PA systems relative to the base category of medium sized farms. Regarding the effect of farmers' belief about the adequacy of information on precision agriculture, respondents in doubt about the phenomena (Info = 2) are found to have lower probability of adopting the system relative to those who clearly reported that information is lacking. Thus, uncertainty appears to negatively affect adoption more strongly than clear perception on the lack of information on PA.

Attendance of workshops and exhibitions exhibits a positive and statistically significant effect on the probability of adoption in the full sample but its statistical significance deteriorated with the exclusion of the 'unclear adoption' sample. On the other hand, Education, Perception about the benefits of PA, number of field staff and amount of office time do not appear to have any important effect on the adoption of PA. To sum up, farmers' age, farm size, farmers' belief about the availability of enough information on precision agriculture, participation in workshops and exhibitions are found to significantly affect the adoption of precision agriculture for the case of the sample studied.

Discussion

In this study, an attempt has been made to identify the most important farm and operator factors influencing farmers' adoption of precision agriculture practices defined as the use of auto-guidance and/or GPS assisted precision agriculture. The analysis employs a binary logit model on a cross-section survey data from Germany and Denmark.

Table 1. Label and description of categorical variables.

Variable	Label and Description	Reference group
Adoption	0 (Not adopted)	0
	1 (Adopted)	
Info	0 (PA info not available enough)	0
	1 (Info about PA is enough)	
	2 (Do not know or missing value)	
Workshop	0 (Do not attend)	0
	1 (Attend)	
Country	1 (Denmark)	1
	2 (Germany)	
Perception	0 (PA not perceived to have economic potential);	0
	1 (PA perceived good);	
	2 (Don't know/missing value)	
Agegroup	1 (Young)	2
	2 (Old)	
Farmsize	1 (Small)	2
	2 (Medium)	
	3 (Large)	
Education	0 (primary school)	0
	1 (Short training after primary school)	
	2 (Longer education including University)	

In support of the hypothesis that innovations with high fixed transaction and/or information costs are less likely to be adopted by small farmers (Daberkow and McBride 2003), small farm size reduced the probability of adopting precision agriculture systems in the sample analyzed as can be inferred from Table 2. Farmers operating large farms would more likely adopt precision technologies to take advantage of economies of scale by amortising fixed cost (Pierpaolia et al. 2013). This is in line with Lambert et al. (2015) who found that farmers operating larger operations have higher propensity to adopt precision agriculture practices. This could be explained by the fact that most PA technologies are embodied in expensive equipment (Swinton and Lowenberg-Debour 2001) and that many of the machineries are indivisible. This indivisibility problem might be reduced through the expansion of custom service provision and consultancy (Feder et al. 1985).

Table 2. Binary logit regression results from model 1.

Parameter	Class	Estimate	Standard error	Wald X^2	$Pr > X^2$
Intercept		−1.928	1.1923	2.615	0.1059
Agegroup	1	0.742	0.4202	3.122	**0.0772***
Farmsize	1	−1.228	0.4513	7.404	**0.0065*****
Farmsize	3	0.116	0.813	0.02	0.8863
Toffice		0	0.0002	0.176	0.6747
L_employed		0.065	0.0403	2.564	0.1093
Info	1	−1.148	0.7742	2.197	0.1383
Info	2	−1.929	0.8124	5.64	**0.0176****
Perception	1	0.663	0.5913	1.256	0.2624
Perception	2	−0.075	0.6077	0.015	0.902
Workshop	1	1.163	0.5153	5.092	**0.0240****
Country	2	1.223	0.4887	6.26	**0.0124****
Education	1	0.486	0.6362	0.583	0.4452
Education	2	0.323	0.632	0.261	0.6095

Notes: ***denotes statistical significance at 1%; **at 5%; *at 10%. Agegroup 1 = young; Farmsize 1 = small, 3 = large; Info 1 = enough info about PA, 2 = don't know or missing; Perception 1 = PA perceived as good, 2 = don't know or missing; Workshop 1 = attend; Country 2 = Germany; Education 1 = short training after high school, 2 = longer education including University.

