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Article

Farmers' preference for digital credit: Does the delivery channel matter?

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Abstract

Previous studies highlight the limited credit access for farmers compared to non-agricultural firms in sub-Saharan Africa. A new innovation that has the potential to serve the financing needs of farmers in sub-Saharan Africa is digital credit. However, empirical studies on farmers' preferences for digital credit are limited. Formal financial institutions and mobile network operators are two different delivery channels for digital credit with different loan characteristics. We apply a discrete choice experiment to investigate smallholder farmers' preferences for digital credit in Madagascar. Our results show that digital credit is more attractive for farmers if it offers a lower interest rate per month, longer loan duration, and flexible repayment conditions adapted to farmers' production needs. Our results highlight the potential of digital credit for rural farmers if mobile network operators could provide digital credit with longer loan maturities, and formal financial institutions could offer digital credit with more flexible repayment conditions.

Keywords: Digital credit, Discrete choice experiment, Financial institution, Mobile network operator, Smallholder farmers.

JEL codes: G21, O16, Q14

1. Introduction

It has been established that access to financial services can improve economic growth, investment, women's empowerment, and help households to better manage risks (e.g. Karlan and Morduch 2009; Ashraf et al. 2010; Dupas and Robinson 2013; Inoue and Hamori 2016). It is also argued that access to financial services can help households to smoothen consumption in times of shocks (Suri et al. 2021). Despite the importance of access to financial services, credit access for farmers in low-income countries remains low, particularly in sub-Saharan Africa (SSA) (e.g. Simtowe et al. 2008; Akudugu et al. 2009; Weber and Musshoff 2012). Credit access in this context is defined as the approval of a loan application to a formal financial institution (bank/microfinance institution (MFI)).

In the past few years, digital finance has expanded quickly in SSA, improving the availability of formal financial services, even for individuals in rural areas (e.g. Munyegera and Matsumoto 2018; Brailovskaya et al. 2021). One branch of digital finance that has the ability to improve credit access for farmers in SSA is digital credit. Digital credit is a loan product that is 'instant, automated, and remote' (Chen and Mazer 2016), indicating that loans are disbursed promptly following application, credit decisions (loan rejection/approval) are determined by algorithms, and it involves limited human interaction (Robinson et al. 2022).

Digital credit reduces the operational costs of providing credit, particularly by allowing lenders to provide financial services without the need to build expensive brick and mortar infrastructure (Chen and Mazer 2016; Francis et al. 2017). This makes digital credit especially interesting for people in remote rural areas who do not generally have the chance to use formal financial services. The provision of digital credit often involves a partnership between a mobile network operator (MNO) and a bank (Kaffenberger and Totolo 2018), even though there are digital credit products that are solely provided by non-bank lenders (e.g. Mpoko Rahishi and Branch in Kenya) (Hwang and Tellez 2016; Robinson et al. 2022) or a financial institution.[1]

Despite the rapid spread and growth of digital credit products in SSA, it is argued that the design of most digital credit products is not suitable for individuals characterized by irregular cash flows (Kaffenberger and Totolo 2018). For example, the loan duration is generally shorter (usually 1 month), repayment conditions are less flexible, and the annual interest rate is higher compared to conventional credit (Francis et al. 2017). Such credit characteristics may not be suitable for farmers because agricultural production is characterized by high seasonality of income (Binswanger and Rosenzweig 1986). Furthermore, the high default rate among digital credit borrowers (e.g. Johnen et al. 2021) could also suggest that the repayment conditions of digital credit products may not be favourable for digital credit borrowers.

Also, critics argue that digital credit products are burdened with data privacy issues (Chen and Faz 2015; Blechman 2016). This is because the credit evaluation criteria depend on the digital data of potential borrowers, which they consider as private/secretive data (Francis et al. 2017; Björkegren and Gressen 2020). Digital data of potential borrowers comprises of call histories, mobile phone credit/data top-ups, frequency of usage of mobile money services, and others (Hwang and Tellez 2016).

Previous literature on digital credit[2] has concentrated on the ability of digital credit to increase credit access to individuals in low-income countries (e.g. Björkegren and Grissen 2018; Benami and Carter 2021; Johnen et al. 2021; Sarfo et al. 2021) or focused on impacts on household welfare (e.g. Karlan et al. 2020; Brailovskaya et al. 2021; Suri et al. 2021; Björkegren et al. 2022; Robinson et al. 2022), as well as data privacy and protection (e.g. Chen and Faz 2015; Blechman 2016), or on borrowers' repayment behaviour (Burlando et al. 2021). Financial institutions and MNOs are two different delivery channels for digital credit with different loan characteristics (e.g. loan duration, interest rate per month). Up until now, little is known about farmers' preferences for digital credit in general, and the effect of loan characteristics of digital credit provided by financial institutions and MNOs on farmers' preferences for digital credit in particular. Furthermore, little is known about the necessary information on farmers' preferences for digital credit, which could especially help central banks in SSA to provide the appropriate legislation for digital credit provision. The only study that provides insights into farmers' preferences for digital credit characteristics is Sarfo et al. (2021). However, they did not focus solely on digital credit, and neither did they provide information about farmers' preferences for digital credit provided by a financial institution.

So, the objective of this study is to investigate farmers' preference for digital credit. In particular, we look at the effect of interest rate, loan duration, repayment conditions, and data requirements for evaluating creditworthiness on farmers' preferences for digital credit. Accordingly, we apply a discrete choice experiment (DCE) to collect primary data from farmers in rural Madagascar. A DCE is suitable for this study because it is an approved method in the literature to investigate individuals' preferences for goods and services (e.g. Kolstad et al. 2021; Mariel and Arata 2022; Tanaka et al. 2022). Furthermore, a DCE is particularly useful when testing a new product or service, especially a product/service that respondents are not familiar with (Burton et al. 2020)—such as digital credit in the study setting. Special attention is given to Madagascar because the country has one of the fastest internet connection speeds in the world with a compelling information and communication technology private sector that could be leveraged to deliver digital financial services to the people of the country (World Bank 2020a). Moreover, the study was done in cooperation with AccèsBanque Madagascar (ABM), an MFI that has a special focus on farmers and is also exploring the potential of digital credit in the country.

To the best of our knowledge, this paper is the first to investigate farmers' preferences for digital credit in general, and the effects of loan characteristics of digital credit provided by financial institutions and MNOs on farmers' preferences for digital credit in Madagascar in particular. Financial institutions and MNOs are relevant in this context because they are two different delivery channels for digital credit with different loan characteristics. The findings of the study will help (potential) suppliers of digital credit like ABM or MNOs to design suitable digital credit products for their borrowers. Also, the findings of this study can help the Central Bank of Madagascar to provide the necessary information on farmers' digital credit preferences to digital credit lenders in the country, and also, to provide the appropriate legislation for the provision of digital credit.

The rest of the paper is organized as follows: Section 2 provides a literature review and formulates the hypotheses for the study. In Section 3, we describe the area of investigation and data used for the study. In Section 4, we describe the experimental design and the methods underpinning the study. This is followed by the results and discussion in Section 5, and we conclude the paper in Section 6.

2. Literature review and hypotheses

Financial institutions and MNOs are two different delivery channels for digital credit and have their pros and cons. Whereas digital credit provided by MNOs is available to a wider range of people (both bank and non-bank clients), digital credit provided by a financial institution could only be accessed by the clients of the financial institution. Also, and more importantly, digital credit products provided by financial institutions and MNOs have different loan characteristics regarding the interest cost, loan duration, repayment flexibility, and credit evaluation criteria. For example, the loan duration for digital credit provided by MNOs is shorter, and the annual interest rate is higher compared to loan products typically provided by financial institutions (e.g. Hwang and Tellez 2016; Brailovskaya et al. 2021).

