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Exploring the role of interest rates, macroeconomic environment, agricultural cycle, and gender on loan demand in the agricultural sector: Evidence from Mali

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Abstract

Formal credit plays an important role for the development of the agriculture sector in developing countries because many farmers are characterized as liquidity constrained. Access to credit can increase farmers' purchasing power for inputs and agricultural technology, thus raising the overall productivity. Farmers in Mali are particularly vulnerable to shocks, such as heavy precipitation events. Access to liquidity to increase the resilience of the agricultural sector is essential. Therefore, higher financing volumes are required, which make the analysis of loan demand in agriculture of interest. The purpose of this paper is to empirically investigate the role of the interest rate, the macroeconomic environment, the agricultural cycle and the gender of the farmer on the loan demand in the agricultural sector from a country in the Sahel. Unique and comprehensive loan data at the farm level, provided by a commercial Malian bank, is used for this analysis. The

Abbreviations: BNDA, Banque Nationale de Développement Agricole; CV, cross validation; ECOWAS, economic community of west african states; FE, fixed effects; GVA, gross value added; Lasso, least absolute shrinkage and selection operator; MFI, microfinance institutions; minBic, minimizes the bayesian information criteria; MIS, management information system; ML, machine learning; MSE, mean squared error; OLS, ordinary least square; SDG, sustainable development goal.

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analysis covers the period from 2010 to 2020. Two different estimation strategies are combined. First, an ordinary least square regression is applied with the granted loan amount as the dependent variable. Second, the machine learning technique, least absolute shrinkage and selection operator, is applied to select the most relevant features to be used as explanatory variables in the estimation. The results reveal that the interest rate, the gross value added, the farmer's gender as well as the agricultural cycle have statistically significant effects on the granted loan demand in agriculture. These results are of interest to policymakers, who deal with financial inclusion as well as market failures, and agricultural financial institutions who could incorporate such information in the design of future loan products to stimulate farmers' loan demand, especially for female farmers. [EconLit Citations: G20, G21, O13, O16, Q14, Q18].

KEYWORDS

agricultural credit, agricultural cycle, agricultural finance, gender, interest rate elasticity, loan demand, Mali

1 | INTRODUCTION

According to the FAO, almost 2.37 billion people did not have adequate access to food in 2020 (FAO, IFAD, UNICEF, WFP, WHO, 2021). In the Sahel, the food security situation is even worsening and many households face growing hunger and uncertainty (FAO, 2023; FAO, IFAD, UNICEF, WFP, WHO, 2021). The fragility of the current food systems in the Sahel highlights the need for changes to sustain a better future and get back on track toward achieving the sustainable development goal (SDG) number 2 (ending hunger, food insecurity and all forms of malnutrition) (Lain et al., 2021). Therefore, strengthening the resilience of agriculture and increasing productivity in the agricultural sector are of great importance.

Diamoutene and Jatoo (2020) highlight that credit plays a critical role as a complementary input for achieving success in agricultural production in Mali. Similarly, Martey et al. (2019) demonstrate that production credit is crucial for improving the technical efficiency of smallholder farmers in Africa. This is mainly because credit access allows for timely purchase and efficient allocation of agricultural inputs and provides access to extension services (Martey et al., 2019). Owning physical assets such as livestock or farm equipment can have considerable impacts on the lives of the most vulnerable groups in the developing world (Hänke & Barkmann, 2017; Ma et al., 2018).

However, several studies have indicated the underinvestment in profitable technologies in the agricultural sector in the Global South. Barriers to technology adoption (such as lack of money or information, risk aversion, and social norms) hinder the strengthening of farmers' resilience and slow down welfare-improvements (e.g., Bryan et al., 2014; Dzanku et al., 2021; Mobarak & Saldanha, 2022). For example, Channa et al. (2021) argue that farmers in Tanzania underinvest in profitable storage systems due to credit constraints. Additionally, many people in

developing countries have been under-served by the banking system. However, there is a huge literature focusing on how credits have positive effects on borrowing firms (e.g., Banerjee & Duflo, 2014; De Mel et al., 2008). In this literature, three main factors that drive smallholders' credit constraints are discussed: First, the interest rates and collateral requirements are relatively high in the agricultural sector. One reason is imperfect information (Hoff & Stiglitz, 1990). Second, credit constraints exist, especially for long-term investments that are characterized by uncertainty (Garicano & Steinwender, 2016). Third, farm size is often used as a proxy for unobserved farm characteristics. This proxy leads to a discrimination of small farms (Twumasi et al., 2020). Therefore, access to finance remains a crucial factor for farmers to satisfy the high financing requirements and volumes. Additionally, agricultural credits have the potential to considerably improve rural incomes by fostering economic growth within the agricultural sector (Nadolnyak et al., 2016).

Many studies in agricultural finance in the Global South have focused on the lenders' decision-making process (e.g., Sarfo et al., 2019; Weber & Musshoff, 2012, 2017) or the effect of credit on agricultural outputs (e.g., Diamoutene & Jatoe, 2020; Khandker & Koolwal, 2016). In the literature, there are already some studies, which have analyzed certain specific characteristics of the demand side of credit. Those studies focused on for example, the relationship between farmers individual risk attitudes and credits (e.g., Kuhn & Bobojonov, 2021; Possner et al., 2021), the motives to take up a formal credit (e.g., Asante-Addo et al., 2017; Sarfo et al., 2021, 2023) or the socioeconomic characteristics of farmers who participate in the credit market (e.g., Chandio et al., 2020; Dang et al., 2019; Diamoutene & Jatoe, 2020; Jumpah et al., 2019; Sakprachawut & Jourdain, 2016; Silong & Gadanakis, 2019). Summarizing the main results indicate that taking up a credit and the choice of a credit source depend on farmer's risk attitude (Possner et al., 2021). The loan attributes also affect the choice to take up a formal credit (Sarfo et al., 2021, 2023; Wahbi et al., 2023) and socioeconomic characteristics such as the age and the number of dependents within the farming household matter (Jumpah et al., 2019). However, other factors that might affect the loan demand, such as the macroeconomic environment and the different phases of the crop cycles have far less been investigated. Fecke et al. (2016) investigated the determinants of loan demand of farmers in Germany using loan data covering 5 years. However, the high degree of mechanization and digitalization that characterize the German agricultural sector makes it difficult to generalize these results to the Global South.

This paper addresses the question of what factors determine farmers' demand for credit in the Malian agricultural sector. To be more precise, we are investigating the effect of the interest rate, macroeconomic environment, agricultural cycle, and the farmers gender on credit demand in the Malian agriculture sector. Our study based on actual granted loan data covering the time from 2010 to 2020 to exploit the unique characteristics of the agricultural credit market. Econometric and machine learning (ML) methods are combined to identify key factors affecting the loan demand in Malian agriculture. Our main dependent variable is the granted loan amount in CFA-Franc measured as logarithm. We include all types of granted credits for agricultural clients in our analysis. The set of factors influencing credit demand is hypothesized to include the interest rate, the macroeconomic environment, the agricultural cycle as well as the farmer's gender.

We focus on Mali because agriculture accounts for 36% of the Malian gross domestic product (GDP) in 2021 (World Bank, 2022a). Cotton is the main cash crop (Lambert et al., 2018). Focusing on the production of cereals in Mali in 2021, maize accounts for about 41%, rice 27% and millet 17% of the total Malian cereal production (FAO, 2022). In 2019, 62% of all employed Malian people worked in agriculture (World Bank, 2021). Nevertheless, Mali is a food-deficit country (FAO, 2017). The majority of Malian maize farmers do not have the necessary funds for fertilizers (Laris et al., 2015). Most smallholder farmers in Mali are dependent on rain-fed irrigation. In recent years, seasons have become less predictable, and extreme weather events have been more frequent. In short, climate variability is a major risk for Malian farmers (Huet et al., 2020). The weather unpredictability contributes to higher volatility of the agricultural output, affects food prices, and makes it more difficult for Malian farmers to obtain agricultural loans. This restricts farmers' ability to grow their businesses and strengthen their resilience even further (Kakpo et al., 2022; World Bank, 2022b). According to the World Bank (2015a, 2015b), Malian banks play a crucial role as the primary providers of agricultural credit in Mali. In 2015, 14 banks accounted for approximately

97% of the country's financial sector assets. Additionally, the microfinance sector facilitated over 1 million deposit accounts. The rapid growth of mobile money offers potential for extending financial services to rural areas that are not easily accessible through traditional branch banking (World Bank, 2015a, 2015b). Farmers are facing inadequate access to finance and the financial sector is unable to provide sufficient credit to smallholders (FAO, 2017). Consequently, small farmers have to rely on their limited savings to manage their crops and harvests, and the inadequacy of financial services is also impacting their income-generating capabilities. This situation is compelling small farmers to grow low-risk and low-return crops.

To the best of our knowledge, this is the first study to analyze farmers' demand for credit based on data on granted loans, provided by a commercial lender without a social mission. Additionally, this study is the first to investigate granted credit of farmers in combination with ML and regression techniques, utilizing a unique and comprehensive data set derived from the Banque Nationale de Développement Agricole (BNDA). By combining theoretical considerations with data-driven elements, this estimation strategy makes a valuable contribution to the methodological literature. Furthermore, the different stages of the harvest cycle, among other things, is included in the analysis of credit demand, which is another novelty. Our research question is relevant for financial institutions to provide better financial products for clients in the agricultural sector. The important role of the Malian agricultural sector makes the results relevant for political leaders to adjust market failures and strengthen economic development by, for example, by providing a favorable investment environment that lowers the interest rate and collateral requirements.

The rest of the paper is structured as follows. Section 2 discusses several research hypotheses on the basis of a literature review. Section 3 presents the data and Section 4 the applied econometric models. Section 5 displays and discusses the results and Section 6 focuses on some concluding remarks.

2 | HYPOTHESES

In this section, we derive research hypotheses from the literature based on identified literature gaps. The price elasticity of credit demand is highly relevant and has major implications for development as it provides information on the importance of interest rate subsidies and ceilings designed to increase access to credit, as well as on the pricing strategies of microfinance institutions (Karlan & Zinman, 2005). Based on economic intuition, high-interest rates reduce loan demand. Empirical studies further support this notion, indicating that the interest rate elasticities for credit demand are negative. Chiu et al. (2014) found that the elasticity of credit demand is different among distinct groups of rural credit recipients using data from Mexico and China. Jumpah et al. (2019) estimated a negative relationship between interest rates and participation in a microfinance program for smallholder farmers in Ghana. DeFusco and Paciorek (2017) investigated the elasticity of mortgage demand in the United States of America and highlighted a negative relationship. Turvey et al. (2012) estimated an inverse relationship between interest rates and credit demand for farm households in China, in general, and heterogeneous elasticities for certain subsamples. Some farm households have nearly perfectly inelastic demands for credit, others have elastic demands (Turvey et al., 2012). Hence, this inverse relationship between interest rates and credit demand should also apply to farmers' loan demand in Mali. This led to the first hypothesis:

H1 The interest rate elasticity of farmers' loan amount is statistically significantly negative.

The macroeconomic environment should also affect the loan demand. A favorable macroeconomic situation should enhance the loan demand and vice versa. Fecke et al. (2016) estimated a positive and inelastic association of farmer's loan demand with respect to gross value added (GVA). Calza et al. (2003) calculated a positive and elastic GDP elasticity of loan demand for the Euro area. According to Wagner and Winkler (2013), the global financial crisis of 2007 had a strong negative impact on new loans granted by microfinance institutions. Krauss and Walter (2009)

investigated the correlation between microfinance portfolios and different types of asset categories using a cross-country analysis. They found that microfinance institutions (MFI) display no statistically significant relationship with global market movements. Following Krauss and Walter (2009) and Fecke et al. (2016), GVA and the lagged GVA in the agricultural sector are used as indicators of economic development in the agricultural sector to analyze if the macroeconomic environment enhances the loan demand. The GVA is a proxy for domestic market risk. The use of domestic GVA instead of, for example, domestic stock indexes are preferred because emerging market stock indexes are often limited to a few locally listed firms. This might not adequately reflect the underlying national economic performance, especially if the focus is on the agricultural sector in Mali (Krauss & Walter, 2009). Following Fecke et al. (2016) results, we expect that the lagged GVA has a positive effect on the loan amount. This led to the following second hypothesis:

H2 An increase in economic development in the agricultural sector increases the granted loan amount statistically significantly.

Different stages of an agricultural cycle exist (preharvest, harvest, and postharvest). In each of these stages, farmers face different frictions. The relatively large reliance of a large part of the Malian population (62% of all employed people work in agriculture; World Bank, 2021) on agriculture as an income-generating activity leaves farmers more vulnerable to seasonal price fluctuations from harvest cycles (Gilbert et al., 2017; Kakpo et al., 2022). Hence, one can also assume that the credit demand of farmers is following such agricultural cycles, because farmers have different needs for finance during the different stages of the harvest season, for example, to purchase seeds or fertilizers, invest in storage facilities or hire workers. Channa et al. (2022) offered Tanzanian farmers a loan at the end of the harvest period. The high uptake of the credit was interpreted as a reduction of liquidity constraints the farmers faced during the postharvest period. The results of Channa et al. (2022) highlight that farmers have different need for finance at different stages of the harvest season. There are two main reasons discussed in the literature for why farmers face constraints during this period. First, maintaining the quantity and quality of agricultural stocks throughout the year is challenging because of pest damages (Kadjo et al., 2018). Climate change will increase the risk of pests in agriculture even further (IPPC Secretariat, 2021). Second, price seasonality led to lower grain prices at harvest than later in the season. Farmers may end up selling their crops for a relatively low price at harvest to pay off debts and meet other expenses, while at a later point they buy grains for their own consumption when the prices are relatively higher (Channa et al., 2022; Gilbert et al., 2017). Basu and Wong (2015) provided further evidence that imperfections in the savings and the credit markets harm farmers to convert harvest season output into lean season consumption using a randomized controlled trial in Indonesia. The authors demonstrate that credit raised the income of farmers and reduced seasonal gaps. In short, pest damage and economic constraints drive liquidity constraints of farmers during the postharvest season. Following this evidence, it can also be assumed that the agricultural credit demand in the postharvest period in Mali rises statistically significantly. These described stages of the agricultural cycles lead to the following third hypothesis:

H3 The postharvest period increases the granted loan amount statistically significantly.

In areas with little crop diversification, there is a lean season between planting and harvest periods. During this time, cultivators must wait for the crop to grow, and land management tasks do not require as many workers as during planting and harvest. This preharvest lean period constitutes seasonal downturns marked by job scarcity, suppressing expenditures and therefore a change in consumption patterns (Mobarak & Reimão, 2020; Sibhatu & Qaim, 2017). Mali faces a relatively large annual lean season that has considerable implications for food security. Smale et al. (2020) show that especially during the lean season Malian households face difficulties to meet the minimum adequate dietary diversity. Only half of female farmers interviewed meet the minimum adequate dietary diversity during the lean season (Smale et al., 2020). These lead to the following fourth hypothesis:

H4 The lean period decreases the granted loan amount statistically significantly.

The first four hypotheses focus on the role of interest rates, the macroeconomic environment, and the agricultural cycle (lean period and postharvest season) on loan demand in the agricultural sector. The fifth hypothesis focuses on the sociodemographic characteristics of the farmer. Weber and Musshoff (2012) highlighted that the probability of receiving a loan in the Tanzanian agricultural sector is independent of gender. However, Tanzanian women face a statistically significantly stronger volume rationing compared to men. In other words, the probability of receiving the loan is similar for male and female farmers, but the volume of the credit differs statistically significantly by gender (Weber & Musshoff, 2012). Agier and Szafarz (2013) confirmed this result for Brazilian microentrepreneurs using microfinance credits covering 11 years. The authors detect no gender bias in loan denial but find unequal granted credit conditions. The gender differences in the granted loan size increased disproportionately with the size of the borrower's project (Agier & Szafarz, 2013). In contrast, Sarwosri et al. (2016) found a higher rate of loan application approvals for female farmers in Madagascar compared to male farmers. In addition, Jumpah et al. (2019) estimated a positive relationship between being female farmers and the probability of participation in a microfinance program for smallholder farmers in Ghana.

Due to our data structure, which only includes granted loans, an analysis focusing on different credit rationing behavior by gender cannot be included in our analysis. However, it can be investigated if gender differences in the granted loan amount exist. Hence, there is a need to examine loan accessibility for female farmers in Mali compared to their male counterparts from a profit-oriented MFI. The fifth hypothesis is:

H5 Female farmers have a statistically significantly lower granted loan amount compared to male farmers.

An overview of the five proposed hypotheses and the associated variables is provided in Table 1. The fifth column provides an intuition about the expected relationship of the variables. We anticipate an inverse association between the interest rate and the loan amount, indicating that as the price of credit increases, the loan amount is expected to decrease. Furthermore, we expect a positive association between GVA and the loan amount, suggesting that a favorable economic environment would enhance the granted loan amount. During the postharvest period, we expect the loan amount to increase, because farmers have an increased need to invest in, for instance, postharvest technologies. Conversely, during the lean period characterized by shortages, we expect to observe an inverse association between the loan amount and the lean period. Finally, we expect that being a female farmer is associated with a lower granted loan amount. One potential explanation could be stronger credit rationing practices targeting female farmers.

3 | DATA

This study is based on granted credit data provided by the BNDA, which is a large commercial bank in Mali with activities in all sectors of the Malian economy. As a commercial lender, the BNDA does not have any social mission. Hence, sampling bias concerns due to a specific targeting of the bank on specific types of farmers does not exist. Mali is divided into 10 regions and one capital district. The BNDA offers its services through 47 branch offices in seven out of 10 regions (Gao, Kayes, Koulikoro, Mopti, Ségou, Sikasso, and Tombouctou) and the capital district (Bamako) in Mali (BNDA, 2021). All granted loans included in the analysis are disbursed between January 2010 and December 2020. One limitation of the data is that it provides only information about the loans that were granted. There is no information about loan applications that were denied, or about farmers that did not apply for loans.

This research study focuses only on borrowers categorized as farmers. Agricultural credits are identified by the profession of the person who requested the credit. Another limitation of the data is that we can only distinguish between the purpose of the loans, for example, whether these loans are for investment in machinery, for rice

TABLE 1 Overview of the proposed hypothesis.

#	Hypothesis	Variable	Definition	Expected relationship
H1	The interest rate elasticity of farmers' loan amount is statistically significantly negative.	Interest rate	Interest rate (as logarithmic value)	-
H2	An increase in economic development in the agricultural sector increases the granted loan amount statistically significantly.	GVA in agriculture	Lagged GVA before tax (as logarithmic value)	+
H3	The postharvest period increases the granted loan amount statistically significantly.	Postharvest dummy	Dummy if credit is granted in the postharvest season (0 = no, 1 = yes)	+
H4	The lean period decreases the granted loan amount statistically significantly.	Lean period dummy	Dummy if credit is granted in the lean season (0 = no, 1 = yes)	-
H5	Female farmers have a statistically significantly lower granted loan amount compared to male farmers.	Gender	Gender dummy (0 = female, 1 = male)	-

Note: This table provides an intuitive overview of the hypotheses and associated variables. The variables are further explained in the summary statistics (Table 2).

Source: Authors' own illustration.

production or for employment purposes, but we do not know, for example, exactly for which agricultural machinery the loans granted are needed.

The data set utilized to explore the five hypotheses (compare Table 1) is extracted from the management information system (MIS) of the BNDA. The raw data set contains 33,360 observations from 10,277 clients who are identified as farmers. This is a selected sample that is not representative of the general population but rather comparable to other commercial financial institutes in Mali. A number of borrower characteristics are collected as part of the credit assessment, including, for example, information on occupation. Client information is manually entered into the system, while loan details such as the loan amount or interest rate are automatically generated by the MIS. During data cleaning, observations with missing values are excluded. The analysis includes a 1-year lag of the independent variable (GVA). Therefore, we also exclude observations for which we cannot apply a lag variable, for example, because the loan was granted in April 2022. Due to the independent variable lagged GVA, we only consider granted credits until December 2020. This reduces the sample size. After data cleaning, 28,764 observations of granted loans from 9,246 farmers remain.

Figure 1 highlights the annual agricultural credit volume over 11 years. It is evident from Figure 1 that there was a sharp decrease in loan volume in 2012. One potential explanation for the decline in 2012 could be the start of the rebellion of the Tuareg separatist group in the north of Mali and a military coup in 2012 (for more information see for example Global Conflict Tracker, 2023). In other words, the BNDA's operations might be affected by the political instability, which might be one theoretical explanation for the discontinuity of the volume of agricultural granted credits in 2012 and an increase in 2013 (compare Figure 1). Especially MFIs have been affected by the political crisis in 2012. Nonperforming loans peaked in 2012, with a portfolio at risk of 90 days of 11.8%. In 2013, the portfolio at risk of 90 days was lower (9.2%) (World Bank, 2015b). Further political shocks such as a coup d'état

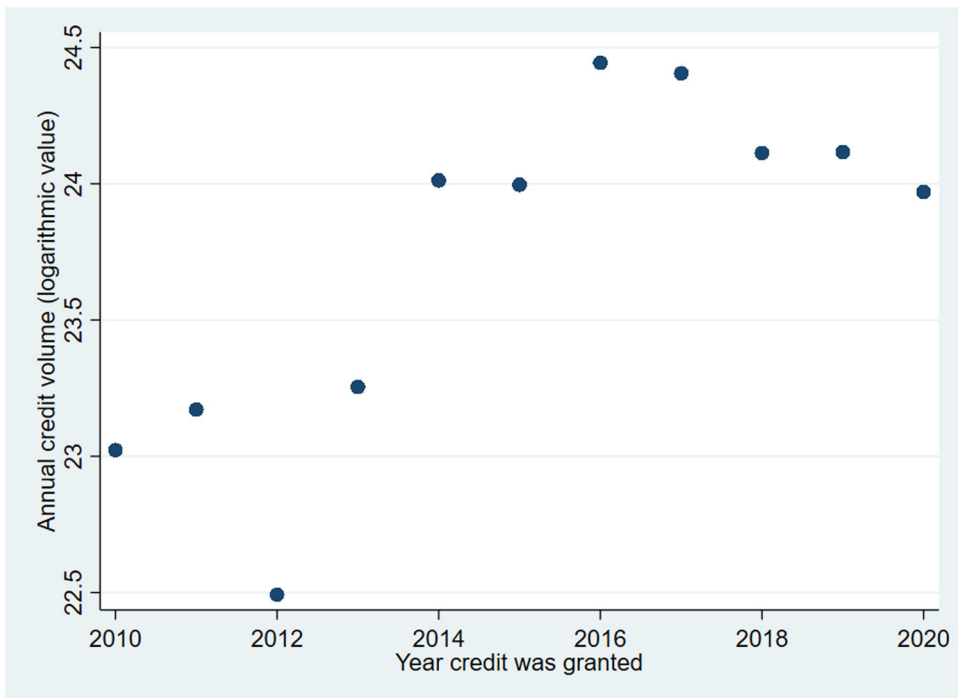


FIGURE 1 Annual agricultural credit volume (as logarithmic value) over time. *Source:* Authors' own calculations based on BNDA data.

on August 18, 2020 led to a temporal economic blockade by Economic Community of West African States (ECOWAS) until October 2020. The credit volume to the agricultural sector was highest in 2016.

Considerable policy changes regarding loans and borrowing for farmers took place during the specified period. In 2012, there was a notable enhancement in credit accessibility through the expansion of acceptable collateral assets. In 2016, Mali introduced regulations to enhance its credit information system, governing the licensing and operations of credit bureaus within the member states of the West African Economic and Monetary Union. Furthermore, in 2017, Mali further improved access to credit information by establishing a new credit bureau (World Bank, 2023a).

Figure 2 highlights the economic environment during the study period, including the interest rate spread (lending rate [in percent] minus deposit rate [in percent]), lending interest rate (in percent), and real interest rate (in percent) over time. The data provided by the World Bank is only available until 2017 (World Bank, 2023b, 2023c, 2023d). The real interest rate has shown considerable variation during the observed time period. In 2005, it was 1% per year. There was a sharp drop in 2011, resulting in a real interest rate of minus 6%. From 2015 to 2017, the real interest rate remained between 3% and 4% per year. By definition, the interest rate spread and the lending interest rate exhibit a correlated trend. The interest rate spread decreased in 2006, reached its lowest point in 2009, and has been steadily but marginally increasing since then. The lending interest rate decreased in 2006 and has remained relatively stable since then, fluctuating between 4% and 6%.

Table 2 displays the summary statistics of the variables of interest. The table shows the dependent variable as well as the independent variable that we include in our estimations. We select the independent variables based on our five hypotheses, which we developed in the previous section. We include three further control variables that we added based on other studies. The amount of interest, the number of due dates and the number of granted credits by client are included in our analysis because Sarwosri et al. (2016) and Karlan and Zinman (2008) show that these variables affect the accessibility to lending opportunities. The continuous variables credit amount disbursed, GVA, lagged GVA, and the amount of interest of the granted credit are used in the logarithmic form. Additionally,

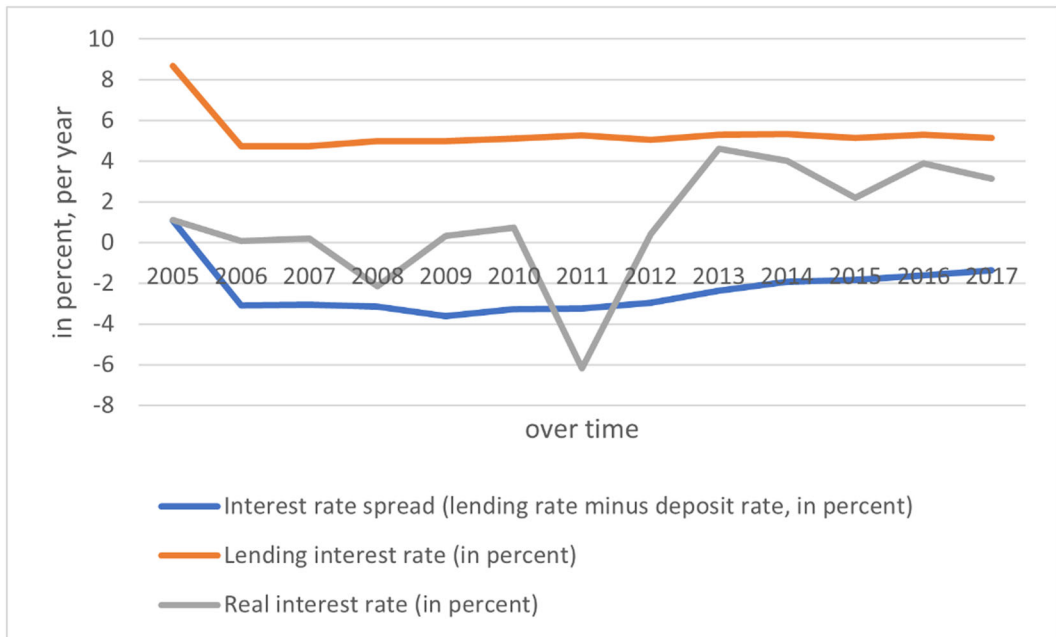


FIGURE 2 Malian interest rates over time. *Source:* Authors' own illustration, based on World Bank (2023b, 2023c, 2023d).

TABLE 2 Summary statistic.

	Mean	SD	Min.	Max.
Outcome of interest				
Credit amount disbursed (in CFA-Franc, continuous value)	8,479,323.949	41,320,002.211	25,000.000	500,000,000.000
Credit amount disbursed (logarithmic value)	14.319	1.371	10.127	20.030
Variables related to the hypotheses				
Interest rate of the granted credit (in percent)	10.045	2.201	0.000	15.000
Interest rate (logarithmic value)	2.350	0.424	0.000	2.773
GVA before tax (logarithmic value)	22.360	0.147	22.110	22.541
Lagged GVA before tax (logarithmic value)	22.323	0.152	22.064	22.541
Dummy if credit is granted in the postharvest season (0 = no, 1 = yes)	0.475	-	0.000	1.000
Dummy if credit is granted in the lean season (0 = no, 1 = yes)	0.132	-	0.000	1.000
Gender dummy (0 = female, 1 = male)	0.966	-	0.000	1.000
Control variables				
Amount of interest of the granted credit (continuous value)	774,769.623	3,611,106.307	0.000	50,000,000.000
Amount of interest (logarithmic value)	11.751	2.250	0.000	17.728
Number of due dates (continuous variable)	6.040	11.817	0.000	120.000
Number of granted credits by client (continuous variable)	9.009	20.147	1.000	217.000
Observations	28,764			

Note: The continuous variables credit amount disbursed, GVA, lagged GVA, and amount of interest of the granted credit as well as interest rate are used in the logarithmic form to interpret the coefficients as elasticities. The summary statistics display the continuous and logarithmic values. The number of due dates and the number of granted credits by client remain in the continuous form.

Source: Authors' own calculations based on BNDA data.

the interest rate varies between 0% and 15% and is also transformed in the logarithmic form. Through this, coefficients can be interpreted as elasticities (Huntington et al., 2019). A total of 96% of borrowers are men. Although we only have 4% of female farmers in our sample, due to the large sample size, this resulted in 977 granted credits for female farmers in our analysis. The number of granted credits per farmer varies between 1 and 217. The average number of credits per farmer is nine. The majority of the credits were granted in the southern regions. Due to the representativity of our data from a commercial bank in Mali, we can conclude that the mean interest rate for an agriculture related credit in Mali is around 10%. The average granted loan is 8,479,324 CFA-Franc, which is equal to around 13,000 Euro. The granted credit amount varies from 25,000 CFA-Franc, which is equal to about 38 Euro, to 500,000,000 CFA-Franc, which is equal to around 762,245 Euro. This highlights the heterogeneity of agricultural credits in our sample.¹ The gross value added of the agricultural sector remains

¹We used the exchange rate from April 16, 2023.

relatively stable from 2010 to 2020, ranging from 33.0% in 2010 to 38.1% in 2012 as a share of total Malian GDP (World Bank, 2022a).

We define a credit as having been granted in the lean season if it was granted in the period from May to August, while we define a credit as having been granted in the harvest season if it is granted in September or October (Lain et al., 2021).

Appendix Table A1 presents the summary statistics of all variables that we have included in the least absolute shrinkage and selection operator (Lasso) feature selection process. In addition to the variables relating to the five hypotheses, these included variables relating to the client's credit history (e.g., number of open and thus not yet repaid loans, number of loans closed and repaid), the characteristics of the loan granted (e.g., repayment frequency) and the time at which the farmer granted the loan. On average, a farmer has already eight granted and repaid loans with the BNDA.

4 | ESTIMATION STRATEGY

Based on the data structure, first, an ordinary least square (OLS) regression model with time and region fixed effects as well as heteroscedasticity robust standard errors is used to analyze the loan demand of farmers. The fixed-effects regression model controls for differences in the levels of variables associated with individual branches in each region. The model implicitly controls for unobserved region-specific and time-invariant heterogeneity (e.g., geography, proportion of arable land, technological changes, or policy reforms) that may influence the amount of credit granted (Angrist & Pischke, 2009). Karlan and Zinman (2005), Fecke et al. (2016), and Chandio et al. (2020) highlight the good performance of a pooled OLS when analyzing credit demand in general and interest rate elasticities in particular. Thus, the following regression equation is estimated:

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \delta_d + \delta_t + \varepsilon, \quad (1)$$

where Y is the granted credit amount measured for individual i and is a function of borrower and credit characteristics. x_1, \dots, x_k are observable explanatory variables and β_0, \dots, β_k are the parameters which shall be estimated. The observable explanatory variables are related to our hypotheses and are the interest rate, the gross value added, the lagged gross value added, a time period that indicates when the credit was requested, and the gender of the client. Further control variables are included such as the number of previous credits and the number of due dates. These variables are included because, for example, Sarwosri et al. (2016) and Karlan and Zinman (2008) indicated that these variables affect the loan demand. δ_d highlights the region fixed effect, δ_t the time fixed effects, and ε is an error term for unobserved heterogeneity, affecting the outcome and is assumed to be uncorrelated with the independent variables in this model. We estimate the pooled OLS with time and region fixed effects, with region fixed effects, with time fixed effects and without fixed effects to control the robustness of the results.

We argue that reverse causality is less problematic in our analysis because we assume, based on existing literature, that in the competitive financial market in Mali (World Bank, 2015a, 2015b), loan amounts are influenced by the interest rate rather than vice versa, as shown by Jiménez et al. (2014). In a competitive financial market, interest rates cannot be flexibly set (Raghunathan et al., 2011), and are instead influenced by factors such as inflation (Azariadis & Smith, 1996), economic growth (Wagner & Winkler, 2013) and monetary policy (Bräuning & Ivashina, 2020; Paligorova & Santos, 2017). The granted loan amounts are determined through interactions between individual borrowers and lenders (Fisman et al., 2017). Factors such as the creditworthiness of the borrower (Wydick et al., 2011), the risk preferences (Possner et al., 2021) and the availability of collateral (Asante-Addo et al., 2017; Kuhn & Bobojonov, 2021) influence the loan amounts. These factors are unlikely to be influenced by interest rates, suggesting that loan size does not directly influence interest rates. Hence, interest rates are

generally seen as the driving force behind changes in borrowing behavior, with loan amounts being a response to changes in interest rates and other economic factors.

Karlan and Zinman (2019) argue that supply constraints could bias estimates of the price elasticity of demand, as these constraints adjust endogenously. However, there is no evidence that the BNDA was constrained in its ability to fund or manage new loans by supply constraints. As shown in Figure 1, the granted loan amount decreased considerably in 2012 and increased considerably after 2012 and has remained at a relatively high and constant level since then.

Second, as already mentioned in the introduction credit demand is linked to a large set of determinants, including features of the granted credits (e.g., previous experience at the credit market, socioeconomic characteristics of farmers). However, not all determinants carry the same importance. In such cases with high dimensionality, the ML technique Lasso is an efficient method for feature selection. Lasso is a regularized regression method, which penalizes the absolute size of coefficient estimates. Therefore, to strengthen the estimation strategy introduced in Equation (1), Lasso, as introduced by Tibshirani (1996), is applied for feature selection.

Lasso is an approximate sparse method, which implies that among a number of regressors of a specific model, only some regressors are relevant to capture the features of a specific regression. Hence, Lasso is useful when only a few of many potential covariates affect the outcome, and it is of interest to include only those covariates that have a stimulating effect (Belloni & Chernozhukov, 2013; Tibshirani, 1996). Lasso has been used for feature selection of irrigation investments for small producers in Nicaragua (Mullally & Chakravarty, 2018), or the analysis of energy consumption in Vietnam (Maruejols et al., 2022).

Lasso aims to minimize the sum of the squared residuals and a penalty λ that penalizes the size of the model through the sum of absolute values of the coefficients, which can be defined as:

$$\arg \min_{\beta} \sum_{i=1}^N (Y_i - \beta^T X_i)^2 + \lambda (|\beta|_q)^{1/q}, \quad (2)$$

where $|\beta|_q = \sum_{k=1}^K |\beta_k|^q$. For $q = 1$, this corresponds to Lasso (Athey & Imbens, 2019; Tibshirani, 1996).

The penalty is determined by the value λ , comprised between 0 and 1. In other words, λ causes Lasso to omit variables. Because of the lowering process some coefficients with little explanatory power decrease to zero and only the most important features are included in the model. λ is commonly chosen by cross-validation (cv) (Athey & Imbens, 2019). To increase robustness, we also select λ that has the minimum Bayes information criterion (minBIC) and an adaptive Lasso (adaptive). Adaptive Lasso was proposed by Zou (2006) and is another selection technique that tends to choose fewer covariates. It uses cv but runs multiple Lassos (Ahrens et al., 2020). In other words, three different Lasso models are estimated and compared, leading to different values for λ and thus to a different selection of features. Two quality criteria (mean squared error [MSE] and R^2) are used to select the specifications that outperform the others.

Following the discussion of Belloni and Chernozhukov (2013) who show that postestimation OLS outperform Lasso in contexts where consistent model selection is feasible, a postmodel estimator that applies OLS to the model selected by Lasso is used. The program lassopack by Ahrens et al. (2020) is used for this purpose. In other words, an OLS is estimated to the data with the regressors that were selected by the Lasso. In short, a data-driven variable selection is applied. Through this, multicollinearity and an overfitting of the model are avoided. Multicollinearity concerns might exist for instance, between the amount of interest (as logarithmic value) and the interest (as logarithmic value) or between the GVA (as logarithmic value) and the lagged GVA (as logarithmic value). With Lasso, we can take these potential multicollinearity concerns into account. Additionally, by employing Lasso for feature selection, we can address any concerns related to p-hacking and strengthening the importance of our theory-based identified and selected hypotheses. However, Lasso is not a silver bullet to solve all endogeneity concerns.

Appendix Table A1 presents all 33 variables ($\beta_1, \dots, \beta_{33}$) that are included in the Lasso selection process. These included variables are, firstly, the independent variables included in the OLS regression (Equation (1)), secondly,

further variables that are, for example, related to the client's credit history (number of open credits, number of closed and repaid credits), thirdly, the characteristics of the granted credit (repayment frequency) and fourthly, related to the time when the farmer granted the credit.

Finally, several robustness tests are applied. We apply the Romano-Wolf multiple hypothesis correction to control for the familywise error rate, i.e., the probability of rejecting at least one true null hypothesis in a family of hypotheses to be tested (Clarke et al., 2020; Romano & Wolf, 2016). The Equation (1) is re-estimated using a different subsample. We filter the granted credit data in a way that we only keep the first granted credit per client in our sample that covers the period from 2010 to 2020. Through this we can control for a hypothetical distortion of the results by interdependent observations. This sample size for this robustness test is 9,246, which is equal to the number of farmers in our sample. Additionally, an unbalanced panel analysis using individual-level and time fixed effects is applied. As mentioned in the descriptive statistics, some individuals only have one observation, while others have multiple. The individual-level fixed effects control for nonobservable issues (e.g., risk aversion) that might bias the main estimation. We estimated a panel regression of the following form:

$$Y_{it} = x_{it}\beta + \delta_t + \delta_i + \varepsilon_{it}, \quad (3)$$

where Y is the granted credit amount measured for individual i in time t . δ_i represents the unit-specific fixed effect, δ_t represents the time specific fixed effects x_{it} represents a vector of explanatory variables for unit i at time t . β is a vector of coefficients representing the effect of the explanatory variables on Y_{it} . We include the same explanatory variables as in the pooled OLS (Equation 1). ε_{it} is the error term.

The analysis was carried out using STATA 18 software.

5 | RESULTS AND DISCUSSION

The results of the OLS estimation are shown in Table 3. There are four models presented. Model (1) contains no fixed effects, model (2) includes only year fixed effects, model (3) includes only regional fixed effects, and model (4) includes year and regional fixed effects. In other words, the results in column (2) controls for time-invariant heterogeneity, column (3) for unobserved region-specific heterogeneity, and column (4) controls for both unobserved region-specific as well as time-invariant heterogeneity.

H1 assumes a negative effect of the interest rate (as logarithmic value) on the granted loan amount (as logarithmic value). The results show that the interest rate elasticity is negative and elastic. This statistically significant result holds across all four model specifications. The respective coefficients in Table 3 and columns (1) to (4) show that the interest rate elasticity is negative and larger than 3. Hence, a 1% change in interest rate leads to a relatively larger change in loan demand of approximately 3%. The inverse relationship is consistent with the findings from other studies. For example, Fecke et al. (2016) found a negative and inelastic association for farmers in Germany. DeFusco and Paciorek (2017) found a negative and elastic interest rate elasticity for mortgage demand with an elasticity coefficient of 2% and 3%, depending on the regression specification. Turvey et al. (2012) found a range of interest rate elasticities with a mean elasticity coefficient of about -0.6. Our estimation of the interest rate elasticity covers a period of 10 years and our observed coefficient is larger than the one observed by Turvey et al. (2012). Our estimated elasticity is observed in the longer run, which strengthens the results. In other words, the interest rate is a crucial explanatory variable for loan demand. When only focusing on the OLS results, we cannot reject H1.

H2 focuses on the hypothesized positive correlation between the lagged GVA (as logarithmic value) and the granted loan amount (as logarithmic value). The estimated lagged GVA elasticity is statistically significantly negatively associated with the credit demand. The value is larger than one across all four specifications, indicating an elastic association. Adding the year fixed effects in column (2) and column (4) leads to a relatively large increase in the effect size. Hence, a 1% change in the lagged GVA (as logarithmic value) leads to a relatively larger change in

TABLE 3 OLS regression results for credit demand.

	(1)	(2)	(3)	(4)
	OLS	OLS with time FE	OLS with regional FE	OLS with time & regional FE
Variables related to the hypotheses				
Interest rate (logarithmic value)	-3.111*** (0.045)	-3.211*** (0.042)	-3.118*** (0.044)	-3.219*** (0.041)
GVA before tax (logarithmic value)	1.223*** (0.090)	5.917*** (0.281)	1.216*** (0.089)	5.921*** (0.279)
Lagged GVA before tax (logarithmic value)	-2.351*** (0.092)	-6.103*** (0.246)	-2.346*** (0.092)	-6.133*** (0.245)
Dummy if credit is granted in the postharvest season (0 = no, 1 = yes)	0.023* (0.012)	0.032*** (0.012)	0.023* (0.012)	0.030** (0.012)
Dummy if credit is granted in the lean season (0 = no, 1 = yes)	-0.131*** (0.009)	-0.144*** (0.009)	-0.128*** (0.009)	-0.143*** (0.009)
Gender dummy (0 = female, 1 = male)	0.361*** (0.032)	0.354*** (0.031)	0.349*** (0.033)	0.342*** (0.032)
Control variables				
Amount of interest (logarithmic value)	0.777*** (0.005)	0.788*** (0.005)	0.778*** (0.005)	0.789*** (0.005)
Number of due dates (continuous variable)	-0.006*** (0.000)	-0.005*** (0.000)	-0.005*** (0.000)	-0.004*** (0.000)
Number of granted credits by client (continuous variable)	0.004*** (0.000)	0.003*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
Regional FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
R ²	0.765	0.772	0.767	0.773
Observations	28,764	28,764	28,764	28,764

Note: Standard errors in parentheses. Independent variable is credit amount disbursed (as logarithmic value).

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Source: Authors' own calculations based on BNDA data.

loan demand, approximately ranging between more than 2% and 6%, depending on the specification. Following the OLS results, H2 can be rejected, because we expected a positive association between the lagged GVA and the granted loan amount. The GVA (as logarithmic value) is positively associated with the loan amount. Accordingly, the macroeconomic environment in the previous year is negatively associated with the granted loan amount, while the GVA in a current year is statistically significantly positively associated with the granted loan amount in Mali. This result is not in line with the literature. For example, Krauss and Walter (2009) display a positively statistically significant relationship between MFIs' performance and domestic GDP using a comprehensive cross-country sample. Fecke et al. (2016) highlight a positive statistically significant relationship between the loan amount in

agricultural finance and the lagged GVA in the German agricultural sector. Additionally, Calza et al. (2003) investigate the relationship between loans and GDP in the Euro area and estimate a positive and elastic association of the loan demand. This shows that the findings of Calza et al. (2003) and Fecke et al. (2016) for developed countries do not apply to all developing countries, as the example of Mali highlights. One potential explanation could be an inverse U-shaped relationship. The positive association between GVA (as a logarithmic value) and the loan amount (as a logarithmic value) suggests that as the overall economic activity increases (reflected by GVA), there is a greater demand for agricultural loans. This could be due to businesses and individuals having more confidence in the economy and seeking financing for investment or expansion. In other words, as GVA (as logarithmic value) increases, it indicates a growing productive capacity and output, which could lead to higher loan demand (as logarithmic value). The negative association between the lagged GVA (as logarithmic value) and the loan amount (as logarithmic value) implies that there may be a diminishing effect after a certain point. Beyond a certain threshold, the relationship turns negative, indicating that the growth of the economy may lead to decreased loan demand. This could be due to factors such as financial constraints or concerns about potential economic downturns in Mali. Moving beyond cross-country analysis, to country-specific research that exploits unique characteristics of a specific emerging market is important, as this result shows.

H3 and H4 focus on different stages of agricultural cycles. The postharvest season is, on average, statistically significantly positively associated with the loan amount. The lean season is, on average, statistically significantly negatively associated with the loan amount. The statistically positive effect of the postharvest season is, however, much smaller than the negative effect of the lean season. This result is in line with theoretical suggestions and evidence that farmers can sell parts of their harvest to pay off debts and/or invest in postharvest technologies and demand credit to complementarily finance an investment. The result is also in line with the empirical literature that farmers are credit constraint in the postharvest period and, therefore, demand credit (e.g., Channa et al., 2022). The result is also in line with studies that showing credit market seasonality exist in other economic sectors, such as the corporate credit market (Murfin & Petersen, 2016). Our results indicate that farmers have different need for finance at different stages of the harvest season. Following the OLS estimation, we cannot reject H3 and H4.

Focusing on H5, male farmers have, on average, higher volumes of granted credits, as the positive value in Table 3 indicates. This result is statistically significant across all four specifications. According to the OLS results, we cannot reject H5. This result is in line with other results that women receive a relatively smaller credit volume (e.g., Agier & Szafarz, 2013; Weber & Musshoff, 2012). Several potential explanations for differences in loan volume between male and female could exist. First, this could indicate a stronger credit rationing of female farmers. Second, female farmers might be applying for smaller quantities simply because they do not require that much credit or because they apply for smaller amounts given their risk aversion. Third, the possibility that differences in creditworthiness between male and female applicants exist cannot be entirely ruled out. Johnen and Mußhoff (2023) argue that gender differences in socioeconomic variables can explain variations in the use of formal digital credit in Kenya. A further theoretical explanation could be that loan officers capture such differences through information that remains unreported and is, hence, not included in the MIS of the BNDA. The gender differences in entrepreneurial characteristics and performances in developed countries are debated in the literature, and the evidence of discrimination remains controversial. For instance, De Mel et al. (2009) provided evidence that grants generate profit increases for male microentrepreneurs but not for their female counterparts in Sri Lanka. Chamboko et al. (2021) showed that clients prefer to transact with agents of their own gender in the Democratic Republic of Congo. Female clients had a robust preference for female agents even when they are less available, particularly when making high-value transactions and when they have higher account balances. The under-representation of female agents may contribute to the persistent gender gap in financial access and usage (Chamboko et al., 2021). Perrin and Hyland (2023) highlight an association between gender equality in legislation and women's access to financial services. Increased legal equality helps decrease women's involuntary financial exclusion. However, adverse social norms can undermine the advantageous outcomes of legal equality (Perrin & Hyland, 2023). Fisman et al. (2017) highlighted that cultural proximity between lenders and borrowers increases credit access as well as

the quantity of granted credits in India. Such ethnic variables might affect the results. However, due to data limitation we cannot investigate the three mentioned channels further.

However, evidence of gender disparities in Mali exists in multiple sectors of the society. Diamoutene and Jatou (2020) showed that being a female maize farmer has a negative effect on access to credit in Mali. Kuépié, (2016) emphasized that women in Mali, even with the same level of education as men, have less chance of getting into the top job segment. Additionally, the author estimated a fertility burden that implies that having a large family is another obstacle for female access to high-quality jobs (Kuépié, 2016). Doss et al. (2015) estimated that the percentage of women landholders is only 3.1% in Mali, despite the high share of females working in agriculture.

Across all four model specifications, the OLS results for the five hypotheses remain robust. The goodness of fit for the regressions is similar and differs only at the second decimal. All selected variables to test the five hypotheses are highly statistically significant, and their coefficients, except the lagged GVA, have the expected association. Additionally, all control variables included in the estimation are statistically significant. For example, the number of due dates and the number of granted credits at the BNDA influence the loan amount statistically significant. However, the estimation in column (4) is our preferred estimation, because it controls for unobserved region-specific and time-invariant heterogeneity.

To assess the robustness of the findings, the sample size is reduced and only one credit for each farmer is included. In other words, we filter all granted credits in such a way that only the first loan granted between 2010 and 2020 is taken into account. The aim of this robustness test is to control for distortions due to interdependent observations. We run the OLS regression (Equation 1) with the reduced sample size of 9,246 observations again. The results are in line with the previous estimated model and also lead to highly statistically significant results. No qualitative differences can be found between the models in Table 3 and the robustness regression (compare Appendix Table A2). Hence, the estimations in Table 3, which include all credit observations of Malian farmers, are appropriate and provide robust results. The results are robust to multiple hypothesis testing (compare Appendix Table A3). Furthermore, the results are also robust when applying an unbalanced panel regression with individual-level fixed effects (compare Appendix Table A4). Only the effect of the postharvest season switches from a positive statistically significant association to a statistically significant negative one when using time and individual fixed effects. Including only time specific fixed effects, the results remain in line with the pooled OLS and the other applied robustness tests.

Above, we show the OLS results for the five hypotheses. However, the data in this study is observational and based on a selected sample, for example, because the access to credit is voluntary or that farmers who receive credits are more capable than others to access these funds because of their wealth, education, production level. A further example would be that clients might enter the loan contract with different experiences, expectations, and preferences. Differences in loan demand behavior may be due to factors that we cannot capture in our estimates (Grohmann et al., 2021). In short, self-selection in access to credit is a potential source of endogeneity as well as that some of the regressions may suffer from unobserved variable bias. In the absence of a randomized control trial, this problem cannot fully be solved. It is possible that some of the patterns we find have other explanations than the ones discussed above.

In the next step, Lasso is applied to strengthen the results. The three different methods for determining λ , introduced in Section 4 are applied (cv, minBic, adaptive). A λ that minimizes the BIC (minBic) and a λ determined by the cv lead to the same variable selection and also to a similar performance when focusing on the quality criteria. Hence, λ that minimizes the cv was selected (compare Appendix Table A5). The final Lasso estimations selected 17 out of 33 hypothetical covariates. The results of the preferred Lasso specification are presented in column (2) of Table 4. For comparison with the OLS results, column (1) highlights the preferred OLS regression from Equation (1) with time and region fixed effects.

The data-driven feature selection led to a different set of covariates that are included in the post-Lasso estimation. All variables considered in the feature selection have been presented in the data section. Appendix Table A1 contains the corresponding summary statistics. Lasso selects all variables related to our hypotheses and all

TABLE 4 OLS and Lasso postestimation results for credit demand.

	(1) OLS with time and regional FE	(2) Lasso
Variables related to the hypothesis		
Interest rate (logarithmic value)	-3.219*** (0.041)	-3.128*** (0.016)
GVA before tax (logarithmic value)	5.921*** (0.279)	2.216*** (0.105)
Lagged GVA before tax (logarithmic value)	-6.133*** (0.245)	-0.904*** (0.128)
Dummy if credit is granted in the postharvest season (0 = no, 1 = yes)	0.030** (0.013)	0.068*** (0.013)
Dummy if credit is granted in the lean season (0 = no, 1 = yes)	-0.143*** (0.009)	-0.132*** (0.009)
Gender dummy (0 = female, 1 = male)	0.342*** (0.032)	0.285*** (0.022)
Control variables		
Number of due dates (continuous variable)	-0.004*** (0.000)	-0.002*** (0.000)
Number of granted credits by client (continuous variable)	0.004*** (0.000)	-0.025*** (0.002)
Amount of interest (logarithmic value)	0.789*** (0.005)	0.772*** (0.003)
Year credit was granted		-0.124*** (0.008)
Code of BNDA agency		0.000 (0.000)
Number of open granted credits by client (continuous variable)		0.088*** (0.009)
Number of closed granted credits by client (continuous variable)		0.030*** (0.002)
Dummy if client has only one granted credit (0 = no, 1 = yes)		-0.065*** (0.014)
Frequency of credit (absolute value)		-0.115*** (0.007)
Dummy if objective of credit is rice (0 = no, 1 = yes)		-0.229*** (0.039)

TABLE 4 (Continued)

	(1) OLS with time and regional FE	(2) Lasso
Dummy if objective of credit is tractor (0 = no, 1 = yes)		-0.080*** (0.027)
Observations	28,764	28,764
R ²	0.773	0.772
Adjusted R ²	0.773	0.772

Note: Standard errors in parentheses. Independent variable is credit amount disbursed (as logarithmic value).

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Source: Authors' own calculations based on BNDA data.

control variables of the OLS estimation (Equation 1). Furthermore, Lasso selects eight additional covariates and included the following additional explanatory variables in the postestimation: the number of granted open and hence, not yet repaid credits, the number of granted repaid credits (closed credits per client), the agency that granted the farmers credit, the frequency of the credit repayment, if the credit was requested to buy a tractor and if the credit was granted in relation to rice production.

Lasso is useful in determining the importance of variables. However, it is important to note that not all statistically significant coefficients in the post-Lasso estimation necessarily imply importance. In other words, while Lasso helps confirm the statistical significance of variables related to our five hypotheses in determining the loan amount, it also identifies additional covariates that are deemed important. As a result, the coefficients may undergo changes, which are discussed in detail in the following sections, to test the robustness of the coefficients.

The Lasso results are in line with the OLS results. Using Lasso leads to a negative interest rate elasticity. The relationship is statistically significant. The coefficient indicates that the loan demand of Malian farmers reacts elastically to a change in interest rate, though slightly smaller when compared to the coefficient obtained from the OLS results. According to the OLS and Lasso results, H1 cannot be rejected. Lasso selects the GVA and the lagged GVA (both as logarithmic value) variable in the final model. The results are in line with the OLS results, but again the coefficient in the post-Lasso estimation is slightly smaller compared to the coