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

Yaw Sarfo[1], Oliver Musshoff[1], Ron Weber[1,2], and Michael Danne[1]

yaw.sarfo@uni-goettingen.de

[1]Department for Agricultural Economics and Rural Development
Georg-August-Universität Göttingen
Platz der Göttinger Sieben 5, D-37073 Göttingen, Germany

[2]Financial & Energy Sector Development, West Africa & Madagascar
KfW Bankengruppe
Palmengartenstraße 5-9, D-60325 Frankfurt, Germany

2021

***Paper prepared for presentation at the 61th annual conference of the GEWISOLA** (German Association of Agricultural Economics)*

„The Transformation of Agricultural and Food Systems: Challenges for Economics and Social Sciences“
Berlin, Germany, September 22th – 24th, 2021

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

Summary

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. 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. Additionally, our results show that instalment repayment condition reduces farmers' WTP for digital credit whilst increasing their WTP for conventional credit. Our results show the potential of digital credit for agricultural finance in rural areas of Madagascar if a certain level of innovation is applied in designing digital credit products.

Key words: Conventional credit, Digital credit, Discrete choice experiment, Smallholder farmers

1. Introduction

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. 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 conventional loans – loans which are granted based on a thorough assessment of the loan applicant's financial situation by a formal financial institution – offered by 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). Conventional 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. Agricultural production is characterized by seasonality of income.

In recent years, digital finance (e.g. digital credit, mobile money service) has developed rapidly in some countries in Sub-Sahara Africa (SSA) such as Madagascar, as an alternative for people who are normally excluded from the formal credit markets (cf. JACK and SURI, 2014; HWANG and TELLEZ, 2016). 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; 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 at most 24 hours from application to loan decision), "automated" (uses digital data[1] of borrowers to evaluate credit worthiness by credit scoring mechanisms), and "remote" (loan application, disbursement, and repayments happen with limited human interactions). The combination of these characteristics "instant, automated, and remote" differentiate digital credit from conventional credit, and underscores its ability to address some, if not all, of the challenges of the rural credit market in developing countries.

The limited number of existing studies on digital credit show that digital credit can improve access to credit 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). 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. 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 condition, 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 the country and for farmers in particular (cf. CONSUMER SURVEY HIGHLIGHTS, 2016). 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 (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 explain the experimental

[1] 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).

design used for the study. This is followed by the methods used for the data analysis in Section 3. Results and discussion are presented in Section 4, and Section 5 concludes the paper.

2. Experimental design

2.1 Data collection

The study uses primary data collected from smallholder farmers from six districts[2] 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 of similar size from six 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. 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.

2.2 Discrete choice experiment

DCEs have been extensively used in the agricultural economics literature to elicit farmers’ preferences for goods and services (WALDMAN et al. 2017; KRAH et al., 2019). 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. DCE is appropriate for our study because digital credit is new in Madagascar so there is no available data.

Based on the digital and conventional credit literature and a pilot study with 20 smallholder farmers in Madagascar, we settled on five attributes for the study: (a) loan duration, (b) interest amount per month, (c) repayment condition, (d) traveling distance, (e) additional credit cost. Loan duration 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 may be very important when choosing a credit product because the duration should be long enough for farmers to make prudent production decisions on their farms. The second attribute, interest amount per month is the cost of borrowing per month excluding the principal credit

---

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

amount. 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 Madagascar, “M-Kajy” has a monthly interest rate of 7% (TOWERCO OF MADAGASCAR, 2018) whereas conventional credit products have an average interest rate of 55.4% p.a. (INTERNATIONAL MONETARY FUND, 2018). Repayment condition 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 Madagascar is particularly low (CONSUMER SURVEY HIGHLIGHTS, 2016), thus, farmers in rural areas have to travel for a considerable distance in order to access conventional credit 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 this study 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 (offers cash-in/cash-out services), who may be a few kilometers (e.g. 0.5 km) from the borrowers’ place of residence, 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).

For this study, based on a labeled design, participating 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. A labeled DCE is preferred for this study 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). In our case, this was necessary as especially the levels for all the attributes except “repayment condition” 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, we use absolute figures for the attributes “interest amount per month” and “additional credit cost” because we realized during the pilot study that the farmers found it difficult to understand and interpret percentage points. In this study, it is essential 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.

Additionally, 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 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.

This is evidenced by the use of digital credit by the farmers in the study districts. 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. With the number of alternatives, attributes and levels presented in Table 1, a full-factorial design results in 23,328 possible decision situations. However, for the sake of practicability, the number of choice sets was reduced. Consequently, 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 alternatives, attributes and their levels used for the experimental design are shown in Table 1.

