Farmers' willingness to pay for digital credit: Evidence from a discrete choice experiment in Madagascar

by Yaw Sarfo, Oliver Musshoff, Ron Weber, and Michael Danne

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Abstract

In recent decades, microfinance institutions (MFIs) with financial products designed for low income groups have been established all over the world. However, credit access for farmers in developing countries remains low. Digital financial services are rapidly expanding globally at the moment. They also bear great potential to address farmers in remote rural areas. Beyond mobile money services, digital credit is successively offered and also discussed in literature. Compared to conventional credit which is granted based on a thorough assessment of the loan applicant's financial situation, digital credit is granted based on an automated analysis of the existing data of the loan applicant. However, empirical research on farmers' preferences and willingness to pay (WTP) for digital credit is non-existent. We employ a discrete choice experiment (DCE) to compare farmers' WTP for digital and conventional credit. The analysis uses primary data collected from 420 smallholder farmers in rural Madagascar. Our results indicate a higher WTP for digital credit compared to conventional credit. Furthermore, we find that longer loan duration has a higher effect on farmers' WTP for digital credit compared to conventional credit. Our results show the potential of digital credit for agricultural finance in developing countries if a certain level of innovation is applied in designing digital credit products.

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1. Introduction

It is frequently reported that farmers in developing countries have a lower probability of credit access[1] or are more credit constrained compared to non-agricultural firms (Simtowe et al., 2008; Akudugu et al., 2009; Weber and Musshoff, 2012). Partly, this is due to the high transaction costs financial institutions have to incur in administering small loans to farmers in rural areas (Gine et al., 2010). Digital finance (e.g. digital credit) presents an opportunity to increase credit access to farmers in developing countries, even in remote rural areas. This is possible because of the rapid spread of mobile phones in developing countries over the past decade (GSMA, 2018) but also due to partnerships between financial institutions and mobile network operators (MNOs).

Previous studies on digital financial services in developing countries primarily focused on the impact of mobile money services on household consumption, income, and food security (cf. Jack and Suri, 2014; Kikulwe et al., 2014; Murendo and Wollni, 2016; Sekabira and Qaim, 2017). These studies generally showed a positive impact of mobile money services on household welfare. However, a branch of digital finance which lacks research concentration in developing countries is digital credit. According to Chen and Mazer (2016), digital credit are loans that are "instant" (takes seconds or a maximum of 24 hours from application to loan decision), "automated" (uses digital data[2] of borrowers to evaluate credit worthiness by credit scoring

[1] In this study, we define credit access as a loan application to a formal financial institution approved (cf. Akudugu et al., 2009). A similar definition of credit access holds for all the papers cited in this study in the context of credit access.

[2] Digital data of borrowers include mobile phone airtime top-up and use, duration of calls, frequent usage of short message service, mobile money transactions money, data top-ups, previous loan status (Hwang and Tellez, 2016).

mechanisms), and "remote" (loan application, disbursement, and repayments happen with limited human interactions). "Instant, automated, and remote" differentiate digital credit from conventional credit based on the time to take decisions, risk management process, and sending information and payments.

The limited number of existing studies on digital credit show that digital credit can improve access to formal financial services to the previously unbanked and underserved population, even in rural areas (cf. Chen and Mazer, 2016; Hwang and Tellez, 2016; Francis et al., 2017; Kaffenberger et al., 2018; Bharadwaj et al., 2019). For example, Francis et al. (2017) looked at the current landscape of digital credit in Sub-Sahara Africa (SSA). The study identified low transaction costs, remote disbursement and repayment of loans, and the use of non-traditional data of potential borrowers' to access credit worthiness as the key advantages of digital credit compared to conventional credit. These characteristics make digital credit a possible option for farmers in rural areas of developing countries to have credit access.

As the potential of digital credit to improve credit access to the unbanked population could be established, little is known about potential borrowers' (e.g. farmers') willingness to pay (WTP) for digital credit. Bridging this knowledge gap is necessary for financial service providers in developing countries to design digital credit products to serve potential borrowers accordingly. Up to now, there is no research paper on digital credit that investigates potential borrowers' WTP for digital credit, specifically from the perspective of farmers in developing countries.

Therefore, the objective of this paper is to investigate farmers' WTP for digital credit. In particular, this paper sheds light on whether farmers' WTP for digital credit differs from their WTP for conventional credit. Furthermore, we investigate if loan duration, repayment flexibility, traveling distance, and additional credit cost (e.g. withdrawal fees) have a different effect on farmers' WTP for digital credit compared to conventional credit.

To our knowledge, this paper is the first to provide insight into WTP for digital credit. We focus our analysis on Madagascar because access to financial services is limited in rural areas of SSA and for farmers in particular (cf. Mpuga, 2010; Dupas et al. 2012). Furthermore, Madagascar is of a particular importance as only about 5.5% of the adult population has a bank account at a formal financial institution, and about 70% of the population (mainly farmers) live in rural areas (Demirguc-Kunt et al., 2018) with wide distribution of mobile phones (cf. GSMA, 2018). This offers an interesting setting for the study. For this study, we use primary data collected from rural farmers in Madagascar.

Our findings will help make adequate policy interventions to increase credit supply to farmers, but also help financial institutions for effective product design, consumer targeting, and to induce the adoption of digital credit products among farmers. The rest of the paper is organized as follows: In Section 2, we provide a brief background of the rural credit market failure and highlight the potential of digital credit to address the problem. This is followed by a description of the materials and methods used for the study in Section 3. Results and discussion are presented in Section 4, and Section 5 concludes the paper.