Digital credit provided by MNOs is more accessible to farmers compared to digital and conventional credit from financial institutions because MNOs have a wider outreach compared to financial institutions (Hwang and Tellez 2016; Francis et al. 2017). So, farmers might prefer digital credit provided by MNOs to digital credit from a financial institution if the loan characteristics of digital credit provided by MNOs would be more flexible/adapted to farmers' production needs. That is changes to the loan characteristics of digital credit provided by MNOs towards cheaper, longer duration and more flexible repayment conditions could have a stronger effect on farmers' preference for digital credit delivered by MNOs compared to digital credit from a financial institution. However, farmers might still prefer digital credit provided by financial institutions simply because of the existing experience with financial institutions or the long-time existence of financial institutions on the market. Thus, we look at the effect of changes to the typical loan characteristics of digital credit delivered through both channels (financial institutions and MNOs) and observe how such changes affect farmers' preferences for digital credit. Hence, the loan characteristics are combined in our experiment to reflect digital credit typically offered by financial institutions and MNOs at the moment. We know that this approach focuses only on the loan characteristics dimension of digital credit provided by financial institutions and MNOs, and does not consider other characteristics of both lenders. Nonetheless, we are convinced that this approach can provide important insights with the goal of accelerating financial services for farmers.

Sarfo et al. (2021) used primary data from rural Madagascar to provide insights into the potential of digital credit for rural farmers by comparing farmers' willingness to pay (WTP) for digital and conventional credit. They find that, conditional on the same credit amount, farmers are on average willing to pay a higher price (interest rate per month) for digital credit compared to conventional credit. The study of Sarfo et al. (2021) and the current study are part of a larger study that seeks to examine the various key issues about the development of digital credit for rural farmers in general and in Madagascar in particular. Even though the two studies are similar in terms of product (i.e. credit), country (Madagascar), and target population (rural farmers), they are different from three perspectives. First, based on the set of attributes in the DCE used for both studies, in this respect, compared to the current study that uses interest amount per month, loan duration, repayment conditions, and data requirement as attributes, Sarfo et al. (2021) considered interest amount per month, loan duration, repayment conditions, travelling distance, and additional credit costs (e.g. withdrawal fees). Second, this study differs from Sarfo et al. (2021) based on the comparison between credit products. In this regard, whereas Sarfo et al. (2021) concentrated on both conventional and digital credit products, the current study focuses on only digital credit products. Third, both studies use different farmers.

Digital credit provided by MNOs is typically more expensive compared to conventional credit. The annualized interest rate could be >100 per cent (Brailovskaya et al. 2021), and sometimes even over 1,000 per cent (Francis et al. 2017). Previous studies suggest that a high-interest rate decreases farmers' demand for (digital) credit (e.g. Fecke et al. 2016; Sarfo et al. 2021). As a result, for digital credit to serve the credit or financing needs of farmers in rural areas, digital credit products need to come at interest rates that consider borrowers' ability to repay (Kaffenberger and Totolo 2018). Accordingly, considering the higher annual interest rate and the higher availability of digital credit provided by MNOs compared to digital and conventional credit from a financial institution, it could be argued that if MNOs offered cheaper digital loans, then farmers would prefer it to digital credit from a financial institution. As a result, it could be stated that a lower interest rate may have a higher effect on farmers' preference for digital credit provided by MNOs compared to digital credit from a financial institution. Hence, the first hypothesis of the study is the following:

> H1 "Interest rate": Interest rate has a higher and statistically significantly effect on farmers' preference for digital credit offered by an MNO compared to digital credit offered by a financial institution.

Furthermore, digital credit provided by MNOs typically has a short loan duration (1 month for most products) (e.g. Brailovskaya et al. 2021; Robinson et al. 2022), which does not seem sufficient for most farmers to finance their farm operations. Conventional loans from financial institutions generally have a longer duration (e.g. up to 1 year) (Cull et al. 2009), which may be more adequate for farmers. In this regard, Sarfo et al. (2021) observed that in Madagascar, rural farmers are willing to pay a higher price for digital credit if they offer a longer loan duration, which may be better adapted to their production needs. Thus, considering the shorter loan duration and higher availability of digital credit provided by MNOs compared to loan products typically offered by financial institutions (Hwang and Tellez 2016), it could be argued that if MNOs offered digital credit with longer maturities that account for farmers' production needs, then farmers would prefer it to digital credit provided by a financial institution. As a result, it could be stated that a longer loan duration may have a higher effect on farmers' preference for digital credit provided by MNOs compared to digital credit from a financial institution. Thus, the second hypothesis of the study is the following:

> H2 "Loan duration": Loan duration has a higher and statistically significantly effect on farmers' preference for digital credit offered by an MNO compared to digital credit offered by a financial institution.

Furthermore, previous research has recommended the delivery of loans that have flexible repayment conditions to farmers (e.g. Dalla Pellegrina 2011; Odhiambo and Upadhyaya 2020; Weber and Musshoff 2013). Loans that have flexible repayment conditions allow farmers to delay loan repayment at the time of low agricultural income (planting) to the time of high agricultural income (harvesting) via predetermined grace periods (Weber and Musshoff 2017). The repayment condition of a credit product may be important to farmers when borrowing due to the seasonality of agricultural production (Binswanger and Rosenzweig 1986). As with most credit products, borrowers of digital credit could repay their credit either at the end of the loan period (i.e. at maturity) or in instalments. In this regard, Sarfo et al. (2021) noticed that in Madagascar, digital credit is more attractive to farmers if lenders offer at maturity repayment condition instead of instalment repayment condition. Accordingly, considering that most MFIs in developing countries mainly offer loans without flexibility and are still reluctant to deliver loans with flexible repayment conditions (e.g. see Weber and Musshoff 2013, 2017 for a discussion on flexible loans), digital credit from MNOs could be more attractive for farmers if they offer flexible repayment conditions adapted to the production needs of farmers. Thus, it could be argued that offering flexible repayment conditions adapted to farmers' production needs (e.g. instalment repayment) may have a higher effect on farmers' preference for digital credit provided by an MNO compared to digital credit from a financial institution. Hence, the third hypothesis of the study is the following:

> H3 "Instalment repayment": Instalment repayment has a higher and statistically significantly effect on farmers' preference for digital credit offered by an MNO compared to digital credit offered by a financial institution.