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 condition	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 condition	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. Estimation procedure

In order to investigate farmers' WTP for digital credit compared to their WTP for conventional credit, 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. Following HENSHER et al. (2015), we model the utility of a farmer n from choosing credit product i among J credit products in choice situation t as:

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

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 condition, 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 (1) is slightly modified to estimate a mixed logit model of the form:

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

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 condition" for both credit products are modeled as effects-coded[3] 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 (1) to indicate the difference between the main price attribute (interest amount per month), P_{nit}, and the other attributes (loan duration, repayment condition, traveling distance, additional credit cost), X_{nit}:

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

Accordingly, we follow Krinsky and Robb procedure using the stata module *wtp* (HOLE, 2007) with 10,000 replications to estimate farmers' WTP for credit products attributes. From equation (3), the ratio of an attribute's coefficient (β_n) to the price coefficient (α_n) is the WTP for that attribute:

(4) $$WTP_n = \frac{\beta_n}{\alpha_n}$$

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. Results and discussion

4.1 Descriptive statistics

Table 2 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 sampled farmers had their application for credit from a formal financial institution approved.

[3] 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).

However, a higher number (51%) is reported if we consider credit to farmers from both formal and non-formal sources.

Table 2: Summary statistics of respondents

Variable	Unit	Mean	SD
Age	Years	39.395	13.141
Credit access (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
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 (Yes)	1/0	0.507	-
Risk attitude [a)]	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 (risk averse) to 10 (risk seeking) (DOHMEN et al., 2011).

4.2 Farmers' preferences and WTP for credit attributes

Table 3 presents the estimation results[4] 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 3 shows 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 3 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% per month 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 rural areas of Madagascar (CONSUMER SURVEY HIGHLIGHTS, 2016). Furthermore, we notice from Table 3 that the difference between farmers' mean WTP for digital credit and conventional credit is statistically significant at 1% significance level. The finding on farmers' WTP for digital credit is largely consistent with the interest rate per month for digital

[4] 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 farmers' socio-economic characteristics.

credit products offered in Madagascar. For example, MVola charges a fixed interest rate of 9% per month (DONKIN, 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% p.a. (INTERNATIONAL MONETARY FUND, 2018). From Tables 3, 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 3 show that loan duration has a positive and statistically significant effect on farmers' preference for digital credit. Further, we observe from Table 3 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 digital credit is generally short (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 3, 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 3 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 3 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 3 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 3 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 from the use of financial services (cf. KARLAN et al., 2016). From our findings in Tables 3, we can state that traveling distance has a statistically significantly higher effect on farmers' WTP for digital credit compared to conventional credit.

Furthermore, Table 3 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 (€0.00) decreases farmers' WTP for digital credit by MGA 107 (€0.03) compared to MGA 5 (€0.00) for conventional credit. We associate this finding to the fact that farmers have to pay the withdrawal fees to a mobile money agent every time they have to change the digital money to physical money compared to loan processing fees for conventional credit which is a very small amount of the total credit amount, and paid per loan application. From Table 3 we can conclude that additional credit cost has a statistically significantly higher effect on farmers' WTP for digital credit compared to conventional credit.

Table 3: 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*** (1.158)	1.000*** (0.266)	20,534***	6,820	34,809
Loan duration	0.162*** (0.045)	-	1,032***	489	1,596
Interest amount per month	-0.016*** (0.002)	-	-	-	-
Repayment condition (Instalment = 1)[a)]	-0.280*** (0.083)	-	-1,779***	-3,042	-725
Traveling distance [a)]	-0.200** (0.090)	1.025***(0.136)	-1,271*	-2,499	-168
Additional credit cost (Withdrawal fees)	-0.017*** (0.003)	0.018*** (0.004)	-107***	-154	-70
Conventional credit					
Constant	4.285*** (1.180)	-	19,244	9,465	29,406
Loan duration	0.024 (0.032)	0.166*** (0.029)	109	-169	404
Interest amount per month	-0.022*** (0.002)	-	-	-	-
Repayment condition (Instalment = 1) [a)]	0.417*** (0.094)	0.963*** (0.130)	1,874	1,040	2,842
Traveling distance	-0.078*** (0.014)	-	-350	-500	-227
Additional credit cost (Transaction fees)	-0.001 (0.002)	-	-5	-26	14
Interaction variables					
Digital credit		-			
Constant x Age	-0.029* (0.017)	-			
Constant x Education	0.123** (0.052)	-			
Constant x Mobile phone access [a)]	0.821*** (0.278)	-			
Constant x Received credit [a)]	-0.558** (0.250)	-			
Constant x Risk attitude	0.577***(0.122)	-			
Conventional credit					
Constant x Age	0.007 (0.017)	-			
Constant x Education	0.072 (0.051)	-			
Constant x Mobile phone access [a)]	0.703*** (0.271)	-			
Constant x Received credit [a)]	-0.708*** (0.249)	0.900*** (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. For mean WTP estimates, significance level is for the difference in farmers' mean WTP between digital credit and conventional credit attributes. We report WTP estimates of non-significant attributes for the sake of comparison. All WTP values are in MGA. MGA: Malagasy Ariary. 1 € = MGA 4,150. SD indicates standard deviation. Only SD coefficients with statistical significance at the 1%, 5% and 10% levels are shown.
[a)] Indicates effects-coded variable. Halton draws = 1,000. Krinsky replications = 10,000.

5. Conclusion

Credit access for farmers in developing countries remains low. Digital credit is a recent innovation that has the potential to improve the situation. However, empirical research on digital credit is limited. We employ a DCE to investigate farmers' WTP for digital and conventional credit in Madagascar. 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 instalment repayment condition reduces 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 Madagascar if a certain level of innovation, for example, in repayment condition is met. With our findings, we can encourage financial service providers in Madagascar to design digital credit products with loan duration sufficient enough to accommodate the production season of farmers. Moreover, offering at maturity repayment condition and an adequate level of additional credit costs should be considered. Taking these findings into account, we think that for digital credit to be successful among farmers in rural areas of the study districts and Madagascar in general, 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 providers. Independent of who is providing 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 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. 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.

References

AKUDUGU, M. A., EGYIR, I. S., and A. MENSAH-BONSU (2009): Women farmers' access to credit from rural banks in Ghana. Agricultural Finance Review 69 (3): 284-299.

BECK, T., A. DEMIRGÜÇ-KUNT and M. S. MARTINEZ PERIA (2008): Banking services for everyone? Barriers to bank access and use around the world. The World Bank Economic Review 22 (3): 397-430.

BLIEMER, M. C., J. M. ROSE and D. A. HENSHER (2009): Efficient stated choice experiments for estimating nested logit models. Transportation Research Part B: Methodological 43 (1): 19-35.

Boucher, S. R., M. R. Carter and C. Guirkinger (2008): Risk rationing and wealth effects in credit markets: Theory and implications for agricultural development. American Journal of Agricultural Economics 90 (2): 409-423.

Boxall, P. C. and W. L. Adamowicz (2002): Understanding heterogeneous preferences in random utility models: a latent class approach. Environmental and resource economics 23 (4): 421-446.

Chen, G. and R. Mazer (2016): Instant, automated, remote: The key attributes of digital credit. CGAP Blog, Washington DC, U.S.A.

Conning, J. and C. Udry (2007): Rural financial markets in developing countries. Handbook of agricultural economics 3, 2857-2908.

Consumer Survey Highlights (2016): Madagascar 2016. Finmark Trust, Johannesburg, South Africa. Available from: https://www.mfw4a.org/publication/consumer-survey-highlights-madagascar-2016

Dalla Pellegrina, L. (2011): Microfinance and investment: A comparison with bank and informal lending. World development 39 (6): 882-897.

Demirguc-Kunt, A., L. Klapper, D. Singer, S. Ansar and J. Hess (2018): The Global Findex Database 2017*:* Measuring financial inclusion and the fintech revolution. The World Bank.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp and G. G. Wagner (2011): Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economic Association 9 (3): 522-550.

Donkin, C. (2017): MVola launches mobile money loans in Madagascar. Available from: https://www.mobileworldlive.com/featured-content/money-home-banner/mvola-launches-mobile-money-loans-in-madagascar

Dupas, P., S. Green, A. Keats and J. Robinson (2012): Challenges in banking the rural poor: Evidence from Kenya's western province, NBER Working Paper Series w17851, National Bureau of Economic Research, Cambridge, Massachusetts, U.S.A.

Francis, E., J. Blumenstock and J. Robinson (2017): Digital credit: A snapshot of the current landscape and open research questions. CEGA White Paper, 1739-76.

Giné, X., P. Jakiela, D. Karlan and J. Morduch (2010): Microfinance games. American Economic Journal: Applied Economics 2 (3): 60-95.

Gsma (2018): The mobile economy. Sub-Sahara Africa. Available from: https://www.gsma.com/subsaharanafrica/resources/the-mobile-economy-west-africa-2018

Guirkinger, C. and S. R. Boucher (2008): Credit constraints and productivity in Peruvian agriculture. Agricultural Economics 39 (3): 295-308.

Hensher, D. A. and W. H. Greene (2011): Valuation of travel time savings in WTP and preference space in the presence of taste and scale heterogeneity. Journal of Transport Economics and Policy (JTEP) 45 (3): 505-525.

Hensher David, A., M. Rose John and H. Greene William (2015): Applied Choice Analysis. Cambridge University Press, Cambridge, UK.

Hole, A. R. (2007): Fitting mixed logit models by using maximum simulated likelihood. The Stata Journal 7 (3): 388-401.

Hwang, B. and C. Tellez (2016): The proliferation of digital credit deployments. CGAP Blog, Washington DC, U.S.A.

International Monetary Fund (2018): International Financial Statistics and data files. Lending interest rate. Available from https://data.worldbank.org/indicator/FR.INR.LEND?locations=MG.

JACK, W. and T. SURI (2014): Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. American Economic Review 104 (1): 183-223.
KAFFENBERGER, M., E. TOTOLO and M. SOURSOURIAN (2018): A Digital Credit Revolution: Insights from Borrowers in Kenya and Tanzania. CGAP Blog, Washington DC, U.S.A.
KARLAN, D., J. KENDALL, R. MANN, R. PANDE, T. SURI and J. ZINMAN (2016): Research and impacts of digital financial services, NBER Working Paper Series w22633, National Bureau of Economic Research, Cambridge, Massachusetts, U.S.A.
KRAH, K., H. MICHELSON, E. PERGE and R. JINDAL (2019): Constraints to adopting soil fertility management practices in Malawi: A choice experiment approach. World Development 124: 1-12.
KRUIJSHAAR, M. E., M. L. ESSINK-BOT, B. DONKERS, C. W. LOOMAN, P. D. SIERSEMA and E. W. STEYERBERG (2009): A labelled discrete choice experiment adds realism to the choices presented: preferences for surveillance tests for Barrett esophagus. BMC Medical Research Methodology 9 (1): 1-10.
LABIE, M., C. LAURETI and A. SZAFARZ (2013): Flexible products in microfinance: Overcoming the demand-supply mismatch, Université Libre de Bruxelles CEB Working Paper No. 13-044, Free University of Brussels, Brussels, Belgium.
MCFADDEN, D. and K. TRAIN (2000): Mixed MNL models for discrete response. Journal of applied Econometrics 15 (5): 447-470.
MPUGA, P. (2010): Constraints in access to and demand for rural credit: Evidence from Uganda. African Development Review 22 (1): 115-148.
MURENDO, C. and M. WOLLNI (2016): Mobile money and household food security in Uganda. GlobalFood Discussion Papers No. 76, Georg-August University of Goettingen, Goettingen, Germany.
SCARPA, R. and J. M. ROSE (2008): Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why. Australian journal of agricultural and resource economics 52 (3): 253-282.
SEKABIRA, H. and M. QAIM (2017): Mobile money, agricultural marketing, and off-farm income in Uganda. Agricultural Economics 48 (5): 597-611.
TOWERCO OF MADAGASCAR (2018): The First Micro Finance Agency (PAMF)-Orange Madagascar: "M-Kajy", instant loan via mobile. Available from: https://www.tom.mg/media-actu/pamf-orange-madagascar-m-kajy-instant-loan-via-mobile/?lang=en#
TRAIN, K. E. (2009): Discrete choice methods with simulation. Cambridge University Press, Cambridge, UK.
TRAIN, K. and M. WEEKS (2005). Discrete choice models in preference space and willingness-to-payspace, in Scarpa, R. and Alberini, A. (ed.), Applications of Simulation Methods in Environmental and Resource Economics, AA Dordrecht, the Netherlands.
WALDMAN, K. B., D. L. ORTEGA, R. B. RICHARDSON and S. S. SNAPP (2017): Estimating demand for perennial pigeon pea in Malawi using choice experiments. Ecological economics 131: 222-230.
WEBER, R. and O. MUSSHOFF (2012): Is agricultural microcredit really more risky? Evidence from Tanzania. Agricultural Finance Review 72 (3): 416-435.
WEBER, R. and O. MUSSHOFF (2013): Can flexible microfinance loans improve credit access for farmers? Agricultural Finance Review 73 (2): 255-271.