Dynamic Incentives in Microfinance – What about the Farmers?

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Abstract

Dynamic incentives have become a common measure in microfinance institutions (MFI) to counteract the risk of default and to strengthen the borrower's identification with his microlender. This study focuses on relaxation in loan volume rationing in the course of the bank-borrower relationship. More particularly, we consider the differentiation in lending politics faced by farmers and non-farmers and match our findings with the repayment performances of both client groups. By means of a rich data set for the years 2007 until 2013 provided by a MFI in Azerbaijan, we demonstrate that farmers face a higher degree of loan volume rationing but outperform the non-farmers with respect to loan repayments. Moreover, our results reveal that relaxation in loan volume rationing works as a tool for risk management in MFIs. In conclusion, we deduce that MFIs have still not recognized the full business potential of their farming clients.

JEL classification: G21, O16, Q14
Keywords: Microfinance; Risk management; Dynamic incentives; Lending relationships; Azerbaijan

1. Introduction

On November 7th 2014, the European Investment Bank (EIB) agreed to launch a € 25 million loan for small and medium sized enterprises (SME) in Azerbaijan. For the first time, the EIB directly engaged in that country acknowledging the SMEs as both the backbone of the Azerbaijani economy and a key factor for economic development, especially in terms of job creation and improvement of living standards. The financial support is channeled through AccessBank Azerbaijan, the major provider of finance to SMEs (EIB, 2014). Considering this large-scale loan and the corresponding high demand for financial support in the private sector, it is all the more of mutual interest to use the aid in the most efficient way. However, in less developed economies like Azerbaijan, microfinance institutions (MFI) face two main daily challenges: first, the acquisition of clients and the establishment of stable bank-borrower relationships to assure the viability of the bank; and secondly, the assurance of loan repayment.

With respect to the first challenge, the rural areas dominated by agricultural production bear a particularly rich acquisitory potential for the MFIs. Unfortunately, as a number of studies reveals, MFIs are more hesitant to provide financial assistance to farmers than to non-farmers (Zeller et al., 1998; Petrick, 2004; Weber and Musshoff, 2012;) although empirical findings confirm that farmers do not necessarily default more often (Vogel, 1981; Raghunathan et al., 2011; Weber and Musshoff, 2012). Accordingly, they deserve the opportunity to become business partner for banks.

Regarding the second challenge – namely the repayment of loans – MFIs apply several risk management instruments. Apart from demanding collateral, MFIs focus on the establishment of stable lending relationships with their clients, particularly in environments with high degree of information asymmetries and lack of legal enforcement (Egli et al., 2006; Menkhoff et al., 2012). One aspect of relationship lending in microfinance is so-called progressive lending. This measure overcomes information asymmetries in rationing the loan volume for first-time borrowers and rewards accurate repayment behavior by increasing the available loan amount for the following loan(s) (e.g. Armendáriz and Morduch, 2010; Behr et al., 2011).

However, Vogelsang (2003), Behr et al. (2011), and Kirschenmann (2014) among others, show that the probability of a repeat client to default does not necessarily decrease. On the basis of progressive lending, Behr et al. (2011) reveal that borrowers who received more than two loans have almost the same default rate as first time borrowers.

To date, there is no study that simultaneously investigates the dynamics in credit volume rationing and repayment performance, and that also distinguishes between farmers and other bank-clients. Previously, Behr et al. (2011), Berg and Kirschenmann (2012), Berg and

Schrader (2012) and Kirschenmann (2014) observed the dynamics in a repeated bank-borrower relationship and the attached benefits for the borrowing side. Berg and Kirschenmann (2012) as well as Berg and Schrader (2012) proved the beneficial effects of repeat clients in the context of economical or environmental crises. Yet, the studies do not focus on the application of dynamic incentives such as progressive lending with respect to agricultural and non-agricultural clients. As farmers generally encounter fewer opportunities for financial assistance in rural areas and commonly face higher obstacles, they might be more interested in establishing a reliable credit history and therefore default later or less than non-farmers (Vogel, 1981).

The aim of this study is twofold. First, we explore the application of progressive lending and if it differs for farmers and non-farmers. To achieve so, we analyze the relaxation of loan volume rationing in the course of the bank-borrower relationships for both client groups. Secondly, we verify if a differentiation of those two borrower types can be justified by their repayment behavior with respect to the loan number. Using a rich data set provided by a commercial microlender in Azerbaijan, we consider the application of progressive lending by means of a Generalized Linear Model. To observe the relationship between the repayment behavior and the loan number for the two client types, we apply a sequential logit model. To our knowledge, this is the first study that simultaneously examines the dynamics in loan volume rationing and loan repayment for different client groups. Furthermore, this study contributes to research on lending relationships in microfinance with special respect to agricultural borrowers in a transition country.

The remainder of this paper is structured as follows. In the second section we give an overview of literature on relationship lending in microfinance and furthermore draw attention on lending to farmers. Subsequently, we derive our hypotheses. In section 3, the data is described, and the applied empirical methods are introduced in section 4. The descriptive statistics and results of the study are presented and discussed in section 5. Lastly, we come to a conclusion in section 6.

2. Literature Overview and Hypotheses

In MFI environments, where insufficient administrative systems (e.g. identification-system) and inappropriate collateral are prevalent, the reliability of borrowers and the prosecution of defaulting clients are hampered (Armendáriz and Morduch, 2010; Giné et al., 2012). That is why MFIs apply lending strategies that should theoretically lower the risk of loan defaults. In particular for individual borrowing, most MFIs demand collateral, albeit the collaterals are generally more of a commitment of the borrower than a security, and in some cases they are merely of an idealistic value (Cassano et al., 2013). Nevertheless, according to other studies collateral is still of importance, particularly in transition countries (Hainz, 2003) and loan terms correlate with the availability of collateral (Ortiz-Molina and Penas, 2008; Steijvers and Voordeckers, 2009).

However, for a MFI in Thailand, Menkhoff et al. (2012) find that most loans lack collateral and that the bank relies on third-party guarantees and relationship lending instead. In this context, Egli et al. (2006) also state that relationship lending plays a crucial role in economies whose financial system lacks transparency and legal enforcement and where the likelihood of strategic defaults is accordingly high. Earlier studies already demonstrated the correlation of repeated bank-borrower relationships with loan availability (Petersen and Rajan, 1994) and loan contract terms (Berger and Udell, 1995) in microfinance. These findings have been more recently confirmed by Cull et al. (2014) who showed that relationships and the respective soft information gains about clients are important for loan access of small borrowers.

In the context of lending relationships, Armendáriz and Morduch (2010) emphasize reputation-based measures, known as dynamic incentives, which appeal to the intrinsic motivation of the borrowers. Progressive lending belongs to such dynamic incentives. This lending method is characterized by a decrease in loan volume rationing in the course of the bank-borrower relationship. It is believed to enhance the loyalty of the client by promising an increase in loan size in case of satisfactory repayment performance. In other words, progressive lending enables a lender to test the repayment behavior of a borrower (Ghosh and Ray, 1999; Von Pischke, 2002; Godquin, 2004). New clients are treated more rigorously but face a relaxation in credit volume restrictions when recognized as reliable (Armendáriz and Morduch, 2010; Behr et al., 2011). Simultaneously, the lender can maintain the appearance of strength that is essential. Bond and Rai (2009) demonstrated the importance of perceived stability from clients' perspective with a case study of a microlender in Ecuador. If borrowers begin to detect hints of possible bankruptcy for a bank, they are more likely to default and the speculation can turn into a self-fulfilling prophecy.

Generally, studies on credit histories in microfinance in countries of Eastern Europe and the former Soviet Union are limited (Brown et al., 2009; Van Gool et al., 2012). Studies on individual based lending are especially rare, although it is increasingly implemented in MFIs (Hermes and Lensink, 2007). Particularly in transition countries, adverse selection and moral hazard are explicit challenges and borrower-lender relationships consequently suffer from such informational obstacles (Brown et al., 2009). Furthermore, most papers that already focused on repayment performances refer to group-lending in the context of field experiments and emphasize the importance of group compositions (e.g. Cassar et al., 2007; Al-Azzam et al., 2012).

For the MFIs, progressive lending is specifically interesting for farming clients. Lending to farmers causes relatively high transaction costs, due to difficulties in monitoring and evaluating farming businesses in less developed countries, where land tenure is often unsettled (Petrick, 2005). Through progressive lending, MFIs can gain experience with their farming clients and use the full client potential at a relatively lower risk level. Agriculture is still one of the most important sectors in less developed economies, especially in the rural areas, and is therefore eligible.

Our study, based on data from Azerbaijan, contributes to fill the gap of research on progressive lending in transition countries, with a special focus on farming clients. In general MFIs perceive agricultural clients as more risky than other clients. The higher risk perception is caused by numerous reasons, such as cyclical or irregular cash flows accompanied by relatively high capital intensity, weather and price risk, as well as the threat of diseases (Binswanger and Rosenzweig, 1986; Pederson and Zech, 2009; Heimfarth and Musshoff, 2011; Jainzik and Pospielovsky, 2014). These various external factors affect agricultural production, cause volatility in income, and consequently impede the ability to repay the loans in due time (Barry, 2001). Yet, the application of progressive lending has not been considered with special respect to farming clients. In the context of progressive lending, we investigate if farmers face an equal loan volume constraint as non-farmers. Our first hypothesis is the following:

Hypothesis 1: Farmers face a higher degree of loan volume rationing than non-farmers.

As mentioned earlier, Behr et al. (2011) already explored the issue of progressive lending. They investigate the effect of the loan number on credit approval and a decrease in loan volume rationing for the case of a microlender in Mozambique. It can be shown that the effect of decrease in the rationing is strongest between the first and the second approval. Generally, the bank rations the credit volume more strictly for their first-time borrowers, but as soon as the first loan is repaid, screening efforts are reduced and the clients face a lump-sum-decrease in loan volume rationing. Yet, the loan number and the corresponding probability for default is not part of their investigation. Vogelsang (2003) finds that repeated borrowing even enhances the probability of late payment. In contrast, Weber and Musshoff (2012) conclude that being a repeat client does not influence the default probability. With respect to loan volume rationing, Kirschenmann (2014) observes that volume-rationed clients are more likely to have arrears in their repayment schedules for their first and second loans than non-rationed clients. According to Armendáriz and Morduch (2010), the motivation to create a reliable credit history diminishes with every additional loan.

Vogel (1981), Raghunathan et al. (2011) as well as Weber and Musshoff (2012) concentrate on the differences in repayment behavior between agricultural clients and other clients, but do not investigate the dynamics in the repayment history. Raghunathan et al. (2011) and Weber and Musshoff (2012) show a better repayment performance from farmers. Likewise, Vogel (1981) detects lower delinquency rates for farmers compared to non-farmers among microborrowers in Costa Rica. When looking at dependence on continuous credit access, Vogel (1981) also concludes that farmers are eager to pay on time due to the limited availability of loans in rural areas. Based on these findings we formulate our second hypothesis:

Hypothesis 2: In the course of the bank-borrower relationship, the probability that non-farmers default is higher than for farmers.

3. Dataset

To analyze the dynamics in loan volume rationing and repayment behavior, we utilize a rich dataset provided by the AccessBank Azerbaijan, which was founded in 2002. This bank is the leading MFI in the country and a stable partner for the European Fund for Southeast Europe (EFSE). As afore mentioned this institution was chosen by the EIB as the intermediate for the € 25 million loan. The AccessBank provides a broad portfolio of products, such as offering loans, saving accounts, credit cards as well as money and payment services. The main clientele consists of micro and small enterprises. Nevertheless, the AccessBank holds a full banking license and can therefore serve larger businesses. Although agriculture accounts for 30 percent of GDP and contributes to the income of about 45 per cent of all households in the country, the AccessBank Azerbaijan neglected financing agricultural borrowers during their first business years but later on recognized the market potential for loans dedicated to the agricultural sector (Jainzik and Pospielovsky, 2014). To meet the special needs of agricultural borrowers, they launched an Agro Loan in 2007, which targets households that are engaged in any type of agricultural production. In fact, the conditions of the Agro Loan are based on the standard micro-loans. However, there are some key differences. First, loan officers are specially trained to assess the risk connected to the loan purpose. Second, the challenge of cyclical cash flow in agricultural production is met by the availability of grace periods in installment payment. Third and lastly, due to the longer production cycle, the maximum maturities are extended. Nevertheless, the pricing for Agro Loans is exactly the same as for standard micro-loans to avoid manipulations of loan applications (Jainzik and Pospielovsky, 2014).

The original dataset contains information generated by the AccessBank's Management Information System on 595,066 business loans between the years 2002 and 2013. It is cleaned of outliers and obvious data entering errors. Additionally, to ensure the comparability of lending politics and repayment behavior for farmers and non-farmers, we exclude all clients that received a loan before the year 2007 since loans for agricultural purposes were not disbursed before. Finally, we utilize 479,326 observations on business loans disbursed between 2007 and 2013 for agricultural and non-agricultural purposes. To differentiate between farmers and non-farmers, the group of farmers only consists of agricultural primary production and excludes any upstream and downstream business.

Since this bank is exclusively doing business with individual borrowers, the pledge of collateral is compulsory in the majority of cases. Real estate, vehicles, home equipment, stock and guarantors are accepted as collateral. Apart from information on credit features (e.g.

credit volume, interest rate, value of collateral), socioeconomic characteristics of the credit borrowers (e.g. age, gender, number of family members) are also available. Moreover, the data contain statistics on the repayment behavior of each borrower.

4. Estimation Methods

We first analyze the extent of loan volume rationing for different client groups – farmers and non-agricultural clients – in the course of the bank-borrower relationships. For this purpose we apply a Generalized Linear Model (GLM) as presented in subsection 4.1. In order to analyze the determinants of repayment behavior, we choose the sequential logit model as presented in subsection 4.2.

4.1. Generalized Linear Model

The dependent variable accounting for loan volume rationing is the ratio of pledged collateral and approved credit volume per loan. This indicator for the degree of loan volume rationing is in line with Behr et al. (2011). In contrast, Kirschenmann (2014) employs a ratio of requested and granted loan amounts. Our ratio bears the advantage that we can neglect learning effects of the borrowers who probably adjust their requests downwards for additional loans. This would affect the demonstration of progressive lending. Furthermore, due to lending politics in the AccessBank, consisting of long-term agreements (five to ten years) on the volume of collateral at the beginning of the relationship and relatively short loan maturities, the registered volumes of collateral of the borrowers remain as a constant denominator. Accordingly, the ratio of disbursed amount and collateral can display the development of loan volume in the course of repeated borrowing.

Since the loan volume ratio is strictly positive, we choose to model the response using GLMs as introduced by Nelder and Wedderburn (1972). This model relaxes the assumption of normality of the dependent variable. As a consequence, it allows for a more realistic treatment of real world data problems, since the assumption of normality is seldom met in practical applications (Rigby and Stasinopoulos, 2005). In its most general form, GLMs can be characterized by three components. The first one is a random component that specifies the distributional assumption, where the distribution of the error terms and hence the response Y_i is assumed to be a member of the exponential family. The second one is a systematic component η_i, also known as the linear predictor, where a linear functional form for the covariate effects $\boldsymbol{x_i} = (x_{i1}, \dots, x_{ik})$ is assumed. For this component a subset of covariates has to be selected. The last and third component is a response function $h(\cdot)$ that links the conditional mean of Y_i with the linear predictor η_i. This response function has to be chosen for describing the relationship between the linear predictor and the expected value of the response. Consequently, in the GLM framework, the conditional mean of the response is modelled via

$$E(Y_i|\boldsymbol{x_i}) = h(\eta_i), \text{ with } \eta_i = \boldsymbol{x_i}'\boldsymbol{\beta}. \quad (1)$$

In order to account for the strict non-negativity of the loan volume ratio, we choose a gamma-distributed response where the response function $h(\eta) = \exp(\eta)$ ensures that $\mu_i > 0$ (Fahrmeir et al., 2013). In the analyses, $\boldsymbol{x_i}$ represents a vector incorporating a farmer-dummy F_i that captures the general discrepancy between farmers and non-farming clients. Moreover, we include loan dummies L_i which control for the effect of loan number on loan volume rationing. As the reference dummy, we chose the first loans. Furthermore, several socioeconomic variables S_i as well as loan characteristics C_i for borrower i are introduced as control variables. Finally, year-quarter dummies Q_i account for seasonal effects and interaction dummies FQ_i display the particular effect of seasonality on agriculture-based borrowing. Accordingly, the linear predictor is structured as follows:

$$\eta_i = \beta_0 + \beta_1 F_i + \beta_2 L_i + \beta_3 S_i + \beta_4 C_i + \beta_5 Q_i + \beta_6 FQ_i. \quad (2)$$

The reference categories for the year-quarter dummies in our estimation are the third year-quarters. According to the FAO (2015), the third year-quarter is the harvest-quarter for the main crops (grain and potatoes) in Azerbaijan. Among others, Behrman et al. (1997) and Khandker (2012) find for the cases of Pakistan and Bangladesh respectively that seasonality in crop supply and commodity prices affects household incomes and consumption. With reference to figure A1 in the appendix, we show with the example of wheat prices between the years 2007 and 2013 that price peaks are always reached in the first half of the year and that the bottom prices for wheat are obtained in the third year-quarter (July until September). Likewise, statistics reveal that the average household in Azerbaijan spends almost 43 per cent of income on food consumption in the year 2012, which is a substantial allocation (DESTATIS, 2015). Thus, we assume food prices volatility affects the repayment ability of both farmers and non-farmers. Simultaneously, the price volatility may also be respected by the bank in the loan volume rationing. By introducing the quarter dummies, we account for the dynamics in agricultural production.

4.2. Sequential Logit Model

To investigate the influence of the loan number and client type on the repayment behavior, we introduce three default categories. According to Schreiner (2004), loans with arrears of more than 15 days are particularly costly. Consequently, we differentiate between the degrees of defaults and separate the defaults as follows. Loans for which all installment payments are on time are assigned to the category 1 (Cat.1). To category 2 (Cat.2) and category 3 (Cat.3) we assign those loans with at least one default in an installment payment of at least one day, and of at least 15 days, respectively.

The applied sequential logit model is part of the categorical regression models and is a specification of the GLM with categorical response variables $Y_i \in \{1, \dots, c+1\}$ (Fahrmeir et al., 2013; Tutz, 2005). It is designed as a step-by-step-process via a sequence of binary transitions and it analyses the probabilities for reaching the different default categories Cat.1, Cat.2 and Cat.3. More precisely, the first category Cat.1 is the initial category. The sequential nature of the response is reflected by the fact that Cat.3 can only be attained provided that the second category Cat.2 with at least one late installment payment is reached before.

In our application of the sequential logit model, the following two transitions of defaults in payment are considered: first, the probability for the transition from the Cat.1 of credits, for which all installment payments were paid in time ($Y_i = 1$), to the category of credits with at least one default in an installment payment ($Y_i = 2$); and secondly, the probability for the transition from the category of credits with at least one default of at least one day ($Y_i = 2$) to the category of credits with at least one default in an installment payment of at least 15 days ($Y_i = 3$).

The following notation is based on Fahrmeir et al. (2013). The process starts in ($Y_i = 1$), for the case of punctual payment. The probability that the client defaults and achieves Cat.2, hence the probability for ($Y_i > 1$), is modeled by the following binary model:

$$\mathrm{P}(Y_i = 1) = F(\theta_1 + \boldsymbol{x}_i'\boldsymbol{\beta}) \tag{3}$$

with the logistic distribution function F, the category-specific effect θ_1 and the linear predictor $\boldsymbol{x}_i'\boldsymbol{\beta}$. The transition process stops if the installment payment is on time. For the case of at least one default in an installment payment, the transition from category 1 (Cat.1) to category 2 (Cat.2) is modeled dichotomously in equation (4) as the conditional probability for remaining in ($Y_i = 2$) and complementary probability $1 - \mathrm{P}(Y_i = 2 | Y_i \geq 2)$ for the transition to ($Y_i > 2$):

$$\mathrm{P}(Y_i = 2 | Y_i \geq 2) = F(\theta_2 + \boldsymbol{x}_i'\boldsymbol{\beta}). \tag{4}$$

More generally, the r^{th} transition can be illustrated as follows:

$$\mathrm{P}(Y_i = r | Y_i \geq r) = F(\theta_r + \boldsymbol{x}_i'\boldsymbol{\beta}), \text{ with } r = 1, \ldots, c. \tag{5}$$

As soon as one of the binary transitions is not effected, the process stops and remains in the category r.

It is also possible to reformulate equation (5) in terms of marginal probabilities:

$$\mathrm{P}(Y_i = r) = F(\theta_r + \boldsymbol{x}_i'\boldsymbol{\beta}) \prod_{s=2}^{r-1}(1 - F(\theta_s + \boldsymbol{x}_i'\boldsymbol{\beta})), \text{ with } r = 1, \dots, c. \tag{6}$$

Based on the conditional transition probabilities the sequential logit model can alternatively be expressed as

$$\log \frac{\mathrm{P}(Y_i = r | Y_i \geq r)}{1 - \mathrm{P}(Y_i = r | Y_i \geq r)} = \theta_r + \boldsymbol{x}_i'\boldsymbol{\beta}. \tag{7}$$

By means of the logistic distribution function, it is possible to interpret the fitted values of the linear predictor as probabilities within 0 and 1. The vector $\boldsymbol{x}_i$ contains the same variables as already introduced in equation (2) in subsection 4.1:

$$\boldsymbol{x}_i'\boldsymbol{\beta} = \beta_0 + \beta_1 F_i + \beta_2 L_i + \beta_3 S_i + \beta_4 C_i + \beta_5 Q_i + \beta_i F Q_i. \tag{8}$$

Again, the reference categories for the year-quarter dummies are the third year-quarters.

5. Results

In the following, we provide descriptive statistics in subsection 5.1. Subsequently, the results on loan volume rationing and repayment behavior are presented and discussed in subsection 5.2 and 5.3, respectively.

5.1. Descriptive Statistics

In table 1, we present descriptive statistics for loan-specific characteristics as well as socio-economic variables. We first consider loan-specific characteristics, which reveal that non-farmers can offer more collateral on average (7,321 USD) when compared to farmers (5,713 USD). Similarly, the disbursed amount for non-farmers (3,123 USD) exceeds the farmer's loan amounts (2,459 USD), and non-farmers also have marginally more deposits at the bank (275 USD) compared to farmers (263 USD). In microfinance, the number of installments is an indicator of the loan maturity. The statistics show that the maturity of farmers' loans is slightly higher, with on average 14.00 installments compared to 13.66 installments for non-farmers. The mean interest rate for agricultural loans, around 2.82 per cent, is higher than for other loans, which is about 2.73 per cent on average.

[Insert Table 1 here]

Regarding the socioeconomic variables, we can state that farmers – with a mean age of around 47 years – are on average 3 years older than non-farmers. The farming families consist of five members, in contrast to four family members for non-farmers, and the agricultural borrower is more often male (87 per cent male borrowers) than the non-agricultural borrower (73 per cent). Likewise, the married-dummy reveals a higher percentage for farming borrowers, with 84 per cent compared to 74 per cent for non-farmers. Overall, the majority of both borrowing farmers and non-farmers is male and married.

[Insert Figure 1 here]

As mentioned in section 4, our central variable for analyzing the loan volume rationing for farmers and non-farmers is the ratio of pledged collateral and approved credit volume per loan. In Figure 1, the development of the mean of loan volume ratio by loan number for farmers and non-farmers is illustrated. In some cases, our observations on approved loans sum up to nineteen loans. However, after the fifth loan, we combine the additional loans in one variable (>=6) since we have comparably few observations for the following loans. The progressive lending in terms of a decreasing loan volume ratio is consequently applied for both client groups. It can be shown that up to the fourth loan, farmers face a higher degree of loan volume rationing compared to non-farmers, especially for initial loans. Thus, the farmers pledge relatively more collateral than non-farmers to obtain the same loan amount. The shape of the graph shows that the farmers and non-farmers experience a continuous relaxation in loan volume rationing. Generally, the range of reduction in loan volume rationing is higher for farmers. We observe a decline in the average ratio from more than 2.5 to approximately 1.8 for farmers, compared to a decrease from 2.2 to roughly 1.9 for non-farmers. For the fifth loan as well as loan number 6 and so forth, the farmer's ratio falls below the ratio of non-farmers with a difference of approximately 0.5 for the fifth loan, and 1.0 for loan number 6 and so forth. This finding indicates that farmers face a relatively higher decrease in loan volume rationing in the course of their relationship with the bank in comparison to non-farmers. In other words, the reduction of information asymmetries in agriculture-based lending has a higher influence on additional loans when compared to non-agricultural loans, and the farmers seemingly face an initial barrier at the beginning of their bank-relationship. In table 2 we compare the means of loan volume ratios by loan number and client group within a t-test. Up to the third loan, we can observe that the loan volume ratio for farmers is higher. From the first to the third loan, the difference in average ratio is statistically significant at the 0.1 %-level. Loan number 4 reveals an almost nonexistent difference between the loan volume ratios of the client groups. For the fifth loan and for loan number 6 and so forth, the ratio for non-farmers is higher but the difference in mean is not statistically significant.

[Insert Table 2 here]

The dependent variables of the GLM and sequential logit model as well as the number of observations are summarized in table 3. We have 128,604 observations of agricultural loans and 350,722 observations of loans to other clients. Again, we first consider the loan volume ratio, which later becomes the dependent variable, to obtain the extent of loan volume rationing for both client groups with respect to the loan number. The mean of loan volume ratio is significantly lower for non-farmers (2.144) compared to farmers with an average ratio of 2.425.

[Insert Table 3 here]

For the sequential logit model, the different levels of default in installment payments (Cat.1, Cat.2, Cat.3) for the considered client groups serve as dependent variables. About 82 per cent (non-farmers) and 89 per cent (farmers) of the installments were repaid in time and are therefore assigned to Cat.1. The difference in mean is statistically significant, indicating that non-farmers tend to default more often. For 10.80 per cent of agricultural loans, the installment payment is at least one day late, and 0.81 per cent of agricultural loans show defaults of at least 15 days for at least one installment payment. In contrast, our results on non-farmers show that 17.70 per cent of the loans feature at least one default in installment payment, and 1.40 per cent achieve Cat.3. Again, the differences in the mean for the latter categories are statistically significant.

5.2. Loan Volume Rationing

In our first model, we examine the application of loan volume rationing in the course of the bank-borrower relationship by means of the GLM. Table 4 displays the results of the estimation with the loan volume ratio as the dependent variable. The positive coefficient of the farmer-dummy, which captures the discrepancy between farmers and other clients, reveals that the degree of loan volume rationing is generally significantly higher for farmers than for non-farmers.

In summary, our results confirm our first hypothesis, i.e. farmers and non-farmers experience a different loan volume rationing from their bank. Although we can show that the volume restriction relaxes in the course of the relationship, the positive coefficient of the farmer-dummy reveals that farmers generally face a higher level of loan volume rationing. The result of discrimination between farmers and non-farmers is in line with several studies (Zeller et al., 1998; Petrick, 2004; Simtowe et al., 2008; Weber and Musshoff, 2012).

The loan dummies show that the estimated coefficients are statistically significant and increasingly negative with respect to the base dummy, which represents the initial loans. Hence, the loan volume ratio decreases for each additional loan. This finding shows that the bank reacts to the reduction in information asymmetries in increasing the loan volume of additional loans.

[Insert Table 4 here]

Considering certain loan-specific characteristics, we find that the rationing increases with the deposits. Thus, we cannot confirm that the bank rewards deposit building, although savings and deposits are considered to enhance the flexibility of borrowers to react to sudden cash demands (World Bank, 2005).

With respect to the year-quarter dummies, it can be shown that seasonality affects lending politics in general. For all disbursed loans, we observe that at the beginning of the year (Quarter 1) which is also marked by relatively higher commodity prices (see figure A1 in appendix), loans are particularly higher rationed compared to loans in the third year-quarter (July until September). The bank is probably afraid of repayment shortfalls in high-price phases, due to the high percentage of household income that is spent on food in Azerbaijan. Seasonal effects also have a particular influence on farmers' loans. The interaction dummy for the second year-quarter (Farmer*Quarter 2) reveals that farming clients face an even stricter rationing in this time. According to the FAO crop calendar for Azerbaijan (FAO, 2015), the second year-quarter (April until June) is marked by sowing and growing major crops, combined with higher demand for production facilities and decreasing fodder stocks and crop sales. This is also reflected in the relatively higher loan demand in the second year-quarter (see figure A2 in appendix). Visibly, the AccessBank reacts to shortages that might affect repayment abilities by increasing the degree of rationing.

In terms of socioeconomic characteristics, we pay further attention to the positive coefficient of the dummy for male borrowers, which indicates a higher rationing for men. This finding contradicts Bellucci et al. (2010) as well as Agier and Szafarz (2013), who state that women are discriminated against with respect to availability and conditions of loans.

5.3. Repayment Behavior

Table 5 displays the probabilities of defaults for at least one installment payment of at least one day (Cat.2) and at least 15 days (Cat.3). We first consider the loan dummies and their influence on the probability of late payment in the context of Cat.2. As in the GLM, the first loan works as the reference-dummy. Since the coefficients are increasingly negative, it can be concluded that the probability of late payments decreases with each additional loan. A study by Vogelsang (2003) shows the same effect for late payments of at least ten days in a case study in Bolivia. Thus, these results support the reliability of progressive lending as a measure of risk mitigation. However, the default-reducing effect of loan number does not hold for defaults in the context of Cat.3. Regarding the statistical significance of the third and fifth loan, it can be demonstrated that the probability to pay late increases with the loan number, particularly from the second to the third loan. Based on these results one may conclude that borrowers practice a kind of strategic defaulting. It is more likely that a borrower who decides to pay very late or not to repay the loan at all does so for later loans, rather than for loans at the beginning of the bank-relationship.

The negative coefficient of the farmer-dummy for late payments in Cat.2 reveals that farmers are less likely to pay late compared to non-farmers. However, this outcome does not hold for farmers when considering the positive coefficient of the farmer-dummy for the probability of late payments in Cat.3. While this effect might also hint at strategic defaulting, one should keep in mind that external factors notably affect agricultural production, and occasionally cause a default in loan repayments. Thus, it is of certain interest to have a closer look on the influence of seasonality on defaults.

[Insert Table 5 here]

First of all, in Cat.2 the positive and statistically significant coefficients of the dummies for the first and second year-quarter reveal that the probability for defaults in all observed loans is higher for those loans that were disbursed in the first half of the year, compared to loans disbursed in Quarter 3 (reference-dummy) and Quarter 4. Secondly, it can be shown that the interaction-dummies of year-quarter and farmers show statistical significant effects on defaults in the context of Cat.3, and yet do not feature statistical significance in Cat.2. Thus, the generally higher default-probability of the farmer-dummy in Cat.3 is strongly influenced by the aspect of seasonality. Compared to farmers' loans that are disbursed in the third year-quarter (harvest period), defaults are less likely for loans that are disbursed in Quarter 1, Quarter 2 and Quarter 4. For Quarter 1 we can even observe that the default probability is in total negative for farmers, in contrast to the positive coefficient of the quarter-dummy for all observed loans that were disbursed in the first year-quarter. For a possible explanation we refer to Dostie et al. (2002) who demonstrate the relationship between rice price fluctuations and standards of living for the case of Madagascar. The volatility of commodity prices that we present using wheat prices as an example in figure A1 of the appendix may explain our finding as well. At first glance it is evident that price peaks are achieved in the first or second quarter of the year. As mentioned in section 3, households in Azerbaijan spend more than 40 per cent of income on food. Apparently, there is a relationship between non-farmers' repayment behavior and such commodity price peaks whereas farmers may profit during high-price-phases, either from self-supply or, if they have storage facilities, from higher retail prices.

Our results confirm our second hypothesis stating that farmers default less often than non-farmers. Findings from Vogel (1981), Raghunathan et al. (2011), and Weber and Musshoff (2012) also support similar results. One possible reason for this outcome may be that farmers are more afraid to be denied future access to loans when not behaving properly. They may have a higher intrinsic motivation to repay their installments on time since there are generally fewer possibilities to obtain financial assistance in rural areas. This assumption would be in line with Vogel (1981).

According to the distribution of branch offices of AccessBank Azerbaijan, we can state that there is a relatively high concentration of offices in the urban region surrounding the capital Baku. The provisioning of branch offices is far below that level in the heartland. Hence, the discrepancy in office supply, solely based on the case of the AccessBank Azerbaijan, would confirm the assumption of weaker financial infrastructure in rural areas.

With respect to the loan-specific characteristics in the context of Cat.2, a default-diminishing effect can also be stated for deposits albeit this effect is not continuous. For the probability of at least one default in installment payments in at least 15 days, we find that deposits have an increasing effect. In an experimental setting in Guatemala Atkinson et al. (2013) also find that having a deposit with the bank has a positive influence on repayment performances. The opposite finding for the enhancing effect of deposits in the context of Cat.3 is in line with the results of an experiment from Kropp et al. (2009) who found that poorer clients have better repayment rates. Lastly, examining further socioeconomic characteristics, we find that married borrowers exhibit fewer defaults in both categories. This finding is also obtained for growing family sizes and is confirmed by Weber and Musshoff (2012) as well.

6. Conclusion

By means of a rich dataset of a MFI in Azerbaijan, we investigate the effect of repeat loans on loan volume rationing and repayment performance, and simultaneously differentiate between agricultural and non-agricultural clients. In microfinance literature, the relaxation of loan volume rationing in the course of the bank-borrower relationship, also known as progressive lending, is discussed as a measure for risk mitigation. The aim of our paper is to relate the lending politics of the MFI with the repayment performance of the client types to motivate a possible adjustment of loan disbursement politics.

From our results we can confirm that the studied MFI applies progressive lending, but noticed that farmers and non-farmers do not face the same progressive lending politics. In general, farmers face a significantly higher loan volume rationing, and thus receive smaller loan amounts when offering the same amount of collateral as non-farmers per loan. According to the descriptive statistics, this "rationing-gap" is especially relevant at the beginning of the relationship. Yet, based on the results on repayment performances, this discrimination cannot be justified. We find that in the lower credit risk category, non-farmers are more likely to default. Furthermore, the obtained effects in the lower risk category prove the adequacy of progressive lending, since the likelihood of defaults decreases significantly with every additional loan. In summary, the analyses of the bank's portfolio state that progressive lending is an appropriate method for mitigating defaults.

In the category of lower credit risk, farmers demonstrate a better repayment performance. Nevertheless, we do not know if this is a result of the stronger volume rationing, and if it would still hold given that both client groups faced the same level of volume rationing. For loans in the higher risk category, we furthermore demonstrate that seasonality is particularly relevant for the repayment performances of farmers. Against the background of the EIB-loan that is to be disbursed via the AccessBank in Azerbaijan, it might be worthwhile for the MFI to reassess loan volume rationing politics for farmers, so that the full potential of rural borrowers could be exploited. Moreover, the observed seasonality-dependent repayment performances of agricultural and non-agricultural loans indicate that the availability and use of grace periods could contribute to risk mitigation for agricultural and standard business loans as well.

These results are, however, obtained from a single Azerbaijani MFI. Therefore, we hesitate to generalize our findings or to recommend an equal treatment of these two client groups in every country context. For future research it might be interesting to conduct a cross-country comparison, notably between countries of different economic dependency on agriculture. It would also be interesting to analyze progressive lending and repayment with a differentiation between the agricultural production types such as crop and animal production, which are accompanied by different cash flow structures. The statistical significance of the year-quarter-dummies reveals that external factors such as price volatilities also affect rationing and repayment, and should therefore be respected in future analyses more specifically.

Finally, we have to state that we only have data on accepted loan applications and no further insights on selection bias. The fact that the awareness of collateral is a condition to receive a loan from the investigated bank indicates a concentration on wealthier clients, a tendency which is already confirmed by Cull et al. (2007) and Hermes and Lensink (2007) for the case of individual-based lending. Considering the rich dataset provided, we are nonetheless convinced that our findings are relevant for implementing an efficient allocation of financial resources among borrowers.

7. References

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8. Tables

Table 1

Descriptive statistics

		Non-farmer N=350,722				Farmer N=128,604			
Variable	Unit	Mean	SD	Min	Max	Mean	SD	Min	Max
					Loan-specific characteristics				
Collateral[a)]	USD[b)]	7,321	12,027	1.00	200,800	5,713	6,267	70.00	154,203
Disbursed amount	USD[b)]	3,123	3,547	100	30,000	2,459	2,012	169	30,000
Deposits	USD[b)]	275	2,150	0.00	100,000	263	536	0.00	52,151
Number of installments	Number	13.66	4.19	1.00	120.00	14.00	3.27	2.00	62.00
Interest rate[c)]	Per cent	2.73	0.59	0.00	3.50	2.82	0.20	0.00	3.00
					Socioeconomic characteristics				
Age	Number	44.51	10.65	19.00	92.00	47.47	11.21	19.00	89.00
Male	1/0[d)]	0.73	0.44	0.00	1.00	0.87	0.33	0.00	1.00
Married	1/0[d)]	0.74	0.44	0.00	1.00	0.84	0.36	0.00	1.00
Family size	Number	4.44	1.54	1.00	14.00	5.23	1.75	1.00	14.00

Source. Author's calculations.

Note. a) Due to the generally short loan maturities the value of the collateral remains nearly constant over time. Additionally, AccessBank Azerbaijan often applies long-term collateral agreements (five to ten years) at the beginning of the lending relationship to minimize associated cost (Jainzik and Pospielovsky, 2014). b) USD = US-Dollar. c) Interest rate per month. d) Dummy variable: 1= yes, 0 = no. Mean values for dummy variables (1/0) indicate ratios.

Table 2

t-test for loan volume ratio by loan number for non-farmers and farmers

Loan number	Client group	Observations	Mean[a)]	SD[b)]	Diff. in mean[c)]
1	Non-farmer	173,951	2.197	1.446	-0.364***
	Farmer	71,536	2.561	1.407	
2	Non-farmer	84,480	2.164	1.229	-0.175***
	Farmer	34,655	2.338	1.182	
3	Non-farmer	50,055	2.068	1.178	-0.126***
	Farmer	15,356	2.194	1.111	
4	Non-farmer	26,014	2.000	1.152	-0.008
	Farmer	5,254	2.008	1.043	
5	Non-farmer	11,058	1.944	1.109	0.047
	Farmer	1,411	1.897	1.000	
>=6	Non-farmer	5,164	1.911	1.109	0.087
	Farmer	392	1.823	0.950	

Source. Author's calculations.

Note. a) Mean of loan volume ratio. b) SD = Standard deviation. c) Two sided t-test non-farmers in comparison to farmers.

*p< 0.05.

**p< 0.01.

***p< 0.001.

Table 3

t-test for dependent variables in GLM and sequential logit model

	Variable	Unit	Non-farmer N=350,722 Mean	SD	Farmer N=128,604 Mean	SD	Diff. in mean[a)]	
GLM	Loan volume ratio	-	2.144	1.327	2.425	1.309	-0.281	***
Sequential Logit Model	Cat.1[b)]	1/0[e)]	0.823	0.382	0.892	0.310	-0.069	***
	Cat.2[c)]	1/0[e)]	0.177	0.382	0.108	0.310	0.069	***
	Cat.3[d)]	1/0[e)]	0.014	0.118	0.008	0.090	0.006	***

Source. Author's calculations.

Note. a) Two-sided t-test non-farmers in comparison to farmers. b) Always punctual. c) >=1 day late. d) >=15 days late. e) Dummy variable: 1= yes, 0 = no. Mean values for dummy variables (1/0) indicate ratios. N = 479,326.

*p< 0.05.