2. Rural credit market failure and the potential of digital credit for rural farmers

It is established that rural credit markets in developing countries are imperfect (Conning and Udry, 2007; Guirkinger and Bourcher, 2008). Formal financial institutions tend to concentrate in urban areas with little presence in rural areas (cf. Mpuga, 2010; Dupas et al., 2012). As a result, a large number of people in rural areas are excluded from formal credit markets. This is particularly true for farmers, who in most cases live in rural areas. This might also perhaps explain why agricultural firms are frequently reported to have a lower probability of credit access compared to non-agricultural firms (Akudugu et al., 2009; Weber and Musshoff, 2012).

A major reason often cited in literature is the higher administrative costs that financial institutions have to incur in administering small loans in rural areas (cf. Rosenberg et al., 2009; Gine et al., 2010). Detailed client assessment for credit is demanding and time consuming for loan officers, especially in rural areas given that most farmers may not have sufficient records of their farm activities. In response to the information asymmetries, formal financial institutions normally demand collateral from loan applicants to reduce credit assessment costs and also to secure their investment (cf. Boucher et al., 2008; Guirkinger and Bourcher, 2008). However, for most farmers in rural areas, collateral may not be available, thus, excluding them from formal credit markets.

Furthermore, conditions of standard loans offered by formal financial institutions in developing countries have often been identified as one of the main reasons for the perpetual lack of credit access to farmers in developing countries (cf. Weber and Musshoff, 2013). Standard loans have weekly/monthly repayment obligations which start soon after loan disbursement (Labie et al., 2013). However, such repayment conditions are not suitable for agricultural production. This makes it very difficult for farmers to have credit access from formal financial institutions in times of need. Oftentimes, the only possibility for farmers in rural areas to address their credit needs is to turn to non-formal sources (e.g. family and friends, informal money lenders), which sometimes, may not be available in times of need.

However, in recent years, digital credit has developed rapidly in some countries in SSA such as Madagascar, as an alternative for people who are normally excluded from formal credit markets (cf. Hwang and Tellez, 2016). Unlike conventional credit which is granted based on a thorough assessment of the loan applicant’s financial situation, digital credit is granted based on an automated analysis of the digital data of the loan applicant. Normally, the supply of digital credit involves a partnership between an MNO and a bank (cf. Hwang and Tellez, 2016). The MNO manages the mobile money accounts of customers, agent networks (i.e. network for mobile money agents), and provides the digital data of customers to evaluate credit worthiness, whereas the bank provides the loans (Kaffenberger et al., 2018).

Digital credit has several advantages compared to conventional credit for farmers in rural Madagascar. First, the process from loan application to loan decision is "instant" (Chen and Mazer, 2016), which makes it possible for farmers to have access to credit at the moment of need. Second, the automation of the credit evaluation process makes it possible for digital credit providers to expand credit to a large number of individuals without collateral, who may be excluded from formal credit markets (cf. Francis et al., 2017). Third, loan applications, disbursements, and repayments can be managed remotely without making a trip to the bank (Chen and Mazer, 2016). Normally, a prerequisite for an MNO customer to apply for digital credit is that the customer must be registered for mobile money and be an active user of the MNO for at least six months (cf. Hwang and Tellez, 2016). Once these two conditions are certified, the customer can apply for a loan at any time through the customer's mobile money account with the MNO. Following a loan application, the loan decision is instant and automated based on preset parameters (cf. Chen and Mazer, 2016).

Once a loan application is approved, disbursement is done remotely and the borrower can withdraw the loan at a nearby mobile money agent (a shop where one can change the digital money to physical money) subject to a withdrawal fee. The withdrawal fee is the amount of money that a digital credit borrower has to pay to a mobile money agent in order to change the digital money to physical money. Loans are usually smaller, shorter-term, and more expensive compared to conventional credit (Hwang and Tellez, 2016). When it is time to repay the loan, borrowers have to make payments into their digital account (mobile money account) from a mobile money agent to repay the loan remotely.

The combination of these characteristics "instant, automated, and remote" underscores the ability of digital credit to address some, if not all, of the challenges of the rural credit market in developing countries. For example, the automation of the credit evaluation process reduces client's assessment costs, and eliminates collateral requirements for credit evaluation. Additionally, the automation of the credit evaluation process makes it possible for digital credit providers to by-pass any potential information asymmetries that may arise from the loan applicant in credit evaluation. Furthermore, the "remote" nature of digital credit reduces infrastructural requirements and geographical distance for the provision and access to credit. This makes digital credit particularly important for farmers in rural areas of Madagascar given the low penetration of formal financial institutions in rural areas of the country.

3. Materials and methods

3.1 Data collection

The study uses primary data collected from smallholder farmers from six districts[3] in central Madagascar between December 2019 and February 2020. We conducted interviews with smallholder farmers: some are clients and some are non-clients of a large commercial microfinance bank, Access Bank Madagascar (ABM). The inclusion of ABM clients (mainly farmers) in the study was advantageous because ABM is one of the largest microfinance banks in Madagascar and offers agricultural loans. We applied a multi-stage sampling method to draw the sample for the study. At the first stage, we purposively selected six branches of ABM from six

[3] Districts: Ambatolampy, Ambohidratrimo, Arivoimamo, Betafo, Miarinarivo, and Tsiroanomandidy.

districts, one branch from each district. These branches were selected because they offer agricultural loans in predominantly agricultural communities. These six branches are located mainly in rural areas. For the selection of the non-ABM clients, we randomly selected two villages from each district. At the second stage, we randomly selected from each of the selected six ABM branches approximately 35 farmers who are clients of ABM for interviews. These clients were drawn from a complete list of clients on the agricultural loan portfolio of each branch. Similarly, for the selection of non-ABM clients for the study, in each of the two randomly selected villages at each district, 17 or 18 households were randomly selected from each village for interviews based on complete household lists. Consequently, a sample of 420 smallholder farmers were used for the study.

The sample for the study were predominantly smallholder farmers with a concentration on rice and vegetable production. Rice is the main staple food in Madagascar. These crops are grown mostly for household consumption. We carried out a face-to-face interview with each of the farmers who participated in the survey with the help of highly trained enumerators. Individual interviews were conducted in the local language of the respondents. Before each interview, the enumerator explained the objectives of the research to the respondent. The questionnaire for the study begins with general questions about the respondent's household. It then proceeds to the access to formal financial services, farm information, a discrete choice experiment (DCE), and finally, it investigates farmers' financial knowledge.

3.2 Conceptual framework

We employ a DCE to investigate farmers' WTP for digital credit compared to their WTP for conventional credit. DCEs have been extensively used in the agricultural economics literature to elicit farmers' preferences for goods and services (Coffie et al., 2016; Waldman et al. 2017; Krah et al., 2019). Lancaster's consumer theory and McFadden's random utility theory serve as the basis for choice modelling (Lancaster, 1966; McFadden, 1973). The underlying principle is that consumers derive utility from the characteristics of a good instead of the good itself and consumers choose the good with the maximum utility among a set of alternatives.

Following Hensher et al. (2015) and Coffie et al. (2016), and consistent with random utility theory, we assume that a farmer n faces a choice among J credit products in choice situation t. The utility of farmer n from choosing alternative i in choice situation t can be partitioned into two components: an observed or modeled component, $V(X_{nit}, \beta_n)$, and a residual unobserved and un-modeled component, ε_{nit}, such that:

$$U_{nit} = V_{nit}(X_{nit}, \beta_n) + \varepsilon_{nit} \tag{1}$$

where U_{nit} is the utility a farmer n derives from choosing credit product i in choice situation t. X_{nit} is a vector of observed attributes of alternative i in choice situation t. β_n is a vector of parameters to be estimated which account for the farmer's preferences for credit product attributes, and ε_{nit} is the error term which is independently, identically distributed extreme value (Train, 2009) of the expected utility that is not observed. Following Hensher et al. (2015), we assume that for a given choice set of credit products J, a farmer n in choice situation t will choose credit product i from J if and only if credit product i provides the maximum utility compared to any other alternative j. Therefore, the probability that a farmer n chooses credit product i from the possible credit products J in choice situation t is given by:

$$P_{nit} = Prob\left(U_{nit} > U_{njt}, \forall i \neq j;\ i,j \in J\right)$$

$$= Prob(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt},\ \forall i \neq j;\ i,j \in J) \tag{2}$$

3.3 Credit attributes

Before designing the DCE, we reviewed the digital and conventional credit literature and conducted a pilot study with 20 smallholder farmers in Madagascar to identify the attributes that are important to the farmers when choosing a credit product. Consequently, we settled on five attributes. Table 1 presents the alternatives, attributes and levels used in the experiment. The first attribute is loan duration, which is the time frame for a loan product. Compared to conventional credit, digital credit products have shorter loan duration (Francis et al., 2017). For farmers, the loan duration is very important when choosing a credit product given that the duration should be long enough for farmers to make prudent production decisions on their farms.

The second attribute is interest amount per month, which is the cost of borrowing per month excluding the principal credit amount. In this study, we use interest amount per month instead of interest rate per month because we realized during the pilot study that the farmers found it difficult to understand and interpret percentage points. Hwang and Tellez (2016) and Francis et al. (2017) indicate that the interest rate of digital credit products is normally higher compared to conventional credit from a bank. For example, in Kenya, M-Shwari has a monthly interest rate of 7.5% (Francis et al., 2017) whereas conventional credit products have an average interest rate of 12.44% per annum (International Monetary Fund, 2019). In this study, it is important to note that interest amount per month is the main cost component of both credit products. This differs considerably from additional credit cost (e.g. withdrawal fees) which is one-off cost to the borrower per loan application and especially applied for digital credit.

The third attribute is repayment flexibility, which indicates how a borrower has to repay the loan to the lender. Hwang and Tellez (2016) suggest that digital credit borrowers can repay their loans in instalments or at maturity. The repayment condition of a loan product is particularly important for farmers given the seasonality of agricultural income. The fourth attribute is traveling distance, which indicates how long farmers have to travel in order to access the nearest formal financial institution or mobile money agent. Banks penetration in rural areas of SSA is particularly low (Mpuga, 2010), thus, farmers in rural areas have to travel for a considerable distance in order to access formal financial services in urban areas. The associated transaction costs can be substantial, which could prevent people in rural areas from access to financial services (Karlan et al., 2016).

The fifth attribute of our experiment relates to the additional credit cost that has to be incurred by borrowers apart from the interest amount per month. For example, digital credit borrowers have to pay a withdrawal fee to a mobile money agent in order to withdraw a digital loan. Similarly, conventional credit borrowers have to pay a loan processing fee per loan application (Beck et al., 2008).

Table 1: Alternatives, attributes, and levels

Alternatives	Attributes	Levels
Digital credit		
	Loan durarion	1 month; 3 months; 6 months
	Interest amount per month	MGA 12,000; MGA 16,000; MGA 20,000; MGA 24,000
	Repayment flexibility	1 = Instalment; 0 = At maturity
	Traveling distance	0.5 km; 1 km
	Additional credit cost (withdrawal fees)	MGA 2,000; MGA 6,000; MGA 10,000
Conventional credit		
	Loan duration	3 months; 6 months; 12 months
	Interest amount per month	MGA 8,000; MGA 12,000; MGA 16,000
	Repayment flexibility	1 = Instalment; 0 = At maturity
	Traveling distance	5 km; 10 km; 20 km
	Additional credit cost (transaction fees)	MGA 6,000; MGA 10,000; MGA 14,000

Note: MGA: Malagasy Ariary. Credit amount: MGA 200,000. 1 € = MGA 4,150.

3.4 Experimental design

DCEs underline the stated preference approach, which allows for conclusions to be drawn from previously unarticulated preferences about real choice decisions (Louviere et al., 2000). In a DCE, participants are presented with a number of choice sets, each consisting of different alternatives, and are asked to select one of the given alternatives. Each presented alternative is characterized by pre-defined attributes and their associated levels. DCE is appropriate for our study because digital credit is new in Madagascar so there is no available data.

The DCE utilized in this study presented the following decision situation to the participating farmers: based on a labeled design, the farmers had to choose between a digital credit and conventional credit or could decide not to use either of these alternatives (opt-out). The opt-out alternative was included so that the choice for one of the proposed alternatives is voluntary. In this study, a labeled DCE is preferred because it is the best method to directly analyse the trade-off between digital and conventional credit. This is because in this study, a labeled design allows focusing on the main effects of the two credit products as each credit product conveys information itself for the farmer based on their experience and knowledge (cf. Kruijshaar et al., 2009; De Bekker-Grob et al., 2010). In our case, this was necessary as especially the levels for the attributes "loan duration", "interest rate", "traveling distance" and "additional credit cost" are alternative specific. In our experiment, it is important to note that we do not present the same figures and attribute levels (e.g. interest amount per month) for both credit products because digital credit differs from conventional credit in terms of credit evaluation criteria and making payments (Chen and Mazer, 2016). For example, the credit evaluation criterion for conventional credit is based on a detailed assessment of the loan applicant's business data whereas that of digital credit is based on the digital data of the loan applicant. Furthermore, in the study setting, the traveling distance for conventional credit is a vehicular distance whereas that of digital credit is a walking/bicycle distance, hence, attracting different figures and attribute levels in our experiment. In each decision situation, the participating farmers chose one of the alternatives that were described by the following attributes: loan duration, interest amount per month, repayment flexibility, traveling distance, and additional credit cost. It is important to indicate that even though digital credit differs from conventional credit (Chen and Mazer, 2016), however, in the study setting, a direct comparison of farmers' WTP for both credit products is plausible for two reasons. First, formal financial services in Madagascar are largely concentrated in urban areas with very little presence in rural areas. As a result, farmers in rural areas have to spend considerable time and money to travel to the nearest town/community with a bank/microfinance institution (MFI) in order to apply for conventional credit if needed. This makes digital credit particularly important for rural farmers in the study setting. Second, this study is designed to serve the credit needs of smallholder farmers in rural areas of Madagascar who require a small credit amount per production season for farm operations, for example, to purchase improved seeds or pay workers at the start of the planting season. Therefore, in the study setting, the farmers considered a credit amount of MGA 200,000 (€48) to be sufficient for such purpose(s) regardless of the credit source.

Building a full-factorial design with the number of alternatives, attributes and levels presented in Table 1 results in [(4·3·2·2·3)Digital credit · (3·3·2·3·3)Conventional credit =] 23,328 possible decision situations or choice sets. However, for the sake of practicability, this design was determined to be too extensive and therefore, the number of choice sets was reduced. As a result, a D-efficient Bayesian design (Scarpa and Rose, 2008; Bliemer et al., 2009) with 12 choice sets blocked into two groups of six each were found to be appropriate for the study. Thus, each of the participating farmers in the main survey answered six choice sets. Prior to starting the DCE, detailed explanations on the differences between credit products, attributes, and attribute levels were provided to the farmers. The details of the instructions for the farmers during the DCE are presented in Appendix A. A sample choice set as presented to the farmers during the survey is presented in Table 2.

Table 2: A sample choice set

Attribute	Digital credit	Conventional credit	Opt-out
Loan duration	1 month	6 months	I prefer no
Interest amount per month	MGA 24,000	MGA 16,000	credit
Repayment flexibility	At maturity	At maturity	
Traveling distance	0.5 km	5 km	
Additional credit cost	MGA 2,000	MGA 10,000	
(e.g. withdrawal fees)			
I will choose …	○	○	○

3.5 Estimation procedure

In order to investigate farmers' WTP for digital credit compared to their WTP for conventional credit, first, we determine the factors that influence farmers' preferences for either digital or conventional credit. For this purpose, we apply the mixed logit model (Hole, 2007). The mixed logit model relaxes the restrictive independence of irrelevant alternatives (IIA) assumption of the conditional logit model. McFadden and Train (2000) suggested that the mixed logit is a very flexible model that can estimate any random utility model. It addresses the shortcomings of the standard logit model by allowing for correlation of unobserved factors over time, unrestricted substitution patterns, and taste parameters to vary across individuals (Train, 2009). From equation (1), we model the utility of a farmer n from choosing credit product i among J credit products in choice situation t as:

$$U_{nit} = ASC_i + \beta'_n X_{nit} + \varepsilon_{nit} \qquad (3)$$

where U_{nit} is the utility a farmer n associates with choosing credit product i in choice situation t. ASC_i is the alternative specific constant of alternative i which accounts for the average effect of all the factors that are not included in the model on utility (Train, 2009). X is a vector of alternative specific credit product attributes, which include loan duration, interest amount per month, repayment flexibility, traveling distance, and additional credit cost; β_n are the associated parameters to be estimated for each of the credit product attributes; and ε_{nit} is the error term which is distributed iid extreme.

Even though it is established that the mixed logit model accounts for preference heterogeneity among individuals (cf. Train, 2009; Hensher et al., 2015), Boxall and Adamowicz (2002) suggest that the mixed logit may be constrained when explaining the sources of heterogeneity. They suggest that in many instances, the sources of heterogeneity relate to the socio-economic characteristics of the individual decision maker. Therefore, to account for the potential role of the socio-economic characteristics of a farmer n in choosing a credit product i in choice situation t, equation (3) is slightly modified to estimate a mixed logit model of the form:

$$U_{nit} = ASC_i + \beta'_n X_{nit} + \mu'(ASC_i \text{ x } S_n) + \varepsilon_{nit} \tag{4}$$

where $(ASC_i \text{ x } S_n)$ is a vector of variables accounting for the interactions of smallholder farmers' socio-economic characteristics S_n (e.g. age) and the ASC_i associated with the choice of credit product made by a farmer n; μ are the associated coefficients to be determined.

We use the simulated maximum likelihood estimator with 1,000 Halton draws to estimate the mixed logit model (Hole, 2007). Following Hensher and Green (2011), the main price attribute (i.e. interest amount per month) in the experiment is estimated as a non-random parameter; otherwise it could result in unrealistic WTP estimates. Further, in the estimation of the mixed logit model, the attributes: interest amount per month, loan duration and additional credit cost for each credit product are modeled as continuous variables based on the attributes levels. A similar argument could be presented for the attribute "traveling distance" for conventional credit. However, the attributes "traveling distance" for digital credit and "repayment flexibility" for both credit products are modeled as effects-coded[4] variables. Similarly, all farmers' socio-economic characteristics except age, years of education, and their risk attitude are modeled as effects-coded variables.

In order to estimate farmers' WTP for the different attributes of each credit product, we follow Train and Weeks (2005) to re-specify equation (3) to indicate the difference between the main price attribute (interest amount per month), P_{nit}, and the other attributes (loan duration, repayment flexibility, traveling distance, additional credit cost), X_{nit}:

$$U_{nit} = ASC_i - \alpha_n P_{nit} + \beta'_n X_{nit} + \varepsilon_{nit} \quad (5)$$

Accordingly, we follow Krinsky and Robb (1986) procedure with 10,000 replications to estimate farmers' WTP for credit products attributes. From equation (5), the ratio of an attribute's coefficient (β_n) to the price coefficient (α_n) is the WTP for that attribute:

$$WTP_n = \frac{\beta_n}{\alpha_n} \quad (6)$$

Consequently, we follow Hensher et al. (2015) to apply the Wald test to verify if the difference between corresponding WTP estimates for digital and conventional credit attributes is statistically significantly different from zero.

[4] In this paper, we use effects-coding instead of dummy coding in order to avoid confounding of the base attribute level with the grand mean of the utility function. For a discussion on effects versus dummy coding in DCEs, see Hensher et al. (2015).

4. Results and discussion

4.1 Descriptive statistics

Table 3 shows the summary statistics describing the socio-economic characteristics of the sampled farmers. The mean age of the farmers is about 39 years. The sampled farmers have to travel on average 10 kilometers to the nearest formal financial institution to access financial services (e.g. credit), a condition which highlights the low penetration of banks/MFIs in rural areas of Madagascar. Further, it is observed that during the past 12 months, only 34% of the farmers had their application for credit from a formal financial institution approved. However, a higher number (51%) is reported if we consider credit to farmers from both formal and non-formal sources.

Table 3: Summary statistics of respondents

Variable	Unit	Mean	SD
Age	Years	39.395	13.141
Credit access during the past 12 months (Yes)	1/0	0.343	-
Distance to the nearest formal financial institution	Kilometers	9.558	12.588
Distance to the nearest mobile money agent	Kilometers	0.935	0.468
Education	Years	9.888	4.260
Farming experience	Years	14.865	12.334
Financial knowledge [a)]	Number	4.186	1.285
Gender (Male)	1/0	0.540	-
Household size	Number	4.574	1.691
Land size (Owned land)	Acres	2.945	2.392
Marital status (Married)	1/0	0.867	-
Mobile phone access (Yes)	1/0	0.876	-
Monthly income	MGA	414,008	223,100
Received credit from any source during the past 12 months (Yes)	1/0	0.507	-
Remittances (Yes)	1/0	0.374	-
Risk attitude [b)]	Number	5.790	1.955
Number of participants		420	

Note: MGA: Malagasy Ariary. 1 € = MGA 4,150. Mean values for dummy variables (1/0) indicate ratios. [a)] Measured on a scale from 1 (very low financial knowledge) to 7 (very high financial knowledge) (Lusardi and Tufano, 2015). [b)] Measured on a scale from 1 (risk averse) to 10 (risk seeking) (Dohmen et al., 2011).

4.2 Farmers' preferences and WTP for credit attributes

Table 4 presents the estimation results[5] for the determinants of farmers' preferences for credit products, accounting for their socio-economic characteristics and the calculated WTP for credit product attributes. Furthermore, Table 5 presents the results of the Wald test indicating the difference between corresponding mean WTP estimates for digital and conventional credit attributes. Based on these results, we focus on the mean WTP estimates to evaluate whether farmers' WTP for digital credit differs from their WTP for conventional credit. Similarly, we evaluate whether credit product attributes have a different effect on farmers' WTP for digital credit compared to conventional credit.

Farmers' overall WTP for digital and conventional credit

We observe from Table 4 that the constants of both credit products are positive and statistically significant, suggesting that smallholder farmers prefer to choose either digital credit or conventional credit relative to no credit (opt-out). Further, we observe that relative to no credit (opt-out), farmers' mean WTP for digital credit is MGA 20,534 (€4.95) per month compared to MGA 19,244 (€4.64) for conventional credit. Relating both WTP values to the principal credit amount (MGA 200,000), the results suggest that farmers' are on average willing to pay an amount equivalent to 10.3% per month for digital credit compared to 9.6% for conventional credit. We associate this finding to the characteristics of digital credit ("instant, automated and remote") compared to conventional credit, and the limited access to formal financial services in

[5] We also estimated a model without socio-economic characteristics of the farmers. However, comparing the log-likelihood and AIC values of both models, it emerged that the model with the socio-economic characteristics of farmers better fits the data. Therefore, we present and discuss the results of the model with socio-economic characteristics.

rural areas of SSA (Dupas et al. 2012), and Madagascar in particular. Furthermore, we notice from Table 5 that the difference between farmers' mean WTP for digital credit and conventional credit is statistically significant at 1% significance level (Wald chi-square statistic of 7.19). The finding on farmers' WTP for digital credit is consistent with the interest rate per month for digital credit products offered in SSA. For example, the most popular digital credit product in SSA, M-Shwari, in Kenya charges a fixed interest rate of 7.5% per month whereas M-Pawa of Tanzania charges an interest rate of 9% per month (cf. Hwang and Tellez, 2016; Francis et al., 2017). Initially, there is the inclination to argue that our finding on farmers' WTP for conventional credit per month is high. However, our finding is plausible given that the lending rate for conventional credit in Madagascar can be as high as 55.4% per annum (International Monetary Fund, 2018). From Tables 4 and 5, we can conclude that farmers' WTP for digital credit is statistically significantly higher than their WTP for conventional credit.

Farmers' WTP for credit attributes

The findings in Table 4 show that loan duration has a positive and statistically significant effect on farmers' preference for digital credit. Further, we observe from Table 4 that increasing loan duration by one month increases farmers' WTP for digital credit by MGA 1,032 (€0.25) compared to MGA 109 (€0.03) for conventional credit. We attribute this finding to the characteristics of digital credit compared to conventional credit, and its ability to increase credit access to farmers in rural areas. Furthermore, the loan duration of most digital credit products is one month (cf. Francis et al., 2017), which may not be sufficient for farmers in the study area to make prudent production decisions, thus, causing farmers to pay substantially more for an increase in the loan duration for digital credit compared to conventional credit. From Tables 4 and 5, we can state that loan duration has a statistically significantly higher effect on farmers' WTP for digital credit compared to conventional credit.

We further observe from Table 4 that instalment repayment has a negative and statistically significant effect on farmers' preference for digital credit, suggesting that farmers prefer at maturity repayment to instalment repayment for digital credit, a finding which supports the seasonality of agricultural income. However, instalment repayment has a positive and statistically significant effect on farmers' preference for conventional credit, a finding contradictory to the support for the provision of flexible loans to farmers in the literature (Pellegrina 2011; Weber and Musshoff, 2013). Further, it emerged from Table 4 that instalment repayment on average decreases farmers' WTP for digital credit by MGA 1,779 (€0.43) whereas it increases farmers' WTP for conventional credit by MGA 1,874 (€0.45). This suggests that offering at maturity repayment condition for digital credit will increase farmers' WTP for digital credit. Our findings from Tables 4 and 5 indicate that instalment repayment condition has a statistically significantly lower effect on farmers' WTP for digital credit compared to conventional credit. Also, it emerged from Table 4 that traveling distance has a negative and statistically significant effect on farmers' preference for digital and conventional credit. For both credit products these results are plausible: Traveling long distance allied to the accompanying transaction costs may preclude farmers in rural areas from the use of financial services (cf. Karlan et al., 2016). From our findings in Tables 4 and 5, we can state that traveling distance has a statistically significantly higher effect on farmers' WTP for digital credit compared to conventional credit.

Furthermore, Table 4 shows that additional credit cost has a negative and statistically significant effect on farmers' preference for digital credit. This suggests that farmers are sensitive when fees in addition to the interest rate are charged. We further observe that increasing the additional credit cost by MGA 1,000 (€0.24) decreases farmers' WTP for digital credit by MGA 107 (€0.03) compared to MGA 5 (€0.001) for conventional credit. We associate this finding to the fact that farmers may have to incur high transaction costs in order to withdraw their digital loans if they stay in places where mobile money agents are often far from their place of residence (cf. Hernandez et al., 2018) compared to loan processing fees for conventional credit which is a very small amount of the total credit amount per loan application. From Tables 4 and 5, we can conclude that additional credit cost has a statistically significantly higher effect on farmers' WTP for digital credit compared to conventional credit.

Table 4: Determinants of farmers' preference for credit products estimated by the use of a mixed logit model

Variable	Mean coefficient (Standard error)	SD coefficient (Standard error)	Mean WTP in MGA	Minimum WTP in MGA	Maximum WTP in MGA
Digital credit					
Constant	3.231***	1.000***	20,534***	6,820	34,809
	(1.158)	(0.266)			
Loan duration	0.162***	-	1,032***	489	1,596
	(0.045)				
Interest amount per month	-0.016***	-	-	-	-
	(0.002)				
Repayment flexibility (Instalment = 1)[c)]	-0.280***	-	-1,779***	-3,042	-725
	(0.083)				
Traveling distance [c)]	-0.200**	1.025***	-1,271*	-2,499	-168
	(0.090)	(0.136)			
Additional credit cost (Withdrawal fees)	-0.017***	0.018***	-107***	-154	-70
	(0.003)	(0.004)			
Conventional credit					
Constant	4.285***	-	19,244	9,465	29,406
	(1.180)				
Loan duration	0.024	0.166***	109	-169	404
	(0.032)	(0.029)			
Interest amount per month	-0.022***	-	-	-	-
	(0.002)				
Repayment flexibility (Instalment = 1) [c)]	0.417***	0.963***	1,874	1,040	2,842
	(0.094)	(0.130)			
Traveling distance	-0.078***	-	-350	-500	-227
	(0.014)				
Additional credit cost (Transaction fees)	-0.001	-	-5	-26	14
	(0.002)				
Interaction variables					
Digital credit		-			
Constant x Age	-0.029*	-			
	(0.017)				
Constant x Education	0.123**	-			
	(0.052)				
Constant x Mobile phone access [c)]	0.821***	-			
	(0.278)				
Constant x Received credit [c)]	-0.558**	-			
	(0.250)				
Constant x Risk attitude	0.577***	-			

Table 4 (continued)

	(0.122)	
Conventional credit		
Constant x Age	0.007)	-
	(0.017	
Constant x Education	0.072	-
	(0.051)	
Constant x Mobile phone access [c)]	0.703***	-
	(0.271)	
Constant x Received credit [c)]	-0.708***	0.900***
	(0.249)	(0.285)
Constant x Risk attitude	0.487***	-
	(0.121)	
Participants/Observations	420/7,560	
Goodness of fit measures		
AIC	3,052.648	
BIC	3,246.705	
Log likelihood	-1,498. 324	
LR-Statistic (χ^2) (6 d.f.)	289.650	
Prob > chi2	0.000	

Note: ***, **, and * indicates statistical significance at the 1%, 5% and 10% levels, respectively. Halton draws = 1,000. SD indicates standard deviation. Only SD coefficients with statistical significance are shown. [c)] Indicates effects-coded variable. MGA: Malagasy Ariary. We report WTP estimates of non-significant attributes for the sake of comparison. All WTP values are in MGA. 1 € = MGA 4,150. Krinsky replications = 10,000. For mean WTP estimates, significance level is for the difference in farmers' mean WTP between digital credit and conventional credit attributes.

Table 5: Wald test proving difference in coefficients for both credit products

Test	Wald chi-square statistic	Prob > chi2
Digital=Conventional (constants)	7.19 ***	0.007
Digital loan duration=Conventional loan duration	19.63***	0.000
Digital instalment repayment=Conventional instalment repayment	36.86***	0.000
Digital traveling distance=Conventional traveling distance	2.47*	0.115
Digital additional credit cost=Conventional additional credit cost	24.01***	0.000

Note: ***, **, and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

5. Conclusion

Farmers in developing countries still lack access to credit. Digital credit is a recent innovation that has the potential to improve the situation. However there is no literature which deals with farmers' WTP for digital credit compared to conventional credit in developing countries. We employ a DCE to investigate farmers' WTP for digital and conventional credit in Madagascar. We thereby consider different credit product attributes (loan duration, interest amount per month, repayment flexibility, traveling distance, and additional credit cost) which are important to farmers in the study area when choosing a credit product.

The results show that for a given credit amount, on average, farmers' WTP for digital credit is higher compared to conventional credit. Furthermore, we find that the proximity to withdraw the borrowed money has a higher effect on farmers' WTP for digital credit compared to conventional credit. Our results show that inflexible repayment conditions (instalment repayment) reduce farmers' WTP for digital credit whereas it increases their WTP for conventional credit. Additionally, longer loan duration and higher additional credit cost have a higher effect on farmers' WTP for digital credit compared to conventional credit.