Also, when looking at the credit evaluation criteria for digital credit provided by MNOs and digital credit from a financial institution, MNOs use digital data of potential borrowers to determine credit eligibility, whereas financial institutions depend on the bank history data of their clients for the same purpose. It is suggested that one of the main concerns that borrowers have with digital credit is consumer privacy, particularly for borrowers of digital credit provided by MNOs (Blechman 2016). This is because the data used for evaluating creditworthiness may be categorized as sensitive/private data by some borrowers (Francis et al. 2017; Björkegren and Gressen 2020). In this context, McKee et al. (2015) suggest that borrowers of digital credit from MNOs are concerned about the safety of their data and the possibility for it to be compromised. This is because MNOs fall under different regulatory frameworks regarding the provision of financial services (e.g. telecommunications, banking sectors), and hence, may be less regulated, which makes it difficult to enforce consumer privacy laws (Blechman 2016). In this regard, McKee et al. (2015) indicate that it is not clear to borrowers what data are accessed for credit evaluation, and how these data might be used. However, formal financial institutions are better regulated compared to MNOs. This ensures the respect of consumer privacy laws, and hence, more transparency may be offered about what data might be accessed and used for credit evaluation. Thus, it could be argued that data requirement—which simply refers to the type of data used by financial institutions and MNOs (bank history data versus digital data) to determine the creditworthiness of potential borrowers—may have a higher effect on farmers' preference for digital credit from a financial institution compared to digital credit provided by an MNO. Hence, the fourth hypothesis of the study is the following:

H4 "Data requirement": Data requirement for evaluating credit worthiness has a higher and statistically significantly effect on farmers' preference for digital credit offered by a financial institution compared to digital credit offered by an MNO.

3. Area of investigation and data

3.1 Area of investigation

Madagascar is one of the poorest countries in SSA (Riquet 2013). It has one of the highest poverty rates in the world, and it is estimated that ~75 per cent of the population of the country live below the poverty line of $1.90 per day (World Food Program 2019; World Bank 2020b). Also, it is estimated that ~70 per cent of the population or individuals of the country live in remote and rural areas (Demirguc-Kunt et al. 2018). Due to poor infrastructure such as electricity and road networks, financial institutions (banks, MFIs) in the country are mainly located in urban areas with very little occurrence in remote and rural areas (Consumer Survey Highlights 2016; World Bank 2020b). On average, it is estimated that for every 100,000 people in Madagascar, there are only 2.2 bank branches (World Bank 2018), which are normally located in urban areas. Accordingly, bank account ownership at formal financial institutions in the country is limited to ~5.5 per cent of the adult population (Demirguc-Kunt et al. 2018). Even though MNOs in Madagascar such as Airtel, Orange, and Telma offer mobile money services and digital loans to their customers, the majority of the people in Madagascar lack access to basic formal financial services (World Bank 2018). The situation is particularly dire for individuals who are located in rural areas of the country.

3.2 Data collection

The study builds on primary data collected from rural farmers in the districts of Miarinarivo, Betafo, Arivoimamo, Ambohidratrimo, and Ambatolampy in Madagascar from December 2019 to February 2020. We collected data from smallholder farmers (both clients and non-clients) of one of the largest microfinance banks in Madagascar, ABM.[3] A multi-stage sampling strategy was used to randomly select 300 smallholder farmers for the study. At the first stage, one branch of ABM was purposively selected from each district for interviews. Our decision to select these branches was based on the fact that these branches are stationed in remote rural areas, and largely provide agricultural loans in predominately agricultural towns or communities. Regarding the sampling of non-ABM clients for the study, two villages were randomly selected from each of the five selected districts.

At the second stage, regarding the selection of ABM clients who are farmers for the study, we randomly selected thirty smallholder farmers from each of the five selected branches of ABM used for the study. These farmers were randomly drawn from a complete list of farmers on the agricultural loan profile of each of the selected branches. In respect of the selection of the non-ABM clients for the study, we randomly selected fifteen households from each village according to full household lists. The farmers in our sample are largely subsistence farmers, mainly producers of vegetables (e.g. cucumber, pepper, carrot) and rice—cultivated largely for household consumption. The sample used for the study is largely representative of the farmers in the study area because the farmers in the study districts produce similar crops and have similar demographic characteristics (e.g. years of education). Also, the farmers in the study area are largely comparable considering their access to financial services and infrastructure (e.g. road, electricity).

With locally trained enumerators, we conducted individual face-to-face interviews with each of the farmers who took part in the study. At the start of each interview, the enumerator explains the purpose of the study to the participant. Additionally, the enumerator assures the participant that the data collected during the interview will be treated confidentially, and be used only for research purposes. Farmers' participation in the survey or study was voluntary. The questionnaire for the survey consists of questions on farmers' household, farm information, access to financial services, and a DCE, and concludes with questions on farmers' financial knowledge. Following data cleaning, the sample was reduced to 295 participants given that five respondents did not complete the questionnaire, and failed to provide responses for key questions (e.g. the DCE).

4. Discrete choice modelling

4.1 Experimental design

DCEs have been widely applied in the development and agricultural economics literature to investigate individuals' or consumers' preferences for goods and services (e.g. Krah et al. 2019; Kolstad et al. 2021; Mariel and Arata 2022; Tanaka et al. 2022). Choice modelling is grounded on Lancaster's consumer theory and McFadden's random utility theory (Lancaster 1966; McFadden 1974). The basic assumption is that consumers derive utility from the attributes of a product/good instead of the product itself, and consumers choose the product that maximizes their utility from the set of possible options or alternatives (Hensher et al. 2015). Typically, participants in a DCE are shown a number of choice sets, each comprising of two or more options or alternatives, and they are asked to choose their preferred alternative in each situation.

In this study, based on a labelled design, the farmers were presented with the following decision situation: Participants were offered to choose between a digital credit from a financial institution and a digital credit from an MNO or could decide to choose no credit (opt-out). We included an opt-out alternative because a forced choice would not be consistent with demand theory (Hanley et al. 2001). The explanations of the instructions for the participating farmers for the DCE are shown in Online Appendix A. The attributes for the DCE, their levels and ranges were determined following the hypotheses of the study, digital credit literature, expert advice from ABM, and a pretest with forty farmers in November 2019. This made it possible to identify the key loan characteristics that are relevant to farmers when choosing digital credit. Consequently, we identified four digital credit attributes for the study: interest amount per month, loan duration, repayment condition, and data requirement. The alternatives, attributes, and their levels used for the DCE are shown in Table 1.

From Table 1, based on the number of alternatives, attributes, and levels, a full-factorial design leads to 2,592 possible decision situations. Practically, it is not possible to present all the 2,592 choice sets to a respondent in a survey. Therefore, we used an efficient design approach to reduce the number of choice sets. Following Scarpa and Rose (2008) and Bliemer et al. (2009), a D-efficient Bayesian design with twelve choice sets blocked equally into two groups was used for the study (i.e. six choice sets per block). As a result, each farmer responded to six choice sets during the survey. The six choice sets in both blocks used for the survey are shown in Online Appendix B. A multinomial logit (MNL) model was used to generate the design. As shown by Bliemer and Rose (2010), MNL designs could be used to estimate mixed logit models. Using MNL is advantageous if the choice design is demanding because of complex DCEs where the mixed logit model design struggles to converge. Also, we employed priors that were based on the pretest, and the design has no interactions. The choice sets were designed using Ngene.

Table 1. Alternatives, attributes, and levels used for the experiment (DCE).

Alternatives	Attributes	Levels
Digital credit from a financial institution		
	Interest amount per month	MGA 12,000; MGA 16,000; MGA 20,000
	Loan duration	3 months; 6 months; 12 months
	Repayment conditions	1 = instalment; 0 = at maturity
	Data requirement	1 = transaction history; 0 = credit history
Digital credit from an MNO		
	Interest amount per month	MGA 16,000; MGA 20,000; MGA 24,000; MGA 28,000
	Loan duration	1 month; 3 months; 6 months
	Repayment conditions	1 = instalment; 0 = at maturity
	Data requirement	1 = mobile airtime usage; 2 = mobile money transactions; 3 = social media data

Notes: MGA indicates Malagasy Ariary. Loan amount = MGA 200,000. 1€ = MGA 4,150.