**p< 0.01.

***p< 0.001.

Table 4

Results of the GLM on the influence on loan volume rationing

Loan volume ratio	Unit	Coeff.		Std. Err.	z-value
Farmer_Dummy	1/0[a)]	0.0325	***	0.0039	8.2400
Loan 2	1/0[a)]	-0.0420	***	0.0021	-19.9000
Loan 3	1/0[a)]	-0.0906	***	0.0027	-34.1100
Loan 4	1/0[a)]	-0.1300	***	0.0036	-36.0300
Loan 5	1/0[a)]	-0.1555	***	0.0055	-28.5000
>=Loan 6	1/0[a)]	-0.1709	***	0.0080	-21.3400
Deposits (log)	USD[b)]	0.0268	***	0.0004	67.4400
Deposits_square (log)		0.0018	***	0.0000	47.8400
Number of installments	Number	-0.0406	***	0.0008	-53.8100
Number of installments_square		0.0009	***	0.0000	42.1800
Interest rate	Per cent	0.0586	***	0.0018	32.4400
Quarter 1	1/0[a)]	0.0249	***	0.0249	0.0028
Quarter 2	1/0[a)]	-0.0002	***	-0.0002	0.0027
Quarter 4	1/0[a)]	0.0076	***	0.0076	0.0028
Farmer*Quarter 1	1/0[a)]	-0.0117	***	-0.0117	0.0054
Farmer*Quarter 2	1/0[a)]	0.0323	***	0.0323	0.0053
Farmer*Quarter 4	1/0[a)]	-0.0037	***	-0.0037	0.0055
Age	Number	0.0139	***	0.0139	0.0006
Age_square		-0.0001	***	-0.0001	0.0000
Male	1/0[a)]	0.0969	***	0.0969	0.0021
Married	1/0[a)]	0.0114	***	0.0114	0.0023
Family size	Number	0.0273	***	0.0273	0.0020
Family size_square		-0.0008	***	-0.0008	0.0002
Constant		0.4103	***	0.4103	0.0163
Number of Observations					479,326
Log-likelihood					-856,364
AIC					3.5733
BIC					-6,116,828

Source. Author's calculations.

Note. a) Dummy variable: 1= yes, 0 = no. b) USD = US-Dollar. We also tested for year-effects but omitted the variable due to collinearity.

*p< 0.05.

**p< 0.01.

***p< 0.001.

Table 5

Results of the sequential logit model on the repayment behavior

Late payment	Unit	Coeff.		Std. Err.	z-value
			Cat.1 vs. Cat.2		
Farmer_Dummy	1/0[a)]	-0.4046	***	0.0208	-19.4800
Loan 2	1/0[a)]	-0.2050	***	0.0101	-20.3400
Loan 3	1/0[a)]	-0.3622	***	0.0132	-27.4400
Loan 4	1/0[a)]	-0.5226	***	0.0188	-27.8000
Loan 5	1/0[a)]	-0.6858	***	0.0302	-22.7200
>=Loan 6	1/0[a)]	-0.8583	***	0.0475	-18.0700
Deposits (log)	USD[b)]	-0.0228	***	0.0020	-11.3200
Deposits_square (log)		-0.0013	***	0.0002	-6.9400
Number of installments	Number	0.0619	***	0.0030	20.6300
Number of installments_square		-0.0009	***	0.0001	-11.5600
Interest rate	Per cent	-0.0659	***	0.0069	-9.5200
Quarter 1	1/0[a)]	0.0400	***	0.0128	3.1200
Quarter 2	1/0[a)]	0.1278	***	0.0121	10.5500
Quarter 4	1/0[a)]	-0.0834	***	0.0132	-6.3200
Farmer*Quarter 1	1/0[a)]	-0.0326		0.0286	-1.1400
Farmer*Quarter 2	1/0[a)]	-0.0449		0.0277	-1.6200
Farmer*Quarter 4	1/0[a)]	-0.0280		0.0297	-0.9400
Age	Number	-0.0224	***	0.0028	-7.8900
Age_square		0.0001	***	0.0000	4.3500
Male	1/0[a)]	-0.1723	***	0.0096	-17.9600
Married	1/0[a)]	-0.3156	***	0.0102	-30.8800
Family size	Number	-0.0594	***	0.0095	-6.2800
Family size_square		-0.0001		0.0009	-0.1300
Constant		-0.5336	***	0.0742	-7.1900

(continued)

Late payment	Unit	Coeff.		Std. Err.	z-value
			Cat.2 vs. Cat.3		
Farmer_Dummy	1/0[a)]	0.4075	***	0.0709	5.7500
Loan 2	1/0[a)]	-0.0004		0.0354	-0.0100
Loan 3	1/0[a)]	0.2594	***	0.0425	6.1000
Loan 4	1/0[a)]	0.2983	***	0.0589	5.0600
Loan 5	1/0[a)]	0.3022	**	0.0956	3.1600
>=Loan 6	1/0[a)]	0.2803		0.1506	1.8600
Deposits (log)	USD[b)]	0.0181	*	0.0079	2.2800
Deposits_square (log)		0.0031	***	0.0008	4.0600
Number of installments	Number	0.1385	**	0.0087	15.9400
Number of installments_square		-0.0010		0.0002	-5.2200
Interest rate	Per cent	0.0746	***	0.0214	3.4800
Quarter 1	1/0[a)]	0.1900	***	0.0429	4.4300
Quarter 2	1/0[a)]	0.0537		0.0415	1.2900
Quarter 4	1/0[a)]	0.0073		0.0461	0.1600
Farmer*Quarter 1	1/0[a)]	-0.5032	***	0.1007	-5.0000
Farmer*Quarter 2	1/0[a)]	-0.3413	***	0.0969	-3.5200
Farmer*Quarter 4	1/0[a)]	-0.2172	*	0.1034	-2.1000
Age	Number	0.0825	***	0.0112	7.3900
Age_square		-0.0010	***	0.0001	-8.2600
Male	1/0[a)]	0.4073	***	0.0347	11.7200
Married	1/0[a)]	-0.3565	**	0.0341	-10.4700
Family size	Number	-0.1286	***	0.0311	-4.1400
Family size_square		0.0046		0.0031	1.4900
Constant		-6.1613	***	0.2765	-22.2900
Number of Observations					479,326
Likelihood-Ratio-Test χ^2 (46)					14,230 (p-value< 0.001)
Log-likelihood					-223,440

Source. Author's calculations.

Note. a) Dummy variable: 1= yes, 0 = no. b) USD = US-Dollar.

*$p < 0.05$.

**$p < 0.01$.

***$p < 0.001$.

9. Figures

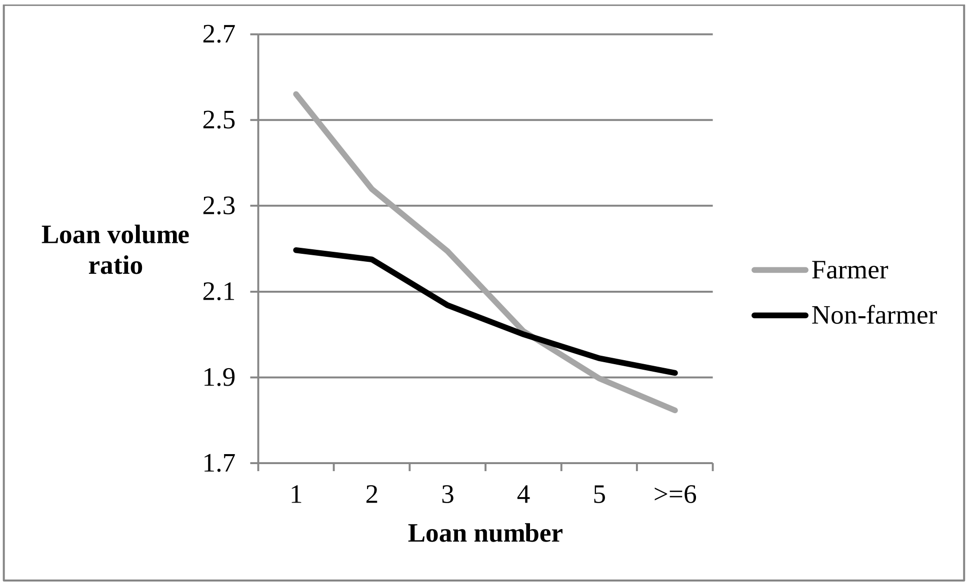

Figure 1. Development of loan volume rationing by loan number for farmers and non-farmers.
Source. Own illustration. N=479,326.

10. Appendix

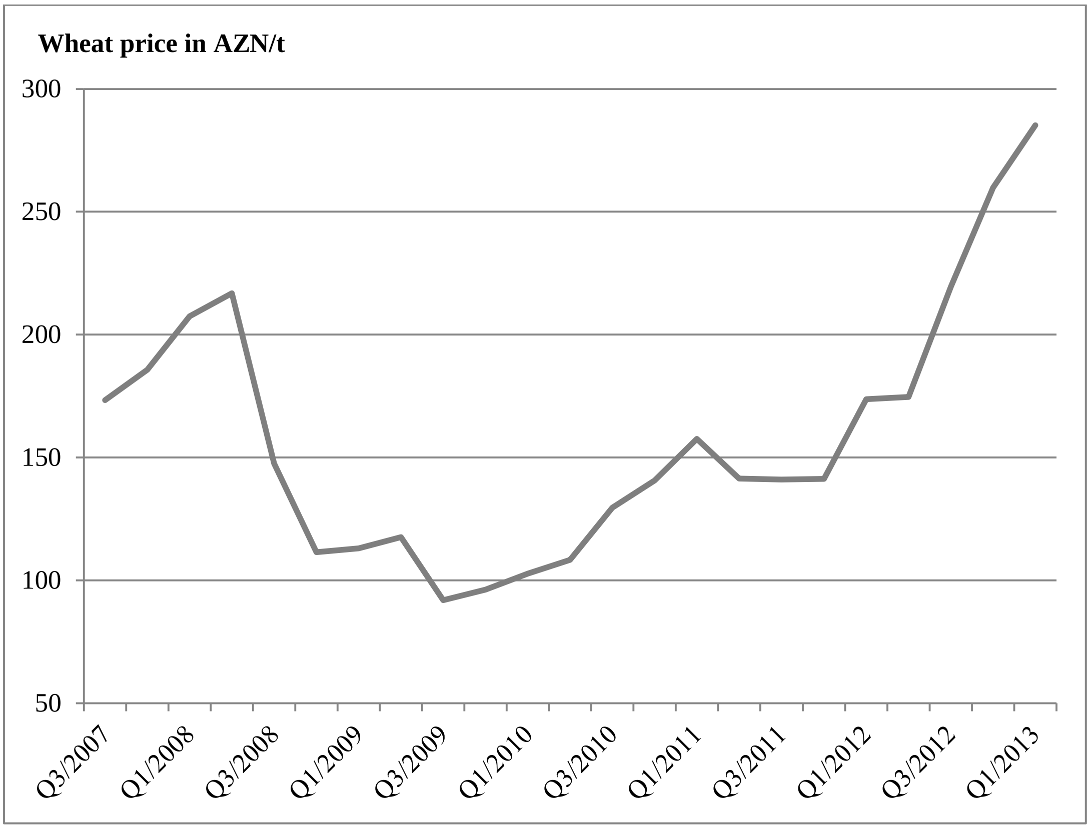

Figure A1. Traded wheat prices per year-quarter for the Caucasus region.
Source. Own illustration. Year-quarter prices are kindly provided by Thomson Reuters News Agency.

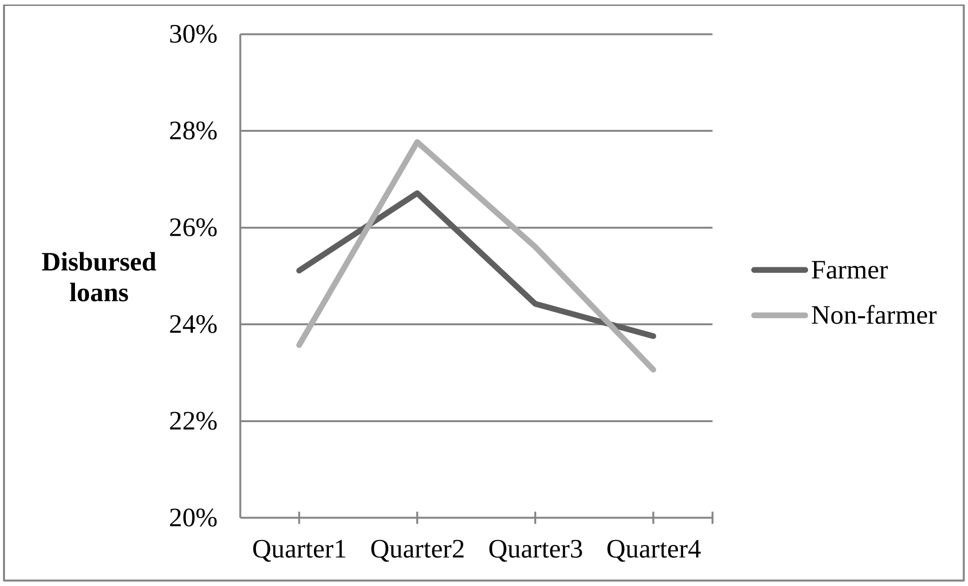

Figure A2. Disbursed loans per year-quarter [in per cent of all disbursed loans] by farmer and non-farmer.
Source. Own illustration. N=479,326.