UNDERSTANDING THE ADOPTION TIMING OF SMARTPHONES IN GERMAN AGRICULTURE

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Abstract

While the adoption of smartphones and apps are already investigated, no study has yet focused on factors affecting the timing of smartphone adoption in agriculture. Understanding the timing of a technology adoption and identifying characteristics of early and late adopters is important to further anticipate and foster the diffusion process. The aim of this study is therefore to analyse the timing of smartphone adoption for agricultural purposes by applying a tobit regression model to a data set of 207 German farmers, which was collected in 2019. Results show that among other factors, farmers' age, risk attitude and gender as well as farm size and farm location affect the timing of smartphone adoption for agricultural purposes. The results are of interest for several groups of interest like agricultural policy makers, agricultural extension services, providers and sellers of smartphones.

Keywords

smartphone; German farmers; technology adoption; timing of adoption; tobit regression

1 Introduction

Smartphones can be described as intelligent mobile devices with computer-like computing capacities, access to mobile internet as well as being equipped with several sensors and cameras. Furthermore, software in form of apps can be (de-)installed according to the users' needs (HÜBLER and HARTJE 2016). Due to their technological advances like independence of landline data networks, HÜBLER and HARTJE (2016) argue that smartphones can contribute to rural technological and economic development. Unsurprisingly, HÜBLER and HARTJE (2016) proposed to foster the spread of smartphones in rural regions by development policies.

Farmers still represent the core of rural economies and communities in many countries (JEFFCOAT et al. 2012). The use of smartphones is not only of interest when connecting these regions digitally via mobile internet, but also when improving farmers' businesses (MICHELS et al. 2020c). In this vein, LANDMANN et al. (2020) emphasize that smartphones offer the opportunity to develop farmers' management capacities by providing constant access to updated and reliable information to make proper and in-time decisions at different stages of the agricultural production. In addition, smartphones are very well suited to farmers' daily working routine due to their mobility, built-in sensors, access to mobile internet and multifunctionality via agricultural apps (PONGNUMKUL et al. 2015; BONKE et al. 2018). The application of apps as decision support tools (DST) in several areas of agricultural production like crop protection (MICHELS et al. 2020a) is already possible and used by some farmer. Furthermore, smartphones are able to be integrated with precision agricultural technologies (PAT) and sensors used on the farms (MICHELS et al. 2020b) to facilitate and mediate data collection and processing (FULTON and PORT 2018). In this vein, smartphones can contribute to a more environmentally friendly and animal-welfare orientated agricultural production since they can be considered as a key instrument in providing access to several stakeholders and disseminate necessary knowledge for each individual farmer irrespective of their country setting.

However, literature on smartphone adoption and use in agriculture is scarce. While the smartphone adoption decision (MICHELS et al. 2020b) has already been investigated, no study has yet focused on the timing of adoption. The timing of adoption is of great importance for a farmer since the decision to be among the early adopters or to delay the adoption to a later date comes with (dis)advantages. Earlier adopters may benefit first from the advantages a new technology offers but simultaneously may face trouble using a new immature technology and having need for assistance. Late adopters may face lower costs and experience a more mature technology, but cannot benefit as much as the early adopter from the use of a new technology.

Timing of adoption or diffusion of agricultural technologies can be understood as a gradual process (JAFFE et al. 2002), which depends on farm and farmers' characteristics (FUGLIE and KASCAK 2001). In line with this, WATCHARAANANTAPONG et al. (2014) showed that farmers and farm characteristics affect timing of PAT adoption. Likewise, MICHELS et al. (2020b) provided empirical evidence that these factors also play a role in the smartphone adoption decision. Consequently, the aim of this study is to identify factors affecting the timing of smartphone adoption. In specific, the objective of this paper is to investigate farm and farmers' characteristics which influence the timing of smartphone adoption in agriculture. Understanding the timing of adoption is crucial to anticipate the process of diffusion by identifying early adopters and farmers, who delay the adoption decision. Furthermore, combining existing knowledge of who is most likely a smartphone adopter with an understanding of the timing of smartphone adoption allows providers and sellers of smartphones, agricultural apps and complementing technologies to target their marketing activities more precisely. In line with this, knowledge from early adopters in terms of barriers and difficulties using a smartphone and agricultural apps could be used to remove barriers and help to improve the user experience. Identifying later adopting farmers could help policy makers and agricultural extension services to develop programs that tackle barriers faced in the adoption of smartphones, agricultural apps and complementing technologies. Consequently, understanding the timing of adoption can also be used to anticipate the process of smartphone diffusion and develop more need-based educational programs tailored to the late adopters probably facing barriers in the adoption. Ultimately, this knowledge can then be used to foster the diffusion of smartphones among farmers by development policy and several other stakeholders.

The article contributes to the literature as follows: This article focuses on factors affecting the timing of smartphone adoption for agricultural purposes. In specific, this study identifies features of farmers and farms that characterize early adopters and the type of farmers who delay the adoption. Timing of adoption is explored using a left-censored tobit regression model applied to a data set of 207 German farmers collected via an online-survey in the first quarter of 2019. The results are of interest for several groups of stakeholders.

2 Hypotheses

As smartphones share characteristics of mobile phones, computers and PAT (PONGNUMKUL et al. 2015) and can also integrate with PAT (MICHELS et al. 2020b), the classification of factors affecting the adoption of PAT by PIERPAOLI et al. (2013) is adopted. Based on that classification, the considered farmers and farm characteristics are subdivided in socio-demographic factors (**H1**, **H2**, **H3**, **H4**, **H5**), financial resources (**H6**, **H7**, **H8**) as well as competitive and contingent factors (**H9**, **H10**, **H11**, **H12**), which are most likely to affect the timing of smartphone adoption.

MICHELS et al. (2020b) showed that younger farmers have a higher likelihood of being a smartphone user than older farmers. They reasoned their findings, among others, that younger farmers have higher skills to work with digital ICTs. Hence, the following hypothesis will be tested:

H1: Farmers' age delays the timing of smartphone adoption (*Age*)

Farmers with a university degree are expected to have better skills in using digital technologies (PAUSTIAN and THEUVSEN 2017). MICHELS et al. (2020b) suggest that using the smartphone as a device for information retrieval is a reason why a farmer with a university degree has a higher likelihood of being a smartphone user. Taking both consideration into account, the following is hypothesized:

H2: Holding a university degree fosters the timing of smartphone adoption (*Education*)

With respect to smartphones, MICHELS et al. (2020b) showed that male and female farmers have the same chances of being a smartphone owner. However, in terms of smartphone use intensity, MICHELS and MUSSHOFF (2020) showed that male farmers use statistically significant more agricultural apps. Despite the mixed results in the literature, it is also expected that male farmer adopts a smartphone at an earlier stage than female farmers, which is also shown in the following hypothesis to be tested:

H3: Being a male farmer fosters the timing of smartphone adoption (*Gender*)

Several studies showed that computer literacy facilitates the adoption of PAT (e. g. PAXTON et al. 2011; TEY and BRINDAL 2012) since these farmers have achieved digital skills which facilitates working with PAT. Likewise, it can be expected that a farmer who is familiar in working with a computer perceives the use of a smartphone easier and therefore adopts a mobile device at an earlier stage than a farmer without computer literacy. This relationship is displayed in the following hypothesis:

H4: Having a laptop or PC fosters the timing of smartphone adoption (*Laptop, PC*)

Farmers' risk attitude is considered to be as an important factor in technology adoption decision processes. A new technology comes with many risks, for instance, farmers may not be sure if the investment would pay off (BAUMGART-GETZ et al. 2012). Likewise, usage of new digital technology like smartphones for business purposes might be risky as this technology might not be fully developed yet. Early adopters tend to be more risk-seeking, while late adopters are more likely to be risk averse. Hence, it can also be expected that earlier smartphone adopters are more willing to take a risk. Therefore, the following hypothesis will be tested:

H5: A less risk-averse attitude fosters the timing of smartphone adoption (*RiskAtt*)

Agricultural contractors are service providers who perform various operational tasks for farmers, e.g. fertilization or harvest. Hence, contractors are in contact with several customers and also have to organize several jobs besides their own farm business for which a smartphone can be more useful than a common mobile phone. The study therefore suggests that agricultural contract farming in addition to individual arable farming fosters an early smartphone adoption as shown in the following hypothesis:

H6: Being an agricultural contractor fosters the timing of smartphone adoption (*Contractor*)

Full-time farmers can be expected to be fully involved with their farm business and therefore have less competition for time than part-time farmer having another job (BATTE, 2005). Furthermore, a full-time farmer might search for several opportunities to support and improve his or her farm business and decisions. As smartphones offer several features which can support the farmer in several on-farm operations, for instance providing constant access to farm related news and agricultural prices (HOFFMANN et al. 2013), the following is hypothesized:

H7: Being a full-time farmer has a positive effect on the timing of adoption (*FullTime*)

Obviously, a farm manager is responsible for every on-farm decision. Considering smartphones and agricultural apps as DST, a farm manager might be more inclined to adopt a smartphone at an earlier stage than, for instance, an employee. The following hypothesis displays these thoughts:

H8: Being the farm manager fosters the timing of smartphone adoption (*Position*)

Some farms serve as locations for trainees in agriculture. Young trainees in agricultural can be expected to be highly interested in ICTs. Hence, a farmer who is in constant contact with young trainees through the training, might also become aware of and interested in smartphone technology for agricultural purposes as shown in the following hypothesis:

H9: A farm serving as a training location for agricultural apprentices fosters the timing of smartphone adoption (*Apprentice*)

MICHELS and MUSSHOFF (2020) showed that conventional farmers have a higher smartphone use intensity than organic farmers in terms of used agricultural apps. They reasoned their findings with the fact that available agricultural apps are more suited for conventional farming. Hence, it can be expected that a conventional farmer therefore adopts a smartphone earlier than an organic farmer, which is displayed in the following hypothesis:

H10: Managing a conventional farm fosters the timing of smartphone adoption (*Conv*)

Literature argues that adoption of PAT is positively correlated with farm size due to high investment costs (TEY and BRINDAL 2012). However, smartphones are less costly than PAT (PONGNUMKUL et al. 2015), still Michels et al. (2020b) find a positive effect on farm size on smartphone adoption since smartphones can be used for organizational purposes which is higher in larger farms compared to smaller farms. Hence, the following hypothesis will be tested:

H11: Farm size in hectares arable land fosters the timing of smartphone adoption (*FarmSize*)

In order to get the full potential out of a smartphone sufficient mobile internet coverage is needed. In this vein, MICHELS et al. (2020b) have shown that smartphone adoption is less likely for farmers living in the southern Federal states of Germany compared to rest of the country. They reasoned their finding with relatively less-developed LTE net coverage. Hence, it can also be expected that the timing of adoption is affected by the farm location which is expressed in the following hypothesis:

H12: Location of the farm in the southern region of Germany with less mobile internet coverage delays the timing of smartphone adoption (*Region*)

3 Material and Methods

3.1 Survey design

In the first quarter of 2019, an online survey addressed to German farmers was conducted. Farmers were invited to participate in the survey using various groups on social media platforms, agricultural online forums and newsletters. Being active in arable farming was a precondition to take part in the survey. The survey was divided into two parts: In the first part, farmers were asked to enter information on socio-demographic and farm related characteristics as presented in the section on hypotheses generation. In the second part of the survey the farmers were asked if they use a computer, laptop, mobile phone and smartphone. With respect to the use of smartphones, farmers were also asked since which year they used it for agricultural purposes. The collected variables and their descriptive statistics are presented in the results section.

3.2 Conceptual and theoretical framework

Following WATCHARAANANTAPONG et al. (2014), it can be assumed the survey was conducted in year t_s and farmer i reported his or her smartphone adoption in year t_a. Hence, the smartphone experience of farmer i in years ($SmExp_i$) as a measure for the timing of adoption can be estimated as follows:

$$SmExp_i = t_s - t_a \tag{1}$$

Hence, if a farmer i did not adopt a smartphone before t_s, the farmer would not report a year of adoption t_a which means $SmExp_i = 0$. If a farmer i adopted a smartphone in year t_a before t_s then $SmExp_i > 0$. A large value for $SmExp$ indicates an early timing of adoption since the difference between the year the survey was conducted and the year of smartphone adoption differs to a greater extent. For a tobit model it is assumed that the dependent variable Y_j for the observations $j = 1, \dots, n$ satisfy (GREENE, 2018):

$$Y_j = \max(Y_j^*, 0) \tag{2}$$

which means that Y is observed for values greater than 0 but not values of 0 or less. Taking these considerations into account, it is suggested to use a tobit model (TOBIN, 1958) to estimate timing of smartphone adoption in German agriculture. Hence, a tobit regression model for the timing of smartphone adoption can be defined as follows (GREENE, 2018):

$$SmExp_i^* = x_i'\beta + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \sigma^2) \tag{3}$$

$$SmExp_i = \begin{cases} SmExp_i^* & if\ SmExp_i^* > 0 \\ 0 & if\ SmExp_i^* \leq 0 \end{cases}$$

where $SmExp_i^*$ is a latent variable, which can be observed if, and only if, the values are greater than 0. β is the vector of explanatory variables (e.g. farmer and farm characteristics (**H1** – **H12**)) and ε_i is a normally distributed error term. By conducting the survey in the first quarter of 2019 the study reduced the chance a farmer reports the start of using a smartphone in 2019 which would also result in $SmExp_i = 0$ according to equation 1 and be therefore censored in the estimation of the tobit regression according to equation 3. The estimation was carried out using STATA 14.2.

4 Results and discussion

4.1 Descriptive results

207 fully completed questionnaires remained as usable records after removing incomplete surveys. Table 1 shows the descriptive statistics for smartphone ownership as well as the years of smartphone use. Furthermore, the considered socio-demographic factors (**H1 – H5**), financial resources (**H6 – H8**) as well as competitive and contingent factors (**H9 – H12**) included in the econometric analysis are also shown in Table 1. 95 % of the farmer in the sample have a smartphone[1] which exceeds the German average of 62 % (AGRIDIRECT DEUTSCHLAND GMBH, 2016). Smartphone users in the sample reported the use of smartphones for 7.62 years on average for agricultural purposes. The average farmer in the sample is 39 years old (**H1**) which is younger than the average German farmer (53 years old). With respect to education, 52 % of the farmer in the sample report holding a university degree (**H2**). In German agriculture, 12 % of the farmer hold a university degree. 6 % of the farmer are female (**H3**), which does not exactly correspond to the German average of 10 % (GERMAN FARMERS FEDERATION, 2020). 79 % of the farmer in the sample report having a PC and 66 % state they have a laptop (**H4**). Risk attitude was measured using the 11-point scale developed by (DOHMEN et al. 2011). A value of 5 on the scale indicates a risk neutral individuum (0 – < 5 = risk averse, 5 = risk-neutral, > 5 – 10 = risk-seeking). The average farmer of the sample can be considered to be slightly risk neutral with an average value on the scale of 5.42 (**H5**). 27 % of the farmers work as agricultural contractors beside arable farming (**H6**).

[1] 16 % of the farmers in the sample stated they also have a mobile phone. By asking for mobile phones it was ensured that farmers were aware of the difference between smartphones and mobile phones.

Table 1: Descriptive statistics (N = 207)

H_0	Variable	Description	Mean	SD	Min	Max	Ger. Avg. [c]
	Smartphone	1, if the farmer has a smartphone for agricultural purposes; 0 otherwise	0.95	-	0	1	0.62
	SmExp [a]	Smartphone experience in years	7.62	2.47	1 [d]	11	n. a.
Socio-demographic factors							
H1	*Age*	Farmers' age in years	39.13	11.90	19	67	53
H2	*Education*	1, if the farmer has a university degree; 0, otherwise	0.52	-	0	1	0.12
H3	*Gender*	1, if the farmer is male; 0, otherwise	0.94	-	0	1	0.90
H4	*Laptop*	1, if the famer uses a laptop; 0, otherwise	0.66	-	0	1	n. a.
	PC	1, if the farmer uses a PC; 0, otherwise	0.79	-	0	1	n. a.
H5	*RiskAtt* [b]	Farmers' risk attitude	5.42	1.75	1	10	n. a.
Financial resources							
H6	*Contractor*	1, if the farmer is an agricultural contractor; 0, otherwise	0.27	-	0	1	n. a.
H7	*FullTime*	1, if the farmer is a full-time farmer; 0, otherwise	0.90	-	0	1	0.48
H9	*Position*	Farmers' position on the farm					
	Farm Manager	1, if the farmer is the farm manager; 0, otherwise	0.66	-	0	1	n. a.
	Farm successor	1, if the farmer is the farm successor; 0, otherwise	0.26	-	0	1	n. a.
	Other	1, if the farmer is a family member or employee on the farm; 0. otherwise	0.08	-	0	1	n. a.
Competitive and contingent factors							
H9	*Apprentice*	1, if the farm is a training location for agricultural apprentices; 0, otherwise	0.66	-	0	1	n. a.
H10	*Conv*	1, if the farm is farmed conventionally; 0, otherwise	0.85	-	0	1	0.89
H11	*FarmSize*	Farm size in hectares of arable land	297.90	486.67	4	3,800	65
H12	*Region*	Farm location in Germany					
	North	Schleswig-Holstein, Lower Saxony or Mecklenburg Western Pomerania	0.37	-	0	1	0.21
	West	North Rhine-Westphalia, Hesse, Rhineland Palatinate or Saarland	0.20	-	0	1	0.24
	East	Brandenburg, Saxony, Saxony-Anhalt or Thuringia	0.31	-	0	1	0.07
	South	Baden-Württemberg or Bavaria	0.12	-	0	1	0.48

[a] Dependent variable, Mean and standard deviation shown for *Smartphone* = 1 (N = 198)
[b] Risk attitude measure on the scale developed by DOHMEN et al. (2011) with 0 – < 5 = risk-averse, 5 = risk neutral, > 5 – 10 = risk-seeking.
[c] GERMAN FARMERS FEDERATION (2020), AGRIDIRECT DEUTSCHLAND GMBH (2016)
[d] No farmer reported the start of using a smartphone for agricultural purposes in the beginning of 2019
SD = Standard deviation; Ger. Avg. = German average; n. a. = not available

Most farmer in the sample (90 %) work as full-time farmers (**H7**) which also exceeds the German average of 48 % full-time farmer (GERMAN FARMERS FEDERATION, 2020). 66 % of the participants were the actual farm manager followed by the farm successors with a share of 27 % in the sample. Only 8 % were labeled as other (family member or employee) in Table 1 (**H8**). 66 % of the farms were training location for agricultural apprentices (**H9**). Furthermore, 85 % of the farms were farmed as conventional farms (**H10**) which is close to the German average of 89 % conventional farms. Farm size (**H11**) amounts on average to 297.90 hectares of arable land which exceeds the German average of 65 hectares of arable land. Most farms in the sample were located in the northern region (37 %) followed by southern region (31 %) and western region (20 %). The least proportion of participants have their farm located in the eastern region (12 %), which does not correspond to the German average (**H12**) (GERMAN FARMERS FEDERATION, 2020).

4.2 Regression results

To control for multicollinearity, VIFs were estimated before running the tobit model. VIFs < 5 indicate that multicollinearity is no threat to the model. None of the estimated VIFs exceed the value of 5 (mean VIF = 1.19, max. 1.55). The statistically significant *F*-statistic (5.89, $p < 0.001$) reveals that at least one coefficient is statistically significant different from zero. Nagelkerke Pseudo R^2 takes a value of 0.306. The coefficients, robust standard errors (SE) as well as marginal effects (ME) in years and corresponding significance levels are given in Table 2. Further goodness-of-fit characteristics and explanations are given below Table 2. The results parallel the observations of PIERPAOLI et al. (2013) that sociodemographic factors, financial resources as well as competitive and contingent factors play a role in the timing of smartphone adoption of agricultural purposes.

Table 2: Tobit results for the timing of smartphone adoption (N = 207) [a]

H_0	Variable	Coefficient	Robust SE	ME	p-Level	Support H_0?
Socio-demographic factors						
H1	*Age*	-0.107	0.021	-0.102***	<0.001	Yes
H2	*Education*	-0.532	0.410	-0.511	0.194	No
H3	*Gender*	1.941	0.944	1.863**	0.040	Yes
H4	*Laptop*	0.336	0.396	0.323	0.397	No
	PC	0.006	0.405	0.005	0.988	
H5	*RiskAtt* [b]	0.236	0.107	0.226**	0.028	Yes
Financial resources						
H6	*Contractor*	0.819	0.389	0.786**	0.036	Yes
H7	*Full-time*	-1.584	0.686	-1.520**	0.020	No
H8	*Position* [c]					No
	FarmSuccessor	0.427	0.510	0.412	0.404	
	Other	-0.770	0.672	-0.730	0.246	
Competitive and contingent factors						
H9	*Apprentice*	0.847	0.466	0.813*	0.069	Yes
H10	*Conv*	0.794	0.539	0.762	0.142	No
H11	*FarmSize*	<0.001	<0.001	<0.001*	0.070	Yes
H12	*Region* [d]					Yes
	North	0.890	0.430	0.857**	0.038	
	West	-0.069	0.486	-0.065	0.887	
	East	0.356	0.731	0.340	0.627	

[a] Dependent variable *SmExp*; F (17, 190) = 5.67, $p < 0.001$; Log pseudolikelihood = -474.27; Nagelkerke Pseudo $R^2 = 0.306$, Cox-Snell Pseudo $R^2 = 0.304$, McFadden Pseudo $R^2 = 0.073$; 0 right-censored observations, 198 uncensored observations, 9 left-censored observations at *SmExp* <= 0 according to equation (3).
[b] Risk attitude measure on the scale developed by DOHMEN et al. (2011) with 0 – < 5 = risk-averse, 5 = risk neutral, > 5 – 10 = risk-seeking
[c] Farm manager was set as the base category
[d] South was set as the base category
*p < 0.1, **p < 0.05, ***p < 0.01, SE = Standard errors, ME = Marginal effects

H1: Farmers' age delays the timing of smartphone adoption (*Age*)

The model supports **H1** since the marginal effect for the variable *Age* is statistically significant and has the expected negative sign (ME = -0.102, p < 0.001). The results suggest that older farmers adopt a smartphone later than younger farmers. According to the marginal effect, an additional year of farmers' age delayed smartphone adoption by 0.102 years. On a larger scale, a ten-year gap delayed the smartphone adoption decision by one year. D'ANTONI et al. (2012) concluded that younger farmers have a higher interest in using PATs. Likewise, TAMIRAT et al. (2018) suggested that younger farmers are more inclined in using a new technology. With respect to the research question, it can also be concluded that younger farmers have a higher interest in adopting a smartphone at an earlier stage than older farmers. The result also suggests that older farmers may face barriers in the adoption and use of smartphones since they may have fewer digital skills to work properly with smartphones than their younger counterparts. This should be considered by agricultural extension services in development of training programs for farmers.

H2: Holding a university degree fosters the timing of smartphone adoption (*Education*)

The variable *Education* has no statistically significant effect on the timing of adoption and the marginal effect has not the expected positive sign (ME = -0.511, p = 0.194). Hence, **H2** is given no support by the model. The results suggest that among the smartphone adopter, education has no statistically significant effect on the timing of smartphone adoption.

H3: Being a male farmer fosters the timing of smartphone adoption (*Gender*)

H3 is supported by the model since the marginal effect for the variable *Gender* is statistically significant and has the expected positive sign (ME = 1.863, p = 0.040). According to the results, a male farmer adopts a smartphone two years earlier than his female counterpart. The results are in contrast to MICHELS et al. (2020b) who found no statistically significant effect on farmers' gender on the general adoption decision. However, the findings are in accordance with MICHELS and MUSSHOFF (2020) who showed that male farmers have a higher smartphone use intensity in terms of applied agricultural apps than female farmers. Hence, women may face no barrier in the adoption decision, but they may face barriers in the timing of smartphone adoption. A possible explanation could be that female farmers tend to be more risk averse (JIANJUN et al. 2015) and therefore delay smartphone adoption for agricultural purposes. Policies targeted to promote technology adoption for female farmers should also consider this result. Nevertheless, it should be clearly stated that the share of female participants in this case study is small. Hence, the resilience of the results should be treated with caution.

H4: Having a laptop or PC fosters the timing of smartphone adoption (*Laptop, PC*)

The model shows no support for **H4**. While the marginal effects for the variables *Laptop* and *PC* have the expected positive signs, the marginal effects for the variable *Laptop* (ME = 0.323, p = 0.397) and *PC* (ME = 0.005, p = 0.988) are not statistically significant. PAUSTIAN and THEUVSEN (2017) suggested that nowadays farmers have a high literacy concerning computers. Hence, skills to work with a computer and/or a laptop might be ubiquitous among farmers and therefore no statistically significant effect was found in this study.

H5: A less risk-averse attitude has a positive effect on the timing of adoption (*RiskAtt*)

Results of the tobit model suggest that a more risk-seeking behavior of the farmer is positively correlated with an early smartphone adoption. The marginal effect of the variable *RiskAtt* is statistically significant and has the expected positive sign (ME = 0.226, p = 0.028). Hence, **H5** is supported. An increase of one-point on the scale increases an earlier smartphone adoption by 0.226 years. Adoption of new technology like smartphones at an earlier stage comes with several risks, for instance, unknown compatibility to the expected field of application or not comprehensively covered issues with data security and safety. Therefore, a risk-seeking farmer is more inclined to adopt a smartphone at an earlier stage. While it can be expected that the effect of the risk attitude on the general decision to adopt a smartphone might diminish with further spread of smartphones, one can assume that risk attitude will still play a role for several areas of applications, for instance, the use of finance and accounting apps due to data security concerns as suggested by MICHELS and MUSSHOFF (2020). Hence, agricultural extension services should consider that some farmers are reluctant to use smartphones for some applications and should strive for clarification of risk associated with the use of smartphones and associated technologies. This applies equally to providers and sellers of smartphones and agricultural apps.

H6: Being an agricultural contractor fosters the timing of smartphone adoption (*Contractor*)

H6 is supported by the model. The statistically significant marginal effect with the expected positive sign for the variable *Contractor* (ME = 0.786, p = 0.036) suggests that if a farmer is an agricultural contractor besides arable farming, he or she adopts a smartphone almost one year earlier than a farmer who is not an agricultural contractor. The result is plausible since this farmer is maybe in contact with several customers and also maybe has to organize his or her employees for which a smartphone can be used to a greater extent than a normal mobile phone (FECKE et al. 2018). Likewise, all contacts, customer orders and locations can be stored in a smartphone.

H7: Being a full-time farmer has a positive effect on the timing of adoption (*FullTime*)

The marginal effect of the variable *FullTime* is statistically significant but has not the expected positive sign (ME = -1.520, p = 0.020). Therefore, no support can be given to **H7**. A positive effect was expected, since a full-time farmer has less competition for his time and might benefit the most from several smartphone functions during day-to-day farming operations. However, the results implicate that a full-time farmer adopts a smartphone one and a half year later than a part-time farmer. This is in line with BATTE (2005), who showed that part-time farmer has a higher likelihood of computer adoption. Considering the fact, that a part-time farmer works outside agriculture, and therefore is more in contact with smartphone adopters or digital technologies in general, might explain the finding. Aspects of digitalization and PAT are not a common in the schooling of farmers (REICHARDT and JÜRGENS 2009). While the study found no effect of education on the timing of adoption (**H3**), this result suggests that in order not to exclude full-time farmers from the advantages of digitalization due to fewer points of contact, teaching content on digitalization should be given greater consideration in agricultural education and training programs.

H8: Being the farm manager fosters the timing of smartphone adoption (*Position*)

To analyse the effect of farmers' position in the agricultural holding on the timing of smartphone adoption, being the farm manager was set as the base category in the econometric analysis. Therefore, results of the marginal effects have to be interpreted in relationship to the position as a farm manager. However, the marginal effects for the variables *FarmSuccessor* (ME = 0.412, p = 0.404), and *Other* (ME = -0.730, p = 0.246) are not statistically significant, while the variable *Other* still has the expected negative sign. Hence, **H8** can be given no support by the model. Nevertheless, it should be clearly stated that the share of participants who are employees or family members in this case study is small. Hence, the resilience of the results should be treated with caution.

H9: A farm serving as a training location for agricultural apprentices fosters the timing of smartphone adoption (*Apprentice*)

H9 is given support by the results for the tobit model. The marginal effect of the variable *Apprentice* has the expected positive sign and is statistically significant (ME = 0.813, p = 0.069).

Hence, farmers who are training apprentices adopt a smartphone one year earlier than farmers who are not participating in the training of young farmers. An agricultural trainer might become aware of smartphone technology for agricultural purposes and therefore adopt them earlier than other farmers. Furthermore, agricultural trainer may also perceive that agricultural trainees expect that they are familiar with technological innovations and therefore are more inclined to adopt a smartphone for agricultural purposes.

