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Heterogeneous choice in the demand for agriculture credit in China: results from an in-the-field choice experiment

Rong Kong
Northwest Agriculture and Forestry University, Yangling, China
Yanling Peng
Institute of Regional Economy and Finance, Sichuan Agricultural University, Chengdu, China
Nan Meng
Dyson School of Applied Economics and Management, Cornell University S C Johnson College of Business, Ithaca, New York, USA
Hong Fu
Shandong University of Finance and Economics, Jinan, China
Li Zhou
Nanjing Agricultural University, Nanjing, China
Yuehua Zhang
Center for Social Welfare and Public Governance and School of Public Affairs, Zhejiang University, Hangzhou, China, and
Calum Greig Turvey
Dyson School of Applied Economics and Management, Cornell University S C Johnson College of Business, Ithaca, New York, USA

Abstract

Purpose – In this study, the authors examined demand-side credit in rural China with the aims of understanding attribute preferences and the willingness of farmers to pay for credit.

Design/methodology/approach – The authors implemented an in-the-field discrete choice experiment (DCE) using a D-optimal block ($6 \times 9 \times 3$) design applied to 420 farm households across five Chinese provinces (Shandong, Sichuan, Shaanxi, Jiangsu and Henan) in the summer and fall of 2018. The DCE included six

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attributes including the interest rate, term of loan, type of loan, type of repayment, type of institution and mobile banking services.
Findings – Conditional and mixed logit results indicated a downward sloping credit demand curve with variable elasticity across regions. Provincial willingness-to-pay (WTP) indicators suggested that farmers were willing to pay a premium for long-term (0.03–0.687%) and low collateral credit loans (0.79–2.93%). Also, four of five provinces indicated a preference for loan amortization rather than lump-sum payment. Interestingly, in comparison to the Agricultural Bank of China (ABC), only farmers in Shandong, Sichuan and Shaanxi indicated a preference for rural credit cooperatives (RCCs)/banks and the Postal Savings Bank of China (PSBC). Another quite surprising result was bank services, in our case, access to mobile banking did not appear to induce WTP for agricultural credit. While conditional and mixed logit regression coefficients were similar (and therefore robust), the authors found that there was substantial heterogeneity across attribute preferences on term of loan, type of loan and amortization. Preferences for type of lender and mobile banking were generally homogenous. This result alone suggested that lenders should consider offering a suite of credit products with different attributes in order to maximize the potential pool of borrowers. While there were some differences across provinces, farmers appeared to be indifferent to lenders, and it did not appear that offering banking services such as mobile banking had any bearing on credit decisions.
Research limitations/implications – This paper presents a first step in using in-the-field choice experiments to better understand rural finance in China. Although the sample size satisfies conventional levels of significance and rank conditions, the authors caution against attributing results to China as a whole. Different provinces have different institutional structures and agricultural growing conditions and economies and these effects may differentially affect WTP for credit. Although by all indications farmers were aware of credit, not all farmers, in fact a minority, actually borrowed from a financial institution. This is not unusual in China, but for these farmers, the DCE was posed as hypothetical. Likewise, the study's design was based on a generic credit product typical of rural China, and the authors caution against making inferences about other products with different attributes and risk structures.
Social implications – This study is motivated by the rapidly changing dynamic in China's agricultural economy. With specific reference to new laws and regulations about the transfer of land use rights (LURs), China's agricultural economy is undergoing significant and rapid change which will require better understanding by policy makers, lenders and practitioners of the changing credit needs of farmers, including the new and emerging class of commercial farmers.
Originality/value – To the best of the authors' knowledge, the authors believe that the result provided in this paper present the first use of in-the-field DCE and are the first to be reported in either the English or Chinese literature on rural credit product design.

Keywords China, Rural finance, Agricultural credit, Discrete choice experiment, WTP, Demand-side

Paper type Research paper

1. Introduction

Given the reformation of agricultural credit policies in China in the 21st century, it is important to understand the drivers of credit demand and any informational and/or institutional gaps between lenders and borrowers (Kong *et al.*, 2014; Turvey *et al.*, 2014; Cao *et al.*, 2016). By and large, the literature related to agricultural finance in China mostly investigates the characteristics of the borrower with surprisingly few examining agricultural credit as a consumer product characterized by a bundle of attributes of varying importance to farmer-borrowers. Examination of these attributes is not only of scholarly interest but also of practical interest to policy makers and lenders. Indeed, our motivation to studying credit demand at the attribute level is in recognizing that recent changes to land laws is going to significantly affect China's agricultural economic growth and with these changes, the institutions and policies required to moderate the economy will have to change accordingly (Lin, 2011, 2019; 2011; Stiglitz 2008, 2011; Meyer 2011). The institutions of concern are financial and regulatory institutions that will increasingly require micro analyses on the changing credit needs of the Chinese farmer. A failure of governments and institutions to deal effectively with large-scale changes in China's agricultural economy can lead to credit rationing, constrain agricultural growth and undermine policy initiatives (Turvey 2012). The institutions of concern in this paper are providers of agricultural credit that will necessarily need to adapt credit products and policies to meet the specific requirements of farmers. Credit is not simply a relationship between loan size and interest rates but a bundle of characteristics or attributes of which the interest rate is a part.