It is also shown that farmers below the age of 50 years showed a higher propensity to adopt as compared to their older counterparts (Table 2). In reality, very young farmers lack the managerial experience and may have little understanding of variabilities in their farm (Kotsiri et al. 2011) whereas old farmers' may be susceptible to traditional resistance to changes and they may not see longer-term economic benefits perhaps because they are considering retiring. The finding confirms the views of Roberts et al. (2004) who argue that older farmers may be less willing to face learning curves or may have a shorter planning horizon than younger farmers. The result is in line with Paudel et al. (2011) and Paxton et al. (2011).

Both the descriptive statistics and the regression results (Table 2) agree that German farmers have a higher propensity to adopt as compared to their Danish counterparts in the sample analyzed. Seen in the light of the finding that farm size significantly affected adoption, it could be because most of the survey respondents are from the Eastern part of Germany where a lot of large farms have been created out of the prior big collective state farms of the socialist tradition. The exclusion of the 'unclear adoption' sample shows the opposite may be because the majority of the observations analyzed in the reduced sample are from Denmark where farm sizes are relatively small and this might have influenced the estimates.

From the descriptive statistics it was observed that adopters generally allot longer times to work with computers at farm office. However, this effect was not found to be statistically significant in the regression analysis even if the direction of influence is as expected. Contrary

to Paxton et al. (2011), farmers with longer education do not have a higher propensity to adopt in our case study. The result may have been influenced by the fact that much of the sample is from Denmark where targeted and skill-oriented short term courses have provided due emphasis on success in businesses like farming. One would expect that the better the availability of PA related information, the higher the probability of adoption; however, our results (Table 2 and Table A5) tell the opposite. Loosely speaking, lack of awareness and information availability does not appear to be a binding constraint to PA adoption as such. Daberkow and McBride (2003) reported similar finding on the effect of awareness on adoption in the case of US.

Drawing on the descriptive and empirical results, it can be concluded that young farmers operating at least midsize farms, attending workshops and exhibitions had higher propensity of adopting precision agriculture practices as defined in this study. As far as country effect is concerned, German farmers appeared to be better adopters in the full sample but the exclusion of the 'unclear adoption sample' reversed the result. In reality, the decision to adopt PA is a complicated problem as several issues like uncertainty in benefits and costs, managerial capability required, lack of useful decision support platforms, etc. influence actual gains versus expected potentials. Even though the scope of this study is limited to the effect of farm and operator characteristics, the results provide important insights that need be given due attention in any effort to promote the adoption of PA.

The reader shall be reminded about the limitations in this study. Even though the survey respondents were asked if they have tried any precision agriculture such as variable rate input application, remote sensing, etc., such disaggregated information as a measure of PA adoption could not be used due to too many missing observations. Instead, the adoption variable is constructed from 'Yes-No' responses for two general questions concerning the use of GPS-assisted PA and auto-guidance. Besides the small size of the dataset, the use of cross section data which may not capture the full picture particularly for attributes that vary significantly from year to year for a particular respondent is also a concern. For some variables, the survey coding did not distinguish between 'no answer' and 'do not know' type responses. In combination, these issues could have an effect on the results. Hence, the results presented should be taken with caution and interpreted in the context of the particular sample analyzed.

Notes

1. The survey included samples from Greece and Finland but there was no PA data on the former and only one Finnish farmer reported to have adopted some precision agriculture.
2. Age and land area variables were defined in the dataset as nearly categorical instead of continuous variables: Age: 20 = [20, 29], 30 = [30, 39], 40 = [40, 49], 50 = [50, 59], and 60 = [60] years old; Land area: 150 = 100–150; 200 = 150–200; 250 = 200–250; 500 = 250–500; 750 = 500–750; 1000 = 750–1000; 1250 = 1000–1250; and 1260 greater than 1250. It was attempted to treat the two variables as continuous variables but due to lack of variability they were redefined as category variables with some regrouping taking into consideration observed distribution across the sample. Due to skewed distribution of the age variable (more than half of the respondents aged 50 and above), only two age groups (below 50 and above 50) appear to be adequate in the regression analysis. Similarly, land area is redefined as categorical variable with three labels: small, medium and large.
3. In the data for whether respondents encourage other farmers to use some of the PA techniques, the data values were confusing because both 2 and −1 were entered but the label defines 2 as a blank answer or 'do not know' type response. For consistency we set all the 24 entries with a data value of −1 to 2 because we do not have a way of distinguishing non-response from that of 'do not know' type response.
4. 'Unclear adoption' means it is not clear as to whether respondents in this category use some PA because they responded 'no' for the use of either 'PA with GPS' or 'auto-guidance' but they did not answer the question for the other.
5. There are no built in capabilities in SAS for direct multicollinearity diagnosis in logit models. Given that multicollinearity concerns the presence of linear relation among explanatory variables, we argue that the problem can sensibly be detected from a linear model using REG procedure.
6. The rule of thumb is that when condition index is greater than 30, eigenvalues are close to zero, and/or variance inflation factor is greater than 5 or 10, multicollinearity is highly likely to affect the reliability of the model.

Acknowledgements

We would like to thank our colleagues, Frank W. Oudshoorn, Aarhus University, Denmark and Luzia Herold, from Leibniz-Centre for Landscape Research (ZALF) Germany for helping with data collection for this survey.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This project was part of the collaborative research project FutureFarm. The research leading to these results has received

funding from the European Community's Seventh Framework Programe (FP7/2007–2013) under grant agreement no 212117 and the study is a part of a PhD study partly financed by the USER-PA ICT-Agri programme.

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Appendices

Table A1. Summary statistics of relevant numeric variables ($N = 260$).

Variable name	Label	Mean	Std. Dev	Minimum	Maximum
Age	Age in years	44.58	10.14	20	60
Landarea	Land area in hectares	268	312.28	20	1260
Tout	Time spent for paperwork and planning out of office(hrs/yr)	73.2	142.75	0	1400
Toffice	Time spent at farm office (hrs/yr)	484.15	878.41	0	7280
L_employed	Number of employed field staff	3.33	8.9	0	112
L_seasonal	Number of seasonal field labourers	3	25.28	0	400
Tilled	Percentage of farm income from tilled crops	52.7	36.46	0	100

Table A2. Multicollinearity diagnosis.

Variable	DF	Estimate	Standard error	*T* value	*Pr* > |*t*|	Tolerance	Variance inflation
Intercept	1	0.080	0.121	0.660	0.512	.	0.000
Agegroup	1	−0.083	0.045	−1.840	0.068	0.866	1.155
Farmsize	1	0.215	0.044	4.890	<.0001	0.591	1.693
Toffice_farmonly	1	0.000	0.000	−0.570	0.573	0.626	1.599
Tout	1	0.000	0.000	0.980	0.327	0.847	1.181
L_employed	1	0.006	0.003	1.930	0.055	0.676	1.478
Tilled	1	0.001	0.001	1.090	0.275	0.881	1.135
Info	1	−0.106	0.037	−2.860	0.005	0.836	1.196
Perception	1	−0.017	0.029	−0.590	0.553	0.942	1.061
Workshop	1	0.120	0.045	2.660	0.008	0.887	1.127
Education	1	−0.008	0.031	−0.270	0.784	0.833	1.201

The multicollinearity test is done using 'collin' function in proc reg. Note: the Country variable is left out as it does not fit the list.

Table A3. Model fit statistics and test of global significance (Model 1, $N = 260$).

Criterion	Intercept only	With covariates
AIC	256.57	197.67
SC	260.13	247.52
−2 Log L	254.57	169.67
Test	**ChiSq**	***Pr* > ChiSq**
LR	84.8935	<.0001
Score	82.891	<.0001
Wald	49.4141	<.0001

Note: ChiSq = chi-squared value.

AIC = −2 Log L + 2((*k*−1) + *s*), where *k* is the number of levels of the dependent variable and *s* is the number of predictors in the model. BSC $= -2\,\text{Log L} + ((k-1)+s)*\log\left(\sum \text{fi}\right)$, where f_i''s are the frequency values of the *i*th observation, and *k* and *s* as defined above. LR is computed as negative two times the log likelihood. Whereas AIC is used for the comparison of models from different samples or non-nested models LR is used in hypothesis tests for nested models. For detailed description of these statistics, visit this page http://www.ats.ucla.edu/stat/sas/output/sas_ologit_output.htm.

Table A4. SAS output: analysis of type 3 effects (Model 1 versus Model 2).

		$N = 260$		$N = 100$	
Variable	DF	Wald Chi-Square	*Pr* > ChiSq	Wald Chi-Square	*Pr* > ChiSq
Agegroup	1	3.1218	0.0772*	4.6169	0.0317**
Farmsize	2	7.5169	0.0233**	4.979	0.083*
Toffice	1	0.1762	0.6747	1.7972	0.18
L_employed	1	2.5639	0.1093	1.7266	0.1888
Info	2	6.4841	0.0391**	4.8213	0.0898*
Perception	2	2.5009	0.2864	3.8131	0.1486
Workshop	1	5.0921	0.024**	2.5637	0.1093
Country	1	6.2599	0.0124**	5.3244	0.021**
Education	2	0.5909	0.7442	0.9732	0.6147

Notes: ***denotes statistical significance at 1%; **at 5%, and *at 10%.; Chisq is chi-squared value.

SAS output provides 'Type 3 Analysis of Effects' which shows hypothesis tests of statistical significance for each of the variables in the model individually. The chi-square test statistics and associated *p*-values shown in Table A4 indicate whether the inclusion of each variable in the model significantly improves the model fit. For continuous variables, this test duplicates the test of the coefficients that is also presented in the maximum likelihood estimates whereas for class variables this table gives the multiple degree of freedom tests for the overall effect of the variable.

Table A5. Regression results from full sample ($N = 260$) versus exclusion of 'unclear adoption' ($N = 100$).

		Model 1: Considering 'unclear adoption sample' as 'non-adopters' ($N = 260$)			Model 2: Excluding unclear adoption sample ($N = 100$)		
Parameter	Class	Estimate	Wald X^2	$Pr > X^2$	Estimate	Wald X^2	$Pr > X^2$
Intercept		−1.928	2.615	0.1059	2.451	2.017	0.1555
Agegroup	1	0.742	3.122	**0.0772***	1.234	4.617	**0.0317****
Farmsize	1	−1.228	7.404	**0.0065*****	−1.283	4.377	**0.0364****
Farmsize	3	0.116	0.02	0.8863	0.453	0.217	0.6411
Toffice		0	0.176	0.6747	0	1.797	0.18
L_employed		0.065	2.564	0.1093	0.047	1.727	0.1888
Info	1	−1.148	2.197	0.1383	−2.702	3.369	**0.0664***
Info	2	−1.929	5.64	**0.0176****	−3.217	4.662	**0.0308****
Perception	1	0.663	1.256	0.2624	0.453	0.384	0.5353
Perception	2	−0.075	0.015	0.902	−0.767	1.05	0.3054
Workshop	1	1.163	5.092	**0.0240****	1.103	2.564	0.1093
Country	2	1.223	6.26	**0.0124****	−1.554	5.324	**0.0210****
Education	1	0.486	0.583	0.4452	0.846	0.89	0.3456
Education	2	0.323	0.261	0.6095	0.467	0.301	0.5834

Notes: ***denotes statistical significance at 1%; **at 5%; *at 10%. Agegroup 1 = young; Farmsize 1 = small, 3 = large; Info 1 = enough info about PA, 2 = don't know or missing; Perception 1 = PA perceived as good, 2 = don't know or missing; Workshop 1 = attend; Country 2 = Germany; Education 1 = short training after high school, 2 = longer education including University.

The significance of explanatory variables from both regressions is somehow comparable with some exceptions. In the model considering 'the unclear adoption category' as no adoption, Farmsize, Information, Workshop and Country are found to have a statistically significant effect on the probability of adopting precision agriculture systems in the sample considered. When the 'unclear adoption' category is excluded from the regression, Farmsize and Info are no more significant at 5% but at 10% whereas workshop attendance does not have a statistically significant effect on adoption even at 10%. The exclusion of that sample generally reduces statistical significance with the exception of the Agegroup variable.