Our results show the potential of digital credit for addressing the credit needs of farmers in rural areas of developing countries if a certain level of innovation, for example, in repayment flexibility is met. With our findings, we can encourage financial service providers (e.g. MFIs, MNOs) in developing countries to design digital credit products with loan duration sufficient enough to accommodate the production season of farmers. Moreover, offering repayment flexibility and an adequate level of additional credit costs should be considered. Taking our findings into account, we think that for digital credit to be successful among farmers in rural areas of Madagascar, it needs more than the three characteristics "instant", "automated", and "remote" (Chen and Mazer, 2016). Offering credit products which are not well adapted to farmers' production needs will not be sufficient. Additionally, the sensitivity of farmers towards the additional credit cost of digital credit shows that the applied fee-practice of mobile money transfers might not be transferable to digital credit: a transparent all costs including interest rate seems to be preferred, and hence, should be achieved by digital credit suppliers. Formal financial institutions, many of them applying responsible finance practices, might have a comparative advantage here over sole digital financial providers like MNOs. Independent from who is offering digital credit, our results show that increasing the number of mobile money agents in farmers' neighborhood could be important for the success of digital credit among farmers in Madagascar. From the perspective of farmers, our study suggest that improving the education of farmers (e.g. through adult education programs) could help farmers take advantage of financial service products such as digital credit when they are available.

From a policy viewpoint, our results suggest that applying responsible finance standards like transparent product pricing without hidden costs can contribute to leverage the potential of digital credit for agricultural finance. Hence, the application of responsible finance standards should be advocated for formal financial institutions and digital financial service providers like MNOs. Finally, policy interventions could be geared towards educating farmers about new financial service products (e.g. digital credit) which could help farmers to address their small credit needs given the limited penetration of formal financial institutions in rural areas of Madagascar. Future studies on digital credit could focus on farmers' preferences for digital credit with respect to who should be offering digital credit to farmers: formal financial institutions or sole digital financial service providers like MNOs? Finally, this study is focusing on Madagascar; therefore, future studies on farmers' WTP for digital credit could focus on other countries in SSA, as the conditions in Madagascar may not be applicable in the context of other countries.

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Appendix A

Instructions for respondents:

Please imagine that for the upcoming planting season, you would like to purchase seeds and pay workers for your farm. For this, you need MGA 200,000. You are prepared to borrow the total amount (MGA 200,000) from a microfinance bank. You have two loan options for the MGA 200,000. The two loans offer different loan assessment procedures, repayment options, approval speed, and costs (e.g. interest cost, disbursement/withdrawal costs). Before I introduce the two loan options to you, please, let me explain the following credit attributes to you.

1. Loan duration: This is the time frame for the loan (e.g. 3 months).
2. Interest amount per month: This is the amount of money you have to pay per month for using the loan excluding the principal loan amount.
3. Repayment flexibility: This is the how you have to pay the borrowed money to the lender (e.g. bank). You can choose to pay in instalment (multiple payments) or at maturity (one-time payment at the end of the loan duration).
4. Traveling distance: For conventional credit, this is the distance from your house to the nearest formal financial institution (e.g. microfinance bank). For digital credit, this is the distance from your house to the nearest mobile money agent.
5. Additional credit cost (e.g. bank charges): For conventional credit, it is called transaction or loan processing fees. It is the amount of money you have to pay to the bank for processing your loan application. It is paid only once per loan application. For digital credit, it is called withdrawal fees. It is the amount of money you have to pay to the mobile money agent in order to change your digital money to physical money. It is paid every time that you have to change your digital money to physical money.

Option one (conventional credit):

You can apply for MGA 200,000 from a microfinance bank which is located in the next town from your place of residence. In order to secure this loan (MGA 200,000), the microfinance bank will conduct a loan assessment with your business data (e.g. income, crop calendar), and you have to provide collateral (e.g. household items or livestock) to the microfinance bank before you can access the loan. Additionally, you have to travel from your place of residence (house) to where the microfinance bank is located to apply for the loan. You may have to wait for some time, up to two weeks before the microfinance bank can take a decision on your loan application.

If the microfinance bank decides to approve your loan application, you have to travel to the microfinance bank's location for the loan disbursement. After the disbursement, you have to visit the microfinance bank several times to make your repayments.

Option two (digital credit):

You can access your bank account via a mobile phone. With a mobile phone, you can apply for MGA 200,000 from a microfinance bank (through a mobile application) at any time on any day. For this loan, the loan application and assessment procedure is different from conventional loan. You have to report your business data (e.g. income, crop calendar) through a mobile application (software) of the microfinance bank to apply for the loan. The microfinance bank sends your reported data to a mobile network operator (MNO) to determine your loan eligibility. The MNO uses your non-traditional data (e.g. frequency and amount of mobile phone airtime top-up) to determine your loan eligibility. You do not have to provide collateral (e.g. household items or livestock) to secure the loan. The loan application and lending decision can be completed within seconds (at most 24 hours). You do not have to visit the microfinance bank to apply for this loan. If your loan application is approved, you have to visit a service point (e.g. mobile money agent) which may be located in your village or a nearby town in order to disburse the loan. When it is time for you to repay the loan, you have to go to the service point to make payments on your digital account to repay the loan. You do not have to visit the microfinance bank to repay the loan.

With this knowledge, please consider the terms and conditions of the following credit products and determine which is suitable for you to finance the purchase of seeds and pay workers for your farm. You can also decide not to choose any of the two credit products (opt out/no credit). Enumerator presents the choice sets to the farmer.