To further understand credit demand, this paper focuses on the attributes of the credit product itself and how these attributes affect credit demand. Thus, the overall objective of this study is to investigate the characteristics affecting credit demand in China. The specific objectives are to identify the characteristics affecting credit demand and to determine the willingness to pay (WTP) for these attributes through development of an in-the-field discrete choice experiment (DCE). By understanding revealed preferences about credit, we can better understand credit policy and the role that rural finance plays in supporting economic development in rural China (Sun *et al.*, 2019; Wen *et al.*, 2020). Based on principles of rural finance theory, the attributes considered in the DCE include interest rate, term of loan, type of loan, type of repayment, institution and mobile banking services. We implemented the DCE in two waves in Shandong, Sichuan, Shaanxi, Henan and Jiangsu provinces in rural China in the summer and fall of 2018 and believe this to be among the first in-the-field DCE to determine attributes of rural credit demand in China (and elsewhere for that matter) [1]. Our findings indicate that farmers are interest rate responsive and are willing to pay a premium for lower collateral, long-term loans and amortization vs lump sum. We find that borrowers' preferences are heterogeneous in these attributes, suggesting that inflexible one-size-fits-all credit products may not optimize the potential pool of borrowers. A somewhat surprising result was a homogenous indifference toward the type of lender: the Agricultural Bank of China (ABC), rural credit cooperatives (RCCs) or the Postal Savings Bank of China (PSBC). In addition, we find that tying financial services to loan demand has no material impact on credit demand and this too was fairly homogenous across all respondents.

The paper proceeds as follows. In the next section, we review the agricultural finance literature related to China. We then provide an overview of random utility models and DCEs. We then present the D-optimal design of experiment and outline our methods. The data are summarized, results are presented and the paper concludes.

2. The review of literature on rural credit in China

In this section, we provide an overview of studies addressing agricultural credit in China. Jia *et al.* (2010) found that demand-side rationing is determined by multiple factors including access to formal credit channels, and Dong *et al.* (2012) found that by removing credit constraints, average agricultural productivity was estimated to be increased by 75%. Ma and Xu (2018) concluded that the main reason for rural credit inhibition in China was demand-based credit suppression caused by risk, but even efforts to provide land titles to farmers appear to have a positive effect on farmers' demand for credit (Jiang *et al.*, 2020). To address these related problems, rural financial development has been at the forefront of agricultural and rural economic development in China in the modern era since at least 2003. This history can be found in Guo and Jia (2009), Shen *et al.* (2010), Fu and Turvey (2018) and Zhou (2020). Policies have been promulgated, and the regulatory and oversight activities of rural credit have been strengthened through the China Banking Regulatory Commission (CBRC). Since being identified as a key objective in the No. 1 Central Document issued by the government in 2006, advancements in credit delivery have made tremendous contributions in supporting and promoting the development of China's agricultural economy. The No.1 Central Document of 2019, promulgated recently, continues to focus on the rural issues including rural financial reforms.

With the development of economic reforms, China's rural formal finance has improved considerably. A multilevel and comprehensive service system of policy and commercial banks, cooperative institutes and new rural financial institutions have now been formed (Zhou, 2020). By the end of 2016, credit files of 172 m farm households had been established and about 92.48 m farm households had obtained loans with a loan balance of 2.7 trillion yuan (National Bureau of Statistics of China). However, He *et al.* (2018) concluded that as strong as the rural credit demand is, formal credit satisfaction is still low and farmers' credit rationing is still serious (see also He 2005; Li 2017; Turvey *et al.*, 2011; Turvey, 2013; Tang and Guo 2017; Verteramo-Chiu *et al.*, 2014).

Understanding the demand side of rural credit is crucial. For example, recent policy initiatives to increase credit supply will be more effective if aggregate credit demand was highly elastic and less so if inelastic (Ma and Xu, 2018). Tang and Guo (2017) showed that households' decisions on whether to borrow are mainly determined by households' production capacity and the transactions costs. Turvey *et al.* (2012) used a multiple bounded discrete choice model and found that the elasticity of credit demand is moderately inelastic (about −0.61 on average) with about 25% of farmers having demand elasticities less than −1.0. They also found that farmers with a credit demand for agricultural production tend to be more inelastic than households with credit demand for nonagricultural investment such as house construction. Turvey and Kong (2009) found that credit demand generally falls as risk relative to returns increases, supporting the notion that credit demand is more inelastic under conditions of risk. Verteramo-Chiu *et al.* (2014) examined risk rationing behavior (see Boucher *et al.*, 2008) of Chinese farmers and found that only 6.2% of farmers were risk rationed, only 14% were credit rationed with 79.9% being price rationed along the credit demand curve. This included a significant number of farmers that had a perfectly inelastic credit demand at zero loans. These findings are consistent with findings by Zhao and Barry (2014) that much of observed rationing in China is self-imposed and that simply increasing supply and access may not increase overall technical efficiency. This is in part due to the fabric of rural credit in China that includes a significant, if not dominant, demand for informal credit through friends and relatives (Cao *et al.*, 2020). Turvey and Kong (2009; see also Turvey *et al.*, 2010) confirmed a relationship between trust and informal lending finding that over 67% of farm households borrow from friends and relatives.

With the continuous development of the rural economy and the deepening of the rural financial reform process, the characteristics of rural credit demand continues to be of economic importance and significance to agricultural growth (Nan *et al.*, 2019; Tian *et al.*, 2020). This is particularly important given recent land reforms that expand that collateral base of land use rights and mortgaging. These land reforms originated with a policy regarding "The Advancement of Rural Reform and Development" in 2008, which made allowances for farmers to lease their contracted farmland or transfer their land use rights. In a second document on policies concerning the Financial Advancement of Economic Development in 2008, the government's objective was to encourage financial institutions to expand the scope of rural collateral and explore various credit products. Provisions to enable farm households to mortgage land-use right (LUR) in some locations was issued by the Central People's Bank of China and the CBRC in 2009 and subsequently, China's first policy documents for 2014 and 2015 – the No.1 central policy – allowed farmers to mortgage LUR in certain locations and under certain conditions. These are known as rural land mortgage loans. On August 10, 2015, the document concerning the trial implementation of rural management rights over contracted land and farmer's homes as collateral for bank loans was approved by the State Council. Chinese farmers would now be allowed to transfer LUR and use LUR and homes to raise mortgages, in addition to converting LUR into shares in large-scale farming entities (Peng and Kong, 2020). The clear intention of the new policies is not only to create a more inclusive financial system that addresses these long-standing policy issues but also to improve the scale of existing operations and advancing entrepreneurial activity (Peng and Kong 2020; Peng and Zhou, 2020; Liu *et al.*, 2019; Turvey and Xiong 2017) and increasing agricultural incomes (by about 25.9% according to a study of 1,279 farm households by Yang *et al.*, 2018).

3. Experiment implementation and data description

As mentioned, our approach to investigating attributes of credit demand involved a 2018 in-the-field DCE. In this section, we provide a brief overview of the conceptual framework and justify its use in our context.

3.1 Random utility theory

According to Hanemann (1984), consumer decisions can be separated into discrete and continuous choices. DCEs were first put forward by Louviere and Hensher (1982) and have been used widely in psychology, economics with random utility theory and environmental valuation. We are unaware of any DCE used to place value on the attributes of agricultural credit as we do in this study. This section describes the implementation of the DCE model.

In this study, we use a mixed random parameter multinomial logit (MMNL) model, which is particularly well suited to analyze multiattribute discrete choice models. In this framework, agricultural credit is described by the bundle of attributes outlined in the DCE. In this context, expected utility is not simply a rational choice trade-off between borrowing and interest rates but a hedonic and random utility derived from a bundle of attributes (McFadden and Zarembka, 1974; McFadden and Train, 2000). In an n-choice situation ($n = 1$, 2, or 3), consumer i's utility (U_{ni}) can be modeled as a linear function of product attributes (X_{nj}):

$$U_{nj} = V_{nj} + \varepsilon_{nj} = X_{nj}\beta + \varepsilon_{nj} \tag{1}$$

Equation (1) is a logit model which is also called "Random Utility Model," where β is a vector of unknown part-worth utilities associated with attribute X_{nj}. The deterministic part, V_{nj} is parameterized by β, which allows estimation of the effect of the variable X_{nj} on utility. The random error term ε_{nj} reflects the fact that decision makers are going to prefer different alternates given that they prefer the attributes of each alternate differently.

The probability that decision maker n selects alternate i is

$$\begin{aligned} p_{ni} &= \text{prob}(U_{ni} > U_{nj},\ \forall j \neq i) \\ &= \text{prob}(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj},\ \forall j \neq i) \\ &= \text{prob}(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj},\ \forall j \neq i) \\ &= \int I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj},\ \forall j \neq i) f(\varepsilon_n) d\varepsilon_n \end{aligned} \tag{2}$$

If $\varepsilon_{nj} \sim iid\ EV$, the choice probability p_{ni} is

$$p_{ni} = \frac{\exp(V_{ni})}{\sum_{j=1}^{J} \exp(V_{nj})} \tag{3}$$

The above logit is a conditional logit, which means attribute x_{nj} is decided by both individuals and alternates and random utility caused by x_{nj} does not depend on alternates j. To be specific, the choice probability can be written as $p(y_j = j|x_{nj})$ because it is a conditional probability. The assumption of the conditional logit model implies that the unobserved factors are uncorrelated over alternates as well as having the same variance for all alternates.

McFadden and Train (2000) developed the mixed logit model and showed that a mixed logit model can approximate any logit model. The fundamental idea behind the mixed logit model is the utility from any one choice is no longer independent of any other choice but rather correlated through the introduction. Generally, a mixed logit model contains two sections: a logit speciation of an individual's probability of choosing a given alternate and a specification of the distribution of the utility (Train, 2016). The mixed logit model is

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta_n X_{nj} + \varepsilon_{nj} \tag{4}$$

where n is the farm households; j is the credit choice decision; X, a matrix, represents the choice attributes (i.e. interest rate; term of loan; credit loan; guaranteed loan; amortization; type of lender (ABC, RCCs/banks, PSBC and mobile banking). The significant difference between the conditional and mixed logit models is that the response parameter varies over n decision makers. In a mixed logit model, elements in vector β are defined as random variables following density function: $\beta_n \sim f(\beta_0, G)$ where β_0 is are the means of β_n and G is the variance matrix. In this study, we assume that β_n are distributed normally, i.e. $\beta_n \sim N(\overline{\beta}, \sigma_\beta)$.

$$p_{ni} = \int \frac{\exp(\beta_n x_i)}{\sum_{j=1}^{J} \exp(\beta_n x_j)} f(\beta) d\beta \tag{5}$$

McFadden and Train (2000) have shown that a mixed logit model can, under benign conditions, approximate any choice model to any degree of accuracy. In simpler terms, the difference between conditional logit and mixed logit models is that the former treats all choices as if all respondents held homogenous beliefs, while latter runs individual logits across DCE choices of each respondent and aggregates the coefficients to obtain a mean response as well as the standard deviation of responses. Standard deviations that are statistically different from 0 indicate heterogeneous choices across attributes and farmers. In this sense, the mixed logit model is more informative. Finally, it is not unusual in the literature of choice experiments to present both the conditional and mixed logit models, as we do in this paper, since consistency in results is an indicator of robustness.

3.2 The discrete choice experiment

We ran two DCEs in two waves. The first wave included farm households in Shandong, Sichuan and Shaanxi in May 2018 and the second was in Jiangsu and Henan in October 2018. We used nonorthogonal D-optimal design (Triefenbach, 2008) in the first wave and Bayesian D-optimal design in the second wave. Sándor and Wedel (2001) introduced Bayesian D-optimal design models to deal with model uncertainty and as a means to eliminate or minimize irrelevant alternates which would lower the standard errors and reduce sample size. The Bayesian D-optimal design takes advantage over D-optimal design (Hoyos, 2010; Jones and Lin 2008) by using the attribute correlation matrix from the first wave to optimize D-optimal design in the second wave. The base D-optimal design in the first wave and Bayesian D-optimal design in the second wave were formulated using JMP software [2].