H10: Managing a conventional farm fosters the timing of smartphone adoption (*Conv*)

The model does not support **H10**. The marginal effect of the variable *Conv* is not statistically significant despite having the expected positive sign (ME = 0.762, p = 0.142). Although MICHELS and Musshoff (2020) have shown that conventional farmers use statistically significant more agricultural smartphone apps than organic farmers, the results suggest that a conventional and an organic farmer show no statistically significant differences in the timing of smartphone adoption. Hence, smartphone use might differ between conventional and organic farmer while the timing of adoption does not show statistically significant differences.

H11: Farm size in hectares arable land fosters the timing of smartphone adoption (*FarmSize*)

H11 is supported by the model since the marginal effect for the variable *FarmSize* is statistically significant and has the expected positive sign (ME = <0.001, p = 0.070). However, it should be clearly stated that the marginal effect on the timing of adoption is very small. On a larger scale, an increase in 1,000 hectares of arable land only results in earlier smartphone adoption by less than one year. Smartphones are less expensive than PAT (PONGNUMKUL et al. 2015), why economies of scale cannot be used as an explanation. However, PAT adoption is also more common on larger farms to which smartphones can used as a complement (MICHELS et al. 2020b). Furthermore, a larger farm size also means a higher degree of organizational complexity that can be managed with the help of smartphones.

H12: Location of the farm in the southern region of Germany with less mobile internet coverage delays the timing of smartphone adoption (*Region*)

The results show that farmers living in the northern region of Germany adopt a smartphone 0.857 years earlier than a farmer residing in the southern regions (base category). The marginal effect in this case is statistically significant and has the expected positive sign (ME = 0.857, p = 0.038). No statistically significant differences are found between southern and eastern as well as southern and western German farmers since the marginal effects for the variable *West* (ME = -0.065, p = 0.887) and *East* (ME = 0.340, p = 0.627) are not statistically significant. The results confirm the observations of MICHELS et al. (2020c)[2] who have shown that mobile device and mobile internet adoption is more likely in the northern Federal states of Germany due to better mobile internet coverage. Hence, it can be expected that farm location as a proxy of (mobile) internet infrastructure also affects timing of smartphone adoption. Without a sufficient net coverage, a farmer might hesitate to adopt a smartphone at an earlier stage since he or she cannot use the mobile device to its full potential. Policy makers are advised to place more of an emphasis on the mobile network expansion.

5 Concluding remarks

The main goal of this study was to gain knowledge about factors influencing the timing of smartphone adoption in agriculture. For this purpose, a sample of 207 German farmers was collected in 2019. A left-censored tobit regression model was estimated to identify farmer and farm characteristics affecting the timing of adoption. Understanding the timing of smartphone adoption is of importance to anticipate the process of diffusion by characterizing farmers who

[2] In the appendix of MICHELS et al (2020c) the net coverage (LTE and 3G) for each federal state is shown.

are early adopters and farmers who delay the adoption. The results show that young, male, less risk-averse farmers from larger farms are the early adopters of smartphones. Moreover, taking part in the training of young farmers and the performance of agricultural contract work have a statistically significant positive effect on the timing of adoption. Furthermore, being a full-time farmer has a negative effect on the timing of adoption according to the results of this study. Results also show that location of the farm as proxy of mobile internet coverage plays a statistically significant role for the timing of adoption in Germany. Finally, no statistically significant effects were found for farmers' education, position on the farm and usage of a PC or Laptop. Several implications for agricultural policy makers, agricultural extension services as well as providers and sellers in terms of marketing activities of smartphone could are given.

While the study was conducted in a specific developed country, the results can, to a certain extent, be used to anticipate the diffusion of smartphones in other countries. Since smartphones are of high interest in developing countries due to their low investment costs and mobile internet connection, and the adoption lags behind developed countries, the implications derived from the results could prove to be even more relevant. Although not all adoption barriers will be exactly the same, tendencies will be similar, thus providing a starting point to facilitate smartphone adoption in developing countries at an earlier stage in the technology diffusion process. However, as the technological infrastructure and needs of farmers vary between different countries, future research should/could validate the results in different country settings.

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