4.1.1 Interest amount per month

The interest amount per month is the cost of the digital credit product per month apart from the principal loan amount. Normally, it is stated as interest rate per month. Nonetheless, in the context of this study, it is referred to as interest amount per month due to the fact that we noticed during the pretest that the sampled farmers found it challenging to comprehend and interpret percentage points. Following the pretest, we selected MGA 16,000, MGA 20,000, MGA 24,000, and MGA 28,000 as the levels for interest amount per month for digital credit from an MNO. These levels signify 8 per cent, 10 per cent, 12 per cent, and 14 per cent of the loan amount (MGA 200,000), respectively. It is important to mention that a loan amount of MGA 200,000 (about €50) was chosen for this study because the farmers in the study districts deemed such an amount to be adequate for their farm activities for a production season, for example, credit to buy a new variety of seeds.

For digital credit from a financial institution, there is no empirical paper to indicate the interest rate per month. However, Jeník et al. (2020) suggest that financial institutions know their clients well (thanks to clients' bank history data), and can offer credit products that are well adapted to the needs of their clients. This is the situation of the investigated micro-finance bank in this study, which offers digital credit with a lower interest rate per month in comparison to digital credit from MNOs in Madagascar. Following the pretest, we selected MGA 12,000, MGA 16,000, and MGA 20,000 as the levels for interest amount per month for digital credit from a financial institution. These levels signify 6 per cent, 8 per cent, and 10 per cent of the loan amount, respectively.

4.1.2 Loan duration

The loan duration of a digital credit product is the period or time frame for the loan product. Digital credit from MNOs is short-term loans (Brailovskaya et al. 2021; Robinson et al. 2022). Following the pretest, we set the levels of the loan duration for digital credit provided by an MNO to 1 month, 3 months, and 6 months. However, digital credit from a financial institution may have a longer loan duration compared to digital credit from MNOs. This is possible because, on average, classical financial institution (bank) loan products have a longer loan duration (Cull et al. 2009) compared to the loan duration of digital credit products from MNOs (Hwang and Tellez 2016). Thus, for digital credit from a financial institution, we set the levels to 3 months, 6 months, and 12 months. The duration of a credit product may be mostly important for farmers because it can influence the type of crop(s) a farmer cultivates.

4.1.3 Repayment condition

Repayment of digital credit by borrowers occurs remotely via mobile phone. This can be done either in instalment (e.g. monthly) or at maturity, that is, at the end of the loan period (Hwang and Tellez 2016). For digital credit products, there is generally little empirical evidence to indicate loan applicants' preferences for repayment conditions and for farmers in particular. The only notable study is Sarfo et al. (2021), who observed in Madagascar that farmers prefer digital credit—mainly provided by MNOs—that offers at maturity repayment condition to digital credit that offers instalment repayment condition. Thus, this attribute is used to investigate farmers' preferences for repayment conditions for digital credit products in the study districts.

4.1.4 Data requirement

Digital credit application occurs over a mobile phone with limited in-person contact between the potential borrower and the financial service provider. Thus, for digital credit from MNOs, lenders rely on the digital data of potential borrowers to evaluate their creditworthiness (Chen and Faz 2015; Hwang and Tellez 2016). This is mainly important for first-time borrowers because repayment history becomes more important for successive loan applications. For this study, mobile airtime usage, mobile money transactions, and social media data of potential borrowers are used to investigate farmers' preferences for data requirement for evaluating creditworthiness for digital credit from an MNO. Hwang and Tellez (2016) suggest that financial service providers could use bank history data of potential borrowers to evaluate their eligibility for digital credit. Thus, for digital credit from a financial institution, potential borrowers' transaction history (e.g. frequency of cash deposits and withdrawals) and credit history with the microfinance bank are used to capture their preference for data requirement when choosing digital credit from a financial institution. Hence, this attribute is used to identify farmers' preference for data requirement (digital data versus bank history data) for determining creditworthiness when choosing a digital credit product. The attribute and their levels reflect the typical credit characteristics of digital credit products in Madagascar because MNOs and some microfinance banks in the country (e.g. ABM, Baobab) provide digital loans to their clients with similar loan characteristics. This is particularly true considering that this study, as already stated, was designed in close collaboration with one of the largest commercial microfinance banks in Madagascar, which offers digital loans to its clients.

In this study, a labelled design is suitable because it is the best approach to present the different credit characteristics of both digital credit products to farmers. This is because both digital credit products have different attribute levels for interest amount per month, loan duration, and data requirement. In particular, the data requirement for evaluating credit eligibility for both digital credit products are different—digital data versus bank history data—which make both credit products alternative-specific. Also, the use of a labelled DCE for this study makes it possible for the farmers to focus on the main credit characteristics of both credit products based on their knowledge and experience (see Kruijshaar et al. 2009; De Bekker-Grob et al. 2010; Hensher et al. 2015 for a discussion on labelled DCEs).

In this experiment, the trade-off for the participating farmers to choose either loan product is conditional on the credit characteristics (e.g. loan duration), data requirement for evaluating credit eligibility (use of digital data versus bank history data), and whether a potential borrower is a client of the financial institution that offers digital credit and/or is registered for mobile money services with an MNO. For example, digital credit from a financial institution borrower may have loans with a longer duration and pay a lower interest amount per month compared to digital credit from an MNO borrower; however, one has to be a client of the financial institution in order to access the loan product. Alternatively, for digital credit from an MNO, borrowers may have to pay a higher interest amount per month and have loans that have a shorter duration compared to digital credit from a financial institution; however, they do not have to be a client of an MFI or a bank in order to access credit from a financial institution. Furthermore, the credit eligibility criterion for digital credit from an MNO relies on more private/secretive data (digital data) of potential borrowers compared to that of digital credit from a financial institution, which relies on less private/secretive data (bank history data) of potential borrowers for similar purpose.

Also, it is worth noting that we present different figures (e.g. loan duration) for both loan products because, in the study setting, the investigated microfinance bank offers digital credit with a lower annual interest rate and a longer loan duration compared to digital credit products provided by MNOs. Additionally, it is important to highlight that a direct comparison of smallholder farmers' preferences for both digital credit products is reasonable for two reasons. First, access to financial institutions (e.g. banks, MFIs) is particularly low in rural areas of Madagascar. This makes digital finance increasingly important for people in rural areas (mainly farmers). Second, this experiment is intended to address the credit or financing needs of farmers in remote rural areas of the country who need small loan amount for the production season for their farm activities.

4.2 Econometric approach

In this study, we apply a DCE to investigate smallholder farmers' preferences for digital credit in Madagascar. Following random utility theory (McFadden 1974), we assume that a smallholder farmer n faces a choice among J digital credit products in choice situation s. The utility of a smallholder farmer n from choosing a digital credit product i in choice situation s can be separated into two components: a modelled component, $V(X_{nis}, \beta_n)$, and an un-modelled component, ε_{nis}, such that:

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

where U_{nis} is the utility perceived by farmer n for digital credit product i in choice situation s. X_{nis} is a vector of observed attributes of digital credit product i in choice situation s. β_n is a vector of parameters to be estimated that indicates the farmer's preferences for digital credit product attributes, and ε_{nis} is the error term of the expected utility that is not observed (Train 2009). Consistent with Hensher et al. (2015), for a given choice set of digital credit products J, the probability that a smallholder farmer n in choice situation s will choose digital credit product i is given as the probability that digital credit product i provides or offers the maximum utility or value when compared to any other alternative j. Thus, the probability of smallholder farmer n choosing digital credit product i from the possible digital credit products J in choice situation s can be specified as

$$\begin{aligned} P_{nis} &= \text{Prob}\left(U_{nis} > U_{njs},\ \forall i \neq j;\ i, j \in J\right) \\ &= \text{Prob}(V_{nis} + \varepsilon_{nis} > V_{njs} + \varepsilon_{njs}, \forall i \neq j;\ i, j \in J). \end{aligned} \tag{2}$$

Equation (2) suggests that the probability of a smallholder farmer n choosing a digital credit product i from a set of J digital credit products in choice situation s is the sum of the deterministic component, V and the error component, ε. Therefore, we can rewrite equation (2) as

$$P_{nis} = \text{Prob}\left(\varepsilon_{nis} - \varepsilon_{njs} > V_{njs} - V_{nis}, \forall i \neq j;\ i, j \in J\right). \tag{3}$$

To investigate farmers' preferences for both digital credit products and subsequently derive their WTP for digital credit attributes, we use the mixed logit model (Hole 2007). The mixed logit model is preferred to other comparable models such as the conditional and the

MNL models in this study because of its (mixed logit model) inherent ability to account for unrestricted substitution patterns, correlation in unobserved factors over time, and random taste variation; hence, preference heterogeneity across individuals could be accounted for in the model estimation (e.g. Train 2009; Hensher et al. 2015). Given that the coefficient vector β is not observed for each n and varies in the population under the mixed logit model (Owusu Coffie et al. 2016), the researcher does not observe β_n. Therefore, the unconditional choice probability is the integral of all the possible variables of β_n. Thus, the probability that a smallholder farmer n selects a digital credit product i from a set of J digital credit products in a choice situation s can be specified as

$$P_{nis}\ (\beta_n) = \int \frac{\exp\left(\beta'_n X_{nis}\right)}{\sum_{j=1}^{J} \exp(\beta'_n X_{njs})}\ f\left(\beta_n|\theta\right) d\beta_n, \tag{4}$$

where $\beta'_n X_{nis}$ is the observed component of the utility, $f(\beta_n|\theta)$ is the cumulative density function of β_n in the population, and θ refers to the parameters of the distribution such as the mean and covariance of β. The utility of a smallholder farmer n from selecting a digital credit product i from a set of J digital credit products in a choice situation s can be specified from equation (1) as

$$U_{nis} = \delta_i + \beta'_n X_{nis} + \varepsilon_{nis}, \tag{5}$$

where U_{nis} is the utility a smallholder farmer n associates with selecting digital credit product i in choice situation s. δ_i is the alternative-specific constant of digital credit product i. X is a vector of alternative-specific digital credit attributes: interest amount per month, loan duration, repayment condition, and data requirement. Furthermore, β_n are the accompanying parameters to be estimated for the selected digital credit product attributes, and ε_{nis} is the error term associated with the model. In order to account for preference heterogeneity across farmers when choosing digital credit products, it is essential to include individual-specific characteristics through interaction terms when estimating the model (Boxall and Adamowicz 2002). Thus, we include farmers' socioeconomic characteristics in the estimation process. Here, we interact farmer's socioeconomic characteristics Z_n with the alternative-specific constant δ_i of the digital credit product i selected by a farmer n in a choice situation s in equation (5) as

$$U_{nis} = \delta_i + \beta'_n X_{nis} + \phi'(\delta_i \ \times \ Z_n) + \varepsilon_{nis} \tag{6}$$

where $(\delta_i \ \times \ Z_n)$ is a vector of variables accounting for the interactions of smallholder farmers' socioeconomic characteristics Z_n (e.g. farmers' years of education, financial knowledge) and the δ_i associated with the digital credit product i selected by a farmer n; ϕ are coefficients to be estimated.

Following Hole (2007), we estimate the mixed logit model in the Stata 15 by using the simulated maximum likelihood estimator with 1,000 Halton draws. In the econometric modelling, the price attribute (interest amount per month) is fixed, whereas the non-price attributes (loan duration, repayment condition, and data requirement) follow a normal distribution (Hensher et al. 2015). Also, it is important to indicate that in the model estimation, the attributes interest amount per month and loan duration are modelled as continuous variables, whereas repayment conditions and data requirements are modelled as effects-coded[4] variables. Thus, the reported coefficient estimate for the attributes interest amount per month (interest rate per month) and loan duration represent farmers' utility for a decrease of 1 per cent in interest rate per month and an increase of 1 month in loan duration of a digital credit product, respectively. For example, if the interest rate per month for digital credit from a financial institution is 3 per cent, then the utility is −0.339 [=3 × −0.113]. Similarly, if the interest rate per month is 5 per cent, then the utility is

−0.565 [=5 × −0.113]. Also, if the loan duration for digital credit from an MNO is 3 months, then the utility is 1.683 [=3 × 0.561]. Also, we model all the socioeconomic characteristics of farmers apart from their age, financial knowledge, and years of education as effects-coded variables. We estimate the mixed logit model in preference space. This was necessary because even though the price attribute (interest amount per month) in our labelled DCE varies by option, the price attribute is alternative-specific based on the digital credit provider so it makes it unrealistic to estimate our labelled DCE models in WTP space. For example, in our DCE, it is not possible to combine an interest rate (amount) per month of 6 per cent (MGA 12,000) with digital credit provided by an MNO. Similarly, it is not feasible to combine an interest rate (amount) per month of 14 per cent (MGA 28,000) with digital credit provided by a financial institution.

To calculate farmers' WTP for the various digital credit products attributes, we divide the estimated coefficient of each non-price attribute in question by the estimated coefficient of the price attribute (Hu et al. 2012; Schulz et al. 2014; Hensher et al. 2015). That is, WTP is the negative ratio of the estimated coefficient of the non-price attribute to the estimated coefficient of the price attribute (Yangui et al. 2019):

$$\mathrm{WTP}_{X_k} = -\frac{\beta_k}{\beta_P}, \tag{7}$$

where β_k is the estimated coefficient of the non-price attribute X_k and β_P is the estimated coefficient of the price attribute P. Following Das et al. (2009) and Lancsar et al. (2017), the parameters of the price attribute were fixed in the estimation process. The WTP estimates and their corresponding confidence intervals were determined following the Krinsky and Robb procedure with 10,000 replications (Hole 2007). From equation (7), we apply the Wald test to investigate whether the difference between farmers' WTP for corresponding credit attributes for both credit products is statistically significant.

5. Results and discussion

5.1 Sample characteristics

Table 2 demonstrates the descriptive statistics of the sample for the study. The farmers have a mean age of ∼41 years. Furthermore, sampled farmers have to travel for ∼l km on average to the nearest mobile money agent to withdraw a digital loan. We further observe that the sampled farmers have on average ∼2 acres of land and ∼12 years of farming experience. It also emerged from Table 2 that ∼92 per cent of the respondents own a mobile phone, a prerequisite device for digital credit usage. In the study setting, a simple phone is sufficient for the use of digital credit. Additionally, over the past 12 months, only 32 per cent of the sampled farmers had credit access from a formal financial institution. Furthermore, when looking at the number of respondents who trust in social media (i.e. Facebook Messenger) for bank transactions, only 32 per cent of the respondents indicated their trust in social media for bank transactions.

5.2 Farmers' preferences and WTP for digital credit attributes

Table 3 shows the estimation results for the determinants of farmers' preference for digital credit attributes by a mixed logit model.[5] The findings in model (1) show that the constants for both digital credit products are positive and statistically significant. The constants (ASCs)—alternative-specific constant for each digital credit product—have to be interpretated in relation to the opt-out option (no credit). A constant with a negative sign indicates that farmers prefer the opt-out option to the credit product, whereas a positive sign indicates that farmers prefer a credit product to the opt-out option. Thus, the findings in model (1) suggest that, relative to no credit (opt-out), farmers prefer to select either of the digital credit products presented to them in the DCE.

Table 2. Descriptive statistics of sampled farmers.

Variable	Unit	Mean	SD
Age	Years	40.925	12.013
Credit access over the past 12 months (yes)	1/0	0.315	–
Delivery channel for digital credit (Facebook Messenger) (yes)	1/0	0.163	–
Distance to the nearest mobile money center or agent	Km	1.135	1.046
Education	Years	10.976	4.410
Farming experience	Years	11.932	11.146
Financial knowledge[a]	Number	4.041	1.186
Gender (male)	1/0	0.502	–
Household size	Number	4.769	1.964
Land size (owned land)	Acres	1.883	2.313
Marital status (married) (yes)	1/0	0.851	–
Mobile phone ownership (yes)	1/0	0.919	–
Monthly income	MGA	478,888	216,271
Acquired credit from formal and/or non-formal sources over the past 12 months (yes)	1/0	0.451	–
Remittances (yes)	1/0	0.295	–
Trust in social media for bank transactions (yes)	1/0	0.342	–
Number of participants		295	

Notes: MGA indicates Malagasy Ariary. 1€ = MGA 4,150. Mean values for binary variables (1/0) indicate ratios.
[a]Following Lusardi and Tufano (2015), financial knowledge is measured on a scale from 1 to 7: 1 indicates very low financial knowledge, and 7 indicates very high financial knowledge.

In this regard, model (1) shows that farmers prefer digital credit that has a lower interest rate per month and/or longer loan duration to digital credit that has a higher interest rate per month and/or shorter loan duration. From model (1), the statistical significance of the standard deviation[6] coefficient of the constants for both digital credit products suggests preference heterogeneity among sampled farmers when choosing digital credit products relative to no credit (opt-out). This is confirmed by the statistical significance of the standard deviation coefficient of some of the random attributes in model (1). Therefore, to identify and explain the source(s) of preference heterogeneity among farmers when choosing digital credit products, we account for the socioeconomic characteristics of the sampled farmers in model (2).

A log-likelihood ratio test to compare models (1) and (2) at the 5 per cent level of statistical significance ($\chi^2_{(12)} = 72.960$, P-value $= 0.000$) indicates that we can reject the null hypothesis that models (1) and (2) fit the data equally; and hence, the log-likelihood ratio test suggests that model (2) is a better fit of the data. Therefore, we focus on the results of model (2) for interpretation and discussion. Furthermore, Table 4 shows farmers' estimated WTP and corresponding confidence intervals for digital credit attributes for both credit products—by Krinsky and Robb method.[7] Additionally, Table 5 shows the results of the Wald test demonstrating the difference between corresponding mean WTP estimates for both digital credit products.

5.2.1 Farmers' WTP for digital credit products (low- versus high-interest rate)

From model (2) in Table 3, the constants of both digital credit products are positive, but only statistically significant for digital credit from a financial institution, suggesting that compared to no credit (opt-out), smallholder farmers prefer digital credit that has a lower interest rate per month to digital credit that has a higher interest rate per month. Furthermore, we observe from Table 4 that, relative to no credit (opt-out), smallholder farmers' mean WTP for digital credit from a financial institution is MGA 29,417 (€7.09) per month

Table 3. Mixed logit estimates for the determinants of farmers preferences for digital credit product.

Variable	Model (1) Mean coefficient (Standard error)	Model (1) SD coefficient (Standard error)	Model (2) Mean coefficient (Standard error)	Model (2) SD coefficient (Standard error)
Digital credit from a financial institution				
Constant	4.427*** (0.385)	0.720*** (0.174)	3.249*** (0.698)	–
Interest amount per month	–0.113*** (0.022)	–	–0.110*** (0.022)	–
Loan duration	0.024 (0.024)	0.071** (0.032)	0.020 (0.023)	–
Repayment conditions (instalment = 1)[a]	0.393*** (0.109)	–	0.390*** (0.111)	–
Data requirement (transaction history = 1)[a]	0.038 (0.076)	–	0.028 (0.077)	–
Digital credit from an MNO				
Constant	1.937*** (0.521)	1.249*** (0.177)	0.827 (0.926)	1.072*** (0.179)
Interest amount per month	–0.160*** (0.022)	–	–0.156*** (0.022)	–
Loan duration	0.561*** (0.057)	–	0.554*** (0.056)	–
Repayment conditions (instalment = 1)[a]	0.331** (0.158)	1.167 *** (0.154)	0.316** (0.158)	1.142*** (0.153)
Data requirement (mobile money transaction = 1)[a]	0.227 (0.152)	–	0.209 (0.152)	–
Data requirement (social media data = 1)[a]	0.090 (0.135)	–	0.091 (0.133)	–
Interaction variables				
Digital credit from a financial institution				
Constant × age			–0.001 (0.010)	–
Constant × delivery channel (Facebook Messenger = 1)[a]			0.338* (0.182)	–
Constant × education			0.057* (0.032)	0.059*** (0.015)
Constant × financial knowledge			0.286*** (0.099)	–
Constant × acquired credit[a]			–0.390*** (0.120)	–
Constant × trust[a]			0.503*** (0.162)	–
Digital credit from an MNO				
Constant × age			–0.003 (0.012)	–
Constant × delivery channel (Facebook Messenger = 1)[a]			0.122 (0.222)	–
Constant × education			0.005 (0.038)	–
Constant × financial knowledge			0.421*** (0.124)	–
Constant × acquired credit[a]			–0.054 (0.152)	–
Constant × trust[a]			0.701*** (0.186)	–

Table 3. Continued

Variable	Model (1)		Model (2)	
	Mean coefficient (Standard error)	SD coefficient (Standard error)	Mean coefficient (Standard error)	SD coefficient (Standard error)
Number of participants/observations	**295/5,310**		**295/5,310**	
Goodness of fit measures				
AIC	2,145		2,096	
BIC	2,243		2,273	
Log-likelihood	–1,057		–1,021	
LR-statistic (χ^2) (4 d.f.)	98		83	
Prob $> \chi^2$	0.000		0.000	

Notes: ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent, and 10 per cent levels, respectively. The models were estimated with 1,000 Halton draws. Model (1) does not account for socioeconomic characteristics of farmers, whereas model (2) does. SD stands for standard deviation. We report only SD coefficients with statistical significance at the 1 per cent, 5 per cent, and 10 per cent levels. This is because 'insignificant parameter estimates for derived standard deviations indicate that the dispersion around the mean is statistically equal to zero, suggesting that all information in the distribution is captured within the mean' (Hensher et al. 2005, 2015).

[a] Indicates effects-coded variable.

Table 4. Smallholder farmers' estimated WTP for digital credit attributes.

Variable	Mean WTP (MGA) (95 per cent confidence interval)
Digital credit from a financial institution	
Constant	29,417***
	(18,349/46,396)
Loan duration	185***
	(−281/587)
Repayment conditions (instalment = 1)	3,527
	(1,551/6,658)
Data requirement (transaction history = 1)	258
	(−1,299/1,647)
Digital credit from an MNO	
Constant	5,304
	(−7,397/15,797)
Loan duration	3,553
	(2,627/5,027)
Repayment conditions (instalment = 1)	2,025
	(19/4,159)
Data requirement (mobile money transactions = 1)	1,341
	(−574/3,500)
Data requirement (social media data = 1)	582
	(−1,236/2,265)

Notes: MGA indicates Malagasy Ariary. Loan amount = MGA 200,000. In order to test our hypotheses, we report WTP estimates for all attributes in model (2) of Table 3 for both digital credit products. WTP estimates are reported in MGA. 1€ = MGA 4,150. WTP values were estimated with 10,000 Krinsky replications. For mean WTP estimates, ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent, and 10 per cent levels, respectively. Significance level is for the difference in smallholder farmers' mean WTP between digital credit from a financial institution and digital credit from an MNO attributes. Number of participants = 295.

Table 5. Wald test showing the difference in coefficients for both digital credit products.

Test	Wald χ^2 statistic	Prob > χ^2
Financial institution = MNO (constants)	14.150***	0.000
Financial institution loan duration = MNO loan duration	80.580***	0.000
Financial institution instalment repayment = MNO instalment repayment	0.070	0.796
Data requirement		
Bank transaction history = MNO mobile money transaction	1.400	0.237
Bank transaction history = MNO social media data	0.110	0.743

Notes: ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent, and 10 per cent levels, respectively. Number of participants = 295.

compared to MGA 5,304 (€1.28) for digital credit from an MNO. If we compare both WTP estimates to the principal loan amount (MGA 200,000), then our findings indicate that the sampled farmers, on average, are willing to pay an amount equal to 14.71 per cent per month for digital credit provided by a financial institution compared to 2.65 per cent per month for digital credit provided by an MNO. The results indicate that for the same credit amount, farmers prefer digital credit that has a lower interest rate per month to digital credit that has a higher interest rate per month. This is in line with previous studies, which suggest that a high-interest rate decreases farmers' demand for digital credit (e.g. Sarfo et al. 2021).

Furthermore, Table 5 shows that the difference between farmers' mean WTP for interest rate per month for digital credit from a financial institution and that for digital credit from an MNO is different from zero at the 1 per cent significance level. Even though digital credit from MNOs may be more accessible to farmers in contrast to digital credit from financial institutions, the results suggest that providing cheaper loans by MNOs may not necessarily increase farmers' uptake of digital credit provided by MNOs compared to financial institutions. As a result, from Tables 4 and 5, H1 'interest rate', which hypothesizes that interest rate has a higher and statistically significantly effect on farmers' preference for digital credit offered by an MNO compared to digital credit offered by a financial institution can be rejected.

5.2.2 Loan duration (long versus short duration)

We observe from model (2) in Table 3 that loan duration has a positive and statistically significant effect on farmers' preference for digital credit that has a shorter loan duration—digital credit provided by an MNO. We also notice from model (2) that loan duration has no statistically significant effect on farmers' preference for digital credit that has a longer loan duration—digital credit provided by a financial institution. We confirm these findings in Table 4. From Table 4, we realize that increasing loan duration of a long-term loan by 1 month increases farmers' WTP for digital credit by MGA 185 (€0.04) compared to MGA 3,553 (€0.86) for short-term digital credit. This suggests that if MNOs would offer digital credit with a longer loan duration (than the 1 month currently offered by most MNOs), then farmers' uptake of digital credit from MNOs would increase.

This finding is plausible when taking into account the business rationale of the type of credit product preferred by farmers or the local production circumstances: Farmers in the study area may require up to 6 months from planting to harvesting of their crops (e.g. rice). However, most digital loan products offered by MNOs in Madagascar have a duration of 1 month (Donkin 2017), which is not sufficient to account for the production season of farmers in the study districts. As a result, farmers are willing to pay considerably more per month for an increase in the loan duration for digital credit from an MNO compared to an increase in the loan duration for digital credit from a financial institution, which may be long enough to support their production activities.

We support our argumentation with the results of the Wald test in Table 5, which indicate that the difference between farmers' mean WTP for 1 month increase in loan duration for digital credit from a financial institution and 1 month increase in loan duration for digital credit from an MNO is statistically significant at the 1 per cent significance level. As a result, from Tables 4 and 5, H2 'loan duration', which hypothesizes that loan duration has a higher and statistically significantly effect on farmers' preference for digital credit offered by an MNO compared to digital credit offered by a financial institution can be accepted.

5.2.3 Repayment conditions (instalment versus at maturity repayment)

It emerged from model (2) of Table 3 that repayment conditions (instalment repayment) have a positive and statistically significant effect on farmers' preference for both digital credit products. This suggests that farmers prefer an instalment repayment to at maturity repayment when choosing either digital credit product. Farmers' preference for an instalment repayment relative to the at maturity repayment is inconsistent with the seasonality of agricultural production (Binswanger and Rosenzweig 1986) and contradictory to the proposition of flexible loans to farmers (e.g. Dalla Pellegrina 2011; Llanto 2007; Weber and Musshoff 2013). However, farmers' preference for instalment repayments to at maturity repayment is plausible in the study context given that the sampled farmers indicate that they prefer to spread the repayment of their loans in small amounts over the loan period (e.g. monthly instalment repayment) instead of waiting to repay their loans at the end of the loan period (i.e. at maturity repayment), for which they may not be certain to have sufficient income to repay the loan.

Furthermore, we notice from Table 4 that the sampled farmers' mean WTP for instalment repayment for digital credit from a financial institution is MGA 3,527 (€0.85) compared to

MGA 2,025 (€0.49) for digital credit from an MNO. This suggests that offering an instalment repayment will increase farmers' WTP for both digital credit products, and the magnitude of the effect is higher for digital credit provided by a financial institution compared to an MNO. This is not surprising considering the reluctance of most financial institutions, in particular in SSA, to offer loans with flexible repayment conditions to their customers (e.g. Weber and Musshoff 2013). From Table 5, the results of the Wald test suggest that the difference between farmers' mean WTP for instalment repayment for digital credit provided by a financial institution and that from an MNO is not statistically significantly different from zero, and hence, H3 'instalment repayment', which hypothesizes that instalment repayment has a higher and statistically significantly effect on farmers' preference for digital credit offered by an MNO compared to digital credit offered by a financial institution can be rejected.

The statistical insignificance of the mean WTP estimates seems surprising at first considering the statistical significance of the model estimates in Table 3. However, this is not surprising given that we are looking at the difference between the mean WTP estimates for corresponding credit attributes. Here, we are testing if the difference between farmers' mean WTP for repayment conditions for both credit products is statistically different from zero. Even though it is observed in Table 3 that the estimates for repayment conditions are statistically significant, it does not necessarily indicate that the difference between farmers' mean WTP for repayment conditions for both credit products is statistically different from zero.

5.2.4 Data requirement (bank history data versus digital data)

It emerged from model (2) of Table 3 that data requirement has no statistically significant effect on farmers' preference for either digital credit product. This is an interesting finding, particularly for digital credit provided by an MNO, given the increasing concerns about borrowers' data privacy and protection with regard to the use of digital credit from MNOs (e.g. Chen and Faz 2015; McKee et al. 2015; Blechman 2016).

Also, it is observed from Table 4 that the sampled farmers' mean WTP for data requirement for evaluating creditworthiness for digital credit is MGA 258 (€0.06) for bank history data compared to MGA 1,341 (€0.32)/MGA 582 (€0.14) for digital data. This suggests that farmers are on average willing to pay a higher price to ensure their data privacy if the credit evaluation criterion for digital credit relies on the use of their digital data (e.g. data relating to borrowers' call history, mobile money transactions, or mobile money balance) compared to the use of their bank history data for the same purpose. Furthermore, Table 5 shows that there is no statistically significant difference between farmers' mean WTP for data requirement for both digital credit products, and hence, H4 'data requirement' which hypothesizes that data requirement for evaluating creditworthiness has a higher and statistically significantly effect on farmers' preference for digital credit offered by a financial institution compared to digital credit offered by an MNO can be rejected.

5.2.5 The role of farmers' demographic characteristics on their preference for digital credit

It is observed from model (2) in Table 3 that farmers' years of education have a positive and statistically significant effect on their preference for digital credit that has a lower interest rate per month and a longer loan duration (i.e. digital credit from a financial institution). This finding is consistent with Sarfo et al. (2021), who report a similar relationship between farmers' years of education and their preference for digital credit in Madagascar. Furthermore, it emerged from model (2) that farmers' financial knowledge has a positive and statistically significant effect on their preference for both digital credit products. Additionally, the findings in model (2) show that farmers who trust in social media (i.e. Facebook Messenger) for bank transactions are more likely to use both digital credit products. This is expected in the context of this study for borrowers of digital credit from a financial institution, given that the delivery channel for ABM's digital credit is Facebook Messenger (MyAccess)—a mobile application of ABM that enables clients to apply, disburse, and repay loans remotely. This finding is further highlighted by the positive and statistically significant effect of the delivery channel (Facebook Messenger) on farmers' preference for digital credit that has a lower interest rate per month and a longer loan duration in model (2)—digital credit from a financial institution. Furthermore, the findings in model (2) show that smallholder farmers who acquired credit from any source during the past 12 months (from both non-formal and formal sources) are less likely to use digital credit from a financial institution relative to no credit. This suggests that, given the low availability of financial institutions in the study setting, farmers who can rely on family and friends or financial institutions for non-digital credit have no purpose to seek other credit options. Particularly interesting to observe from model (2) is the non-significance of the farmers' years of education on their preference for digital credit that has a higher interest rate per month and shorter loan duration—digital credit provided by an MNO—given the high default rates among borrowers of digital credit provided by MNOs (e.g. Johnen et al. 2021).

6. Conclusion

The limited credit access for farmers compared to non-agricultural firms in SSA has been discussed broadly in the literature. In the past few years, digital finance (e.g. digital credit) has emerged as an alternative to address the credit needs of individuals who are generally excluded from the use of formal financial services in SSA. However, the design of digital credit products is often not suitable for individuals characterized by irregular cash flows, such as those who receive their income primarily through agricultural production. For example, the interest rate per month is generally higher, the loan duration is shorter, and repayment conditions are less flexible compared to conventional credit. Financial institutions and MNOs are two different delivery channels for digital credit with different loan characteristics in terms of interest rate per month, loan duration, repayment flexibility, and credit evaluation criteria. Also, the availability of digital credit from a financial institution is limited to the clients of the financial institution only, whereas digital credit from an MNO has a wider outreach. In this study, we apply a DCE to investigate smallholder farmers' preferences for digital credit in Madagascar. In particular, we investigate the effect of loan characteristics of digital credit provided by financial institutions and MNOs on farmers' preference for digital credit—interest rate, loan duration, repayment conditions, and data requirement for evaluating creditworthiness.

Consistent with the literature, our results show that farmers generally prefer digital credit that has a lower interest rate per month, longer loan duration, and offers flexible repayment conditions adapted to their production needs. In particular, our results show that the interest rate per month has a higher effect on farmers' preference for digital credit provided by a financial institution compared to digital credit provided by an MNO. Also, considering the shorter loan duration and higher availability of digital credit provided by MNOs to farmers compared to credit products typically provided by financial institutions, our results show that loan duration has a higher effect on farmers' preference for digital credit provided by an MNO compared to digital credit provided by a financial institution. Moreover, the results show that offering flexible repayment conditions (instalment repayment) adapted to farmers' production needs has a higher effect on farmers' preference for digital credit provided by a financial institution compared to digital credit provided by an MNO. Additionally, given the increasing concerns in the literature about borrowers' data privacy and protection when using digital credit products, our results suggest that farmers do not consider data requirement for evaluating creditworthiness as an important attribute when choosing a digital credit product, although the effect is higher for digital credit provided by an MNO compared to digital credit provided by a financial institution.

From a policy perspective, based on the findings of the study, we encourage financial institutions and MNOs in Madagascar to provide digital credit with flexible repayment conditions and MNOs to offer longer loan durations to enhance the use of digital credit among farmers in the country. Furthermore, we can also encourage the Central Bank of Madagascar to provide digital credit lenders in the country with the necessary information on farmers' preferences for digital credit products and also, to provide the appropriate legislation for the provision of digital credit.

Due to the limited understanding of percentage points by the farmers in the study districts, we presented the cost of both digital credit products per month 'interest amount per month' in our DCE in absolute numbers instead of percentage points. This approach, although necessary for farmers' understanding of the DCE, may have some influence on the results. Thus, future studies should present the cost of digital credit product(s) in percentage points and see how the results compare with the findings of this study. Furthermore, future studies could check the validity of our results by replicating our experiment with farmers from other countries as the situations in Madagascar may be unique to some extent. Additionally, future studies could focus on the use of non-experimental data to investigate farmers' preferences for digital credit attributes. This is necessary given that there were no empirical data available on digital credit in Madagascar at the time of this study.

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Supplementary material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Conflict of Interest

The authors declare that there is no conflict of interest.

Data availability statement

The data underlying this article will be shared on reasonable request to the corresponding author.

End Notes

1 This is the situation of the investigated microfinance bank in this study, and a number of microfinance banks in Madagascar, which rely on the bank history data of their clients (e.g. account balance, loan history, loans outstanding, transaction history, and repayment history) to provide digital credit to their clients.

2 There is also a large body of research on conventional microfinance credit products that focus on the delivery of financial services to individuals in low-income countries (e.g. Van Rooyen et al. 2012; Banerjee 2013; Shuaibu and Nchake 2021).

3 ABM is one of the main commercial microfinance banks in Madagascar and a forerunner in the area of digital finance. Founded in 2007 with the mission of providing financial services to individuals of low-income groups, ABM wants to broaden its digital financial products range. ABM is interested in independent analyses in the area of digital financial services and allowed the researchers to freely conduct our DCE within their business districts.

4 We use effects-coding instead of dummy-coding in this study to prevent the possibility of confounding the base level of the attributes used in the DCE with the grand mean of the utility function (see Hensher et al. 2015 for a discussion on dummy-coding versus effects-coding in the DCE).

5 We also estimated a MNL logit model for the determinants of farmers' preferences for digital credit attributes. We report the estimation results in Table A1 of Online Appendix C. The results are largely consistent with the findings in Table 3.

6 A mixed logit model with the standard deviation distributions of all the random parameters used in the DCE was also estimated. We report the estimation results in Table A2 of Online Appendix D. The results are generally consistent with the findings in Table 3.

7 We also estimated the WTP values based on the delta method. We report the estimation results in Table A3 of Online Appendix E. The average WTP estimates are the same as by the Krinsky and Robb method in Table 4. Only the confidence intervals change.

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