3.3 Attributes and levels identification

Attributes are product characteristics influencing consumer choice (Crouch and Louviere, 2004). The common themes raised in the introduction define these attributes and include interest rate, term of loan, type of loan, type of repayment, type of institution and mobile banking, which are selected to be attributes.

Interest rate is the cost or price of credit, which is the most direct and deterministic characteristic of credit product for farm households. In China, interest rates differ across financial institutions and loan terms. The lending interest rate is a benchmark interest rate from central bank plus floating interest rate from individual banks. The levels of interest rate used in our DCE ranged from 2%, 4%, 6%, 8%, 10%, 12% and 14%.

Term of loan is another distinct characteristic of credit product. According to RCCs, there are five different terms of loan: less than six months, six months to one year, one year to three years, three to five years and more than five years. The longer the term, the higher the interest rate. For borrowers, how to decide among loans with different term is a trade-off between actual situation and price.

Type of loan also affects farm household decision. There are three basic types of loan in rural China: collateral, guaranteed and credit loans. Collateral loan is a loan with higher security and less risk because a collateral increases the expected return of the lender and creates an incentive for borrowers to avoid intentional default (Feder *et al.*, 1988). Collateral loans are particularly important given the recent changes to land transactions and LURs. A guaranteed loan is a loan issued on the condition that a third party provides the corresponding guarantee for the borrower. The most common guaranteed loan in rural China is group guarantee. Farmers form groups such that while they borrow individually, the group as a whole is responsible for each of its members' loans. The economics and importance of joint liability in group lending is presented in detail by Ahlin and Townsend (2007). Policies put in place by lenders to address risk and asymmetric information can also have demand side effects. Kong *et al.* (2015) investigated the group guarantee and found that, generally, farmers did not form group guarantees voluntarily but were required to do so by the lender. Older farmers were less likely to borrow under a group guarantee or voluntarily join a group guarantee as guarantor; guarantors in a group guarantee are more likely to be risk takers or not too risk adverse; farmers who mistrust lenders are less likely to join a group guarantee. A credit loan is a loan issued on the creditworthiness of the borrower and the borrower does not need to provide a guarantee. The three loan types also have different risk characteristics (Feder *et al.*, 1988), with collateral, guaranteed and credit loans ordered lowest to highest and typically are offered with increasing interest rates. For borrowers, how to decide among the three loan types is a trade-off between transaction cost and interest rate.

Type of repayment is the fourth attribute we select. This includes lump-sum payment and amortization. Lump-sum payment means the borrower pays the loan and accrued interest in a single payment at or before the loan term ends. With amortization, the loan will be repaid in equal amounts with decreasing interest every month during the loan period.

Institution is the fifth attribute we use. China's rural credit market is mainly served by RCCs, RCCs and PSBC. The rural credit cooperative financial system (including rural commercial banks, rural cooperative banks and RCCs) is the main server of formal finance in rural China (Turvey *et al.*, 2014). To enhance the efficiency and risk management of RCCs, RCCs have gradually transformed into rural commercial banks (RCBs). Here, RCCs refer to both RCCS and RCBs.

Mobile banking service is the last attribute. With the popularization of the Internet and smartphone, the convenience of terminal applications has become an important factor for consumers to make choices. To adapt the tendency, almost every finance or nonfinance institutions explore their own application. In rural China, high smartphone coverage and mobile banking services have developed rapidly. In theory, mobile banking enables farmers to use financial services anytime and anywhere with reduced transaction costs.

Table 1 summarizes attributes and levels. A key difference between the first and second waves, in addition to the use of Bayesian D-optimality is that in the first wave, we used a six card/block design with only two choices/card but increased this to a nine cards/block with three choices/card in the second wave. Additionally, in the first wave, we presented the choice cards in a tabular format (example in Figure 1), while in the second wave, we developed a pictorial format (example in Figure 2). As these changes could be a source of exogenous variation, we present first and second waves' results separately.

3.4 Implementation of the discrete choice experiment

The first wave included two towns with six villages in Shandong, six towns and 15 villages in Chengdu, Sichuan and five towns with 11 villages in Shaanxi. The second wave, in October 2018, included 21 and ten villages in Jiangsu and Henan, respectively. Ultimately, we interviewed 300 farm households in the first wave and 120 farm households in the second wave and finally collected 3,600 (300 farmers $\times$ 2 choices $\times$ 6 cards) and 3,240 combinations (120 farmers $\times$ 3 choices $\times$ 9 cards), respectively. Farmers were paid a participation stipend of 30 RMB. Table 2 provides a summary of key demographic data collected in a short follow-on survey for each province.

Table 2 shows that age, total number of households, number of farmers, number of works and years engaged in agriculture of farm household in five provinces are similar with slight difference. The average ages of respondents in five provinces are 53.5, 55.1, 60.0, 53.7 and 50.6 years, respectively. The average numbers of people in household in five provinces are 4.0, 4.4, 4.4, 4.6 and 4.8, respectively. The average areas of contracting land in five provinces are 8.3, 7.6, 5.0, 9.7 and 6.7, respectively. However, the size of land transfer, family income and expenditure are different to a large extent. The areas (mu) of transferred land for agriculture in five provinces are 17.7, 29.76, 0.1, 97.3, 0.5, respectively, which indicates that Shaanxi has the smallest area of transferring land and the area of transferring land is largest in Jiangsu. Among five provinces, farmers in Jiangsu have much higher income including agricultural and nonagricultural as well as family expenditure, while Henan's farmers are relatively poor.

3.5 Credit information

In the first experiment, the follow-on survey indicated that 56 respondents had credit demand, while 244 respondents had no credit demand. At the time of the field experiment, only 18%, 17% and 21% of Shandong, Sichuan and Shaanxi farmers, respectively, indicated a demand for credit [3]. There were 119 farmers with credit history, while 181 did not have. Differences in credit demand were observed among three provinces. Table 3 shows that credit demand in Shaanxi is a little bit higher than that in Shandong and Sichuan. However, the proportion of farmers with credit history in three provinces has much larger differences. Shaanxi farmers are four times more likely to have had a credit history than farmers in Shandong and two times more likely than farmers in Sichuan.

As for the familiarity with credit, most farm households understand credit, but knowledge is lower in Shandong and Sichuan than Shaanxi. The most common use of credit was for agricultural production, house construction/renovation and medical expenses. There are also

Attributes	Level						
Interest rate	2%	4%	6%	8%	10%	12%	14%
Term of loan	Less than six months	Six months to one year	One year to three years		Three to five years	More than five years	
Type of loan	Collateral loan		Guaranteed loan		Credit loan		
Type of repayment		Pay off at one			Amortization		
Type of institution	Rural credit cooperatives		The Agricultural Bank of China		The Postal Savings Bank of China		
Mobile banking	Yes				No		

Table 1. Attributes and levels of the discrete choice experiment

	Loan1	Loan2
Interest Rate	8%	10%
Term of Loan	5-30 Year	3-5 Year
Type of Lan	Guaranteed Loan	Credit Loan
Type of Repayment	Pay off at once	Amortization
Type of Institution	RCC	Commercial Bank
Mobile Banking	Yes	NO
Decision		
Level	**1 2 3 4 5**	

Figure 1. Example choice card for the first-wave experiment

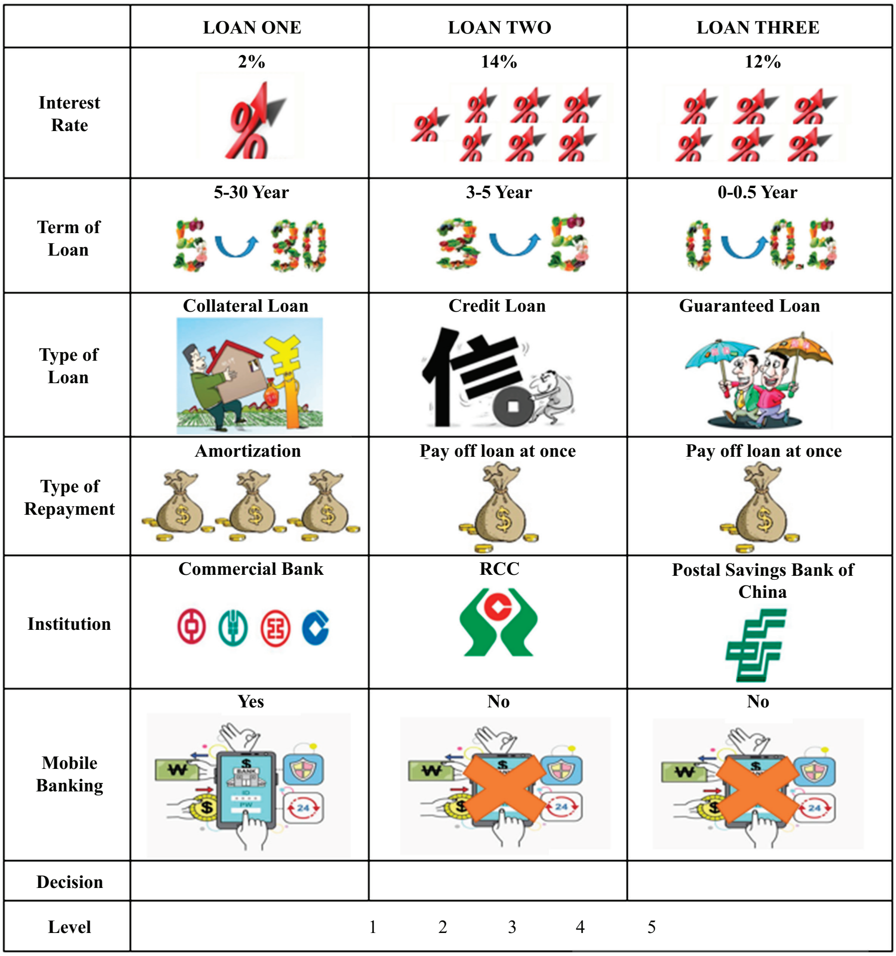

Figure 2.
Example choice card for the second-wave experiment

differences in demand (or use) of informal (mostly between friends and relatives) and formal credit across provinces. For example, 58% of Sichuan farmers have a preference for informal lending, whereas only 33% of Shaanxi farmers prefer borrowing informally.

4. Empirical results

4.1 Heterogeneity in agriculture credit preferences

In our empirical analysis, we used both conditional and mixed logit models. The difference between the two models is that the conditional logit model assumes that farmer respondents are homogenous in their valuation of credit attributes, while the mixed logit model presumes (as a hypothesis) that the preferences for each attribute vary, heterogeneously, across respondents. To capture respondent heterogeneity, the mixed logit model runs a simple logit model on the revealed choices of each respondent and aggregates the individual results to obtain a mean and standard deviation. In many instances, the mean of coefficients from mixed logit are close to conditional logit parameter estimates. In these instances, the

Table 2. Data description of the first experiment

Variable	Mean					Min					Max				
Province	SD	SC	SX	JS	HN	SD	SC	SX	JS	HN	SD	SC	SX	JS	HN
Age	53.5	55.1	60.0	53.7	50.6	22.0	30.0	30.0	30.0	28.0	76.0	83.0	82.0	83.0	72.0
Total number of households	4.0	4.4	4.4	4.6	4.8	1.0	1.0	1.0	1.0	1.0	10.0	14.0	10.0	7.0	8.0
Number of farmers	1.8	1.6	1.7	–	–	0.0	0.0	0.0	–	–	4.0	6.0	4.0	–	–
Number of workers	1.1	1.5	1.6	–	–	0.0	0.0	0.0	–	–	4.0	12.0	8.0	–	–
Years engaged in agriculture	30.3	29.5	37.7	–	–	0.0	0.0	0.0	–	–	60.0	70.0	60.0	–	–
Area of contracting land	8.3	7.6	5.0	9.7	6.7	2.0	0.0	0.4	0.0	0.0	48.0	230.0	12.0	30.0	50.0
Transferred land for agriculture	17.7	29.76	0.1	97.3	0.5	−10.5	−8.0	−8.0	−16.0	−6.0	400.0	490.0	15.0	760.0	10.0
Agricultural income	41.3	141.1	7.0	*302.9*	10.5	0.0	0.0	0.0	0.0	0.0	500.0	4,100.0	302.8	3,68.0	86.0
Nonagricultural income	46.1	65.7	39.4	50.6	34.7	0.0	0.0	0.0	0.0	0.0	153.0	847.0	150.0	175.0	150.0
Total revenue	87.5	206.8	46.3	*353.5*	45.2	2.6	0.0	2.0	170.0	30.0	500.0	3,500.0	303.2	3,763.0	153.0
Production expenditure	36.6	84.0	4.8	*187.1*	4.9	0.0	0.0	0.0	0.0	0.00	1,500.0	1,650.0	272.2	1,200.0	20.0
Consuming expenditure	21.3	25.0	22.6	*42.7*	14.8	1.2	0.0	1.3	3.0	0.2	60.0	300.0	70.0	150.0	60.0
Other expenditure	4.9	9.4	4.4	*13.8*	12.5	0.0	0.0	0.0	0.0	0.00	40.0	100.0	108.8	60.0	400.0
Income surplus	24.6	88.5	14.6	*109.7*	5.9	−1,200.0	−300.0	−33.3	−50.0	−389.0	219.0	18,600.0	108.9	3,393.0	430.0

Note(s): agricultural income, nonagricultural income, total revenue, production expenditure, consuming expenditure, other expenditure and income surplus are in thousands; SD=Shandong; SC=Sichuan; SX= Shaanxi; JS = Jiangsu; HN=Henan

Table 3.
Credit data description

		Shandong (%)	Sichuan (%)	Shaanxi (%)
Credit demand	Have credit demand	18	17	21
	No credit demand	82	83	79
Credit history	Have credit history	17	36	66
	No credit history	83	64	34
Knowledge of credit	Never heard about	6	4	1
	Know a little	54	60	33
	Know a lot	22	15	28
	Be familiar with	18	21	38
Credit purpose (multiple choice)	Agricultural production	27	40	26
	House construction/renovation	16	32	20
	Purchase of car/motorcycle/bicycle	12	6	4
	Household consumption	5	6	7
	Medical expenses	26	27	42
	Education expenses	3	10	6
Preferred credit source	Informal sources	46	58	33
	Formal financial institution	54	42	67
	Other	0	0	0

parameter estimates are seen as robust. As a group, the inferences from the conditional logit model can reliably be used to establish broad economic and credit policies, but if the standard deviations of the aggregated coefficients in the mixed logit model are statistically different from 0, one can expect that client-to-client-revealed preferences and weightings on specific attributes are heterogeneous (Hensher *et al.*, 2005).

Table 4 presents conditional and mixed logit results from first- and second-wave experiments. Generally speaking, the two models are consistent. The mixed logit models have higher mean coefficients than the conditional logit model, which is typically the case. But the differences are not qualitatively different. For example, interest rates in the first wave's mixed and conditional logits are −0.3793 and −0.2925, respectively and for the second wave −0.5267 and −0.4980, respectively. These confirm that the credit demand curve is downward sloping and that increases in interest rates decrease expected utility. However, the results from the mixed logit model indicate that revealed preferences for term of loan, guaranteed loan and amortization vary considerably among farmers, i.e. preferences are heterogeneous. Farmers have a preference for longer loan terms, and the preference for (low collateral/guarantee) credit loan dominates guaranteed or collateral loans. Although the evidence that risk rationing among Chinese farmers is low (Verteramo-Chiu *et al.*, 2014), these results indicate that the demand for collateral or guaranteed loans will be lower than credit loans. This is consistent with the findings of Kong *et al.* (2015). We can infer that the demand for credit loans will be more elastic than the demand for collateral or guarantee loans. Repayment also affects credit demand. The results are, consistent across both waves and estimates indicate a stronger revealed preference for loan amortization over a lump-sum payment, 0.5945/0.3842 for the mixed logit and 0.4534/0.3524 for conditional logit models. Also note that the first-wave coefficients for bank type (RCC and PSBC) are significant but the standard deviations are not, implying that preferences about these attributes are homogenous across respondents. This holds true in the second wave, but the RCC and PSBC coefficients are not statistically significant, suggesting that farmers' willingness to borrow is not necessarily determined by lenders' preferences. Finally, and to some surprise, an offering of mobile services by lenders does not appear to drive credit demand. In fact, second-wave results indicate, quite inexplicably, that mobile phone services can reduce the utility from borrowing.

Tables 5 and 6 provide the mixed and conditional logit results at the provincial level. Recall that the D-optimal block design differed between the first and second waves, with the former including two choices across six cards and the latter three choices across nine cards and with the images being added to the second wave. Under D-optimality, these differences should not

Table 4.
Utility function parameter estimate of first- and second-wave experiments

Variables	Mixed logit				Conditional logit	
	First wave		Second wave		First wave	Second wave
	Mean	SD	Mean	SD		
Interest rate	−0.3739***		−0.5267***		−0.2925***	−0.4980***
Term of loan	0.0936**	0.3877***	0.2598***	0.1672***	0.0599**	0.2458***
Guaranteed loan	0.0762	−0.6348***	0.1616	0.1276	0.0684	0.1856*
Credit loan	0.5900***	0.1531	0.4776***	0.3200***	0.4994***	0.4772***
Amortization	0.5945***	−0.8703***	0.3842***	0.5244***	0.4534***	0.3524***
RCC	0.2952***	−0.3752	−0.0833	−0.1878	0.1984***	−0.0533
PSBC	0.2759**	−0.3205	−0.1025	0.0036	0.2081**	−0.081
Mobile banking	0.0157	0.1505	−0.3548***	−0.0239	0.0286	−0.3326***
Log likelihood	−1,036.9567		−847.00484		−1,060.15	−855.6888
AIC	2,103.913		1,724.01		2,136.303	1,727.378
BIC	2,196.576		1,815.26		2,185.723	1,776.044
Observations	3,600	3,600	3,240	3,240	3,600	3,240

Note(s): ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5.
Mixed logit results of different provinces

Variables	Jiangsu Mean	Jiangsu SD	Henan Mean	Henan SD	Shandong Mean	Shandong SD	Sichuan Mean	Sichuan SD	Shaanxi Mean	Shaanxi SD
Interest rate	−0.7003***		−0.5128***		−0.3459***		−0.5312***		−0.3201***	
Term of loan	0.2335***	0.2631***	0.3524***	0.3620***	0.1589**	0.2555**	0.0177	0.4579***	0.108	0.4700***
Guaranteed loan	0.2861	−0.2614	0.072	0.1966	0.0235	0.4565	0.1865	0.4849	0.0646	0.7603**
Credit loan	0.6452***	0.7613***	0.4064***	0.4620**	0.4827**	0.0493	0.5259**	0.0957	0.9395***	0.6353
Amortization	−0.6864***	1.4518***	0.2566*	0.5943***	0.7732***	0.8189**	0.3386	1.3318***	0.7727***	−0.0416
RCC	−0.0708*	−0.6031***	−0.0033*	−0.1041	0.3412**	0.5566	0.198	0.1321	0.3362*	−0.575
PSBC	−0.0612	−0.2537	−0.1386	−0.0071	0.3168	0.6192	0.4057*	−0.1054	0.2108	−0.2527
Mobile banking	−0.4544***	−0.2705	−0.3411***	−0.1435	−0.0339	−0.2173	0.2243	−0.516	−0.1104	−0.5512
Log likelihood	−383.58448		−430.7824		−338		−329.91702		−347.15222	
AIC	797.169		891.5648		706.0357		689.834		724.3044	
BIC	78.0217		972.4175		781.9042		766.1852		800.6306	
Observations	1,620	1,620	1,620	1,620	1200	1200	1,200	1,200	1,200	1,200

Note(s): ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6. Conditional logit results of different provinces

Variables	Jiangsu	Henan	Shandong	Sichuan	Shaanxi
Interest rate	−0.5473***	−0.4602***	0.1113**	−0.3761***	−0.2336***
Term of loan	0.1779***	0.3103***	−0.2818***	0.0071	0.0629
Guaranteed loan	0.2833**	0.1081	0.0261	0.1248	0.0676
Credit loan	0.5899***	0.3804***	0.4255**	0.3831**	0.7051***
Amortization	−0.4746***	0.2408**	0.6378***	0.1569	0.5791***
RCC	−0.1743	0.0436	0.2465*	0.0884	0.2630**
PSBC	−0.0835	−0.0829	0.2607*	0.2648*	0.1199
Mobile banking	−0.4076***	−0.2798***	0.002	0.191	−0.1003
Log likelihood	−408.981	−440.348	−342.21	−341.955	−358.571
AIC	833.9611	896.6969	700.4197	699.9091	733.1429
BIC	877.0826	939.8184	740.8829	740.6298	733.8502
Observations	1,620	1,620	1,200	1,200	1,200

Note(s): ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 7. Willingness to pay

	Jiangsu	Henan	Shandong	Sichuan	Shaanxi
Term of loan	0.33343	0.68721	0.4593813	0.03332	0.33739
Guaranteed loan	0.40854	0.14041	0.0679387	0.35109	0.20181
Credit loan	0.92132	0.79251	1.39549	0.99002	2.93502
Amortization	−0.9802	0.50039	2.2353281	0.63742	2.41393
RCC	−0.1011	−0.0064	0.9864123	0.37274	1.0503
PSBC	−0.0874	−0.2703	0.9158716	0.76374	0.65854
Mobile banking	−0.6489	−0.6652	−0.098005	0.42225	−0.3449

meaningfully alter the results and these provincial-based results confirm that. The results indicate that there are provincial differences however. The interest rate mean coefficients in Table 5 range from −0.3201 in Shaanxi to −0.7003 in Jiangsu. This is not a surprising result. For example, the typical procedure on guidance and oversight is that the CBRC issues guidance. The guidance is then formulated into provincial policies (for example, the provincial RCCU or RCC union), which is then filtered to county RCCU for implementation. Consequently, there may be differences in how each province interprets and applies the guidance. But there are also related issues in terms of crops grown, local conditions and other fixed and random effects that are provincially distinctive. The results are generally consistent with the aggregated results in Table 4. Jiangsu is an exception in terms of amortization (−0.6864), indicating a reference for lump-sum (presumably post-harvest) payments, and Shandong and Shaanxi farmers have closer ties with the RCC (0.3412 and 03362). Indifference toward mobile banking services is found for Shandong, Sichuan and Shaanxi. These mixed logit results are consistent (robust) with the conditional logit results reported in Table 6.

4.2 Willingness to pay

WTP is applied to measure the change in interest rate associated with a unit change in the attribute (Louviere and Hensher, 1982). The calculation is as follows:

$$\mathrm{WTP}_i = -\frac{\beta_i}{\beta_{\text{interest rate}}} \tag{6}$$

where β_i is the estimate for attribute i and $\beta_{\text{interest rate}}$ is the estimate for interest rate in the mixed logit model. In the mixed logit model, we keep the coefficient for interest rate fixed. We use the estimated mean coefficients to determine the amount that a farmer with average coefficients for interest rate is willing to pay for other parameters. The WTP measures reported in Table 7 can be interpreted as interest rate differentials. For example, on average, Henan farmers are "willing to pay" an addition 0.68% in interest to have a long-term loan, while Sichuan farmers are "willing to pay" only 0.033% in additional interest. The results indicate that the most valuable attribute is credit loan. A credit loan requires the least amount of collateral and is generally riskier to the lender. These results indicate that lenders could charge an additional 0.79% interest for Henan farmers and additional 1.395% and 2.935% to Shandong and Shaanxi farmers, respectively. Jiangsu and Henan farmers are "willing to pay" less for credit from RCCs and PSBC than the ABC, but this is not the case in Shandong, Sichuan and Shaanxi. However, the statistical significance of these choices (Table 5) was low. A possible reason for the negative results is that the RCC and the PSBC are viewed by many farmers as traditional, government-sponsored, lending institutions, so what may be observed is not necessarily a demand for lower interest to bank at RCC or PSBC, but an expectation that the interest rates ought to be lower at those institutions.

5. Conclusion

The overall objective of this paper was to examine attribute preferences for agricultural credit in China. To accomplish this, we ran two waves of in-the-field DCEs across five provinces (Jiangsu, Henan, Shandong, Sichuan and Shaanxi) involving a total of 420 farmers. The DCE included six attributes including the interest rate, term of loan, type of loan, loan repayment, lender type and mobile banking.

Conditional and mixed logit results indicate a downward sloping credit demand curve with variable elasticity across regions. Provincial WTP indicators suggest that farmers are willing to pay a premium for long-term (0.03–0.687%) and low collateral credit loans (0.79–2.93%). Also, four of five provinces indicate a preference for loan amortization rather than lump-sum payment. Interestingly, in comparison to the ABC, only farmers in Shandong, Sichuan and Shaanxi indicate a preference for RCCs/banks and the PSBC. Another quite surprising result is with related bank services. While mobile bank services are often viewed as increasing financial inclusion and increasing access (and hence usage) of credit, we find that access to mobile banking does not appear to induce an incremental "willingness to pay" for agricultural credit. Some of our villages were quite remote and quite poor, so it is possible that farmers did not have the required smart phone technology or cellular access. It would be interesting in future research to run choice experiments to determine whether specific attributes of other "services" that financial services deploy to attract new clients are actually valued by farmers.

An important observation is that it is incorrect to presume that all farmers thing alike. Turvey *et al.* (2012) came to a similar conclusion in their study of credit demand in China, but the results of the present study are more robust since heterogeneity spans multiple attributes and not just interest rates. While conditional and mixed logit regression coefficients are similar (and therefore robust), we find that there is substantial heterogeneity across attribute preferences on term of loan, type of loan and amortization. Preferences for type of lender and mobile banking are generally homogenous. This result alone indicates that lenders should consider offering a suite of credit products with different attributes in order to maximize the potential pool of borrowers. For example, in terms of repayment, our results can be interpreted as valuing flexibility with a series of smaller loan repayments rather than a single lump-sum transfer (Jia *et al.*, 2010). While there are some differences across provinces, farmers appear to be indifferent to lenders, and it does not appear that officering banking services such as mobile banking has any bearing on credit decisions.

Although we used conventional mixed and conditional logit regressions to analyze the DCE, we do make a methodological contribution in changing the D-optimal design of the DCE between the first and second waves. More specifically, in the first wave, we issued farmers six tabular choice cards with two choices each, while in the second wave we used nine pictorial cards with three choices each. By definition of D-optimal design, there is no reason to anticipate that the results would differ across the two waves and there is no indication that they did. For researchers attempting to determine the block structure in DCE models, the final decision should be based on more practical matters so long as econometric rank conditions are satisfied.

Finally, with China's emergent commercial agriculture under the new land transfer and mortgaging rules, there will be an immense need to determine shifts in the demand for credit and product attributes, as well as the balancing of business and financial risks. The current study examines credit relationships without considering the underlying risks that farmers face. A study by Turvey and Kong (2009), for example, found evidence that Chinese farmers balance business and financial risks in their credit decisions. A promising avenue of research would be to investigate the risk-balancing hypothesis directly using DCE techniques. This paper has made a start on identifying these factors and proving that classical DCE approaches that can be applied to problems of rural credit.

Notes

1. We did find two related Chinese articles (see Dong *et al.*, 2018; Yang *et al.*, 2020) using the DCE to do some research related to finance products. Dong *et al.* (2018) studied risk preference based on the different sorts of seed selection and estimated the intervention effect of interlinked credit and insurance on farmers' credit risk rationings. Yang *et al.* (2020) estimated the impact of marketing strategies on farmers' preferences and willingness to pay for catastrophe insurance. Both of these employed the DCE. But did not focus specifically on rural credit product preferences and WTP.

2. The correlations among variables in the first wave were weak. Nonetheless, these were used to design the blocks and choice cards in the second wave. Because the D-optimal block designs might not be identical, aggregating the two might introduce bias. Therefore, we elected to analyze both waves separately. The weak correlations also indicated that the strength of the model was in the main effects. For this reason, we do not include interactive terms in the conditional and mixed logit regressions. This is a common approach in DCE models (see for example Waldman *et al.* (2017); Yu *et al.* (2018); or Schaafsma *et al.* (2019). For example of the model that includes interactive terms in related disciplines see Ortega *et al.* (2011); Quan *et al.* (2017); Logar and Brouwer, 2018.

3. The data in Table 3 were collected only for Shandong, Sichuan and Shaanxi and are representative only of this sample and the villages from which the data were drawn. As is typical of in-the-field experiments in China, the research team relies on local leadership to identify villages and gain access (and trust) to farmer respondents. Because of the length and time required of the survey in the first wave, we did not collect these data for the second wave.

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Corresponding author
Yanling Peng can be contacted at: jxyanling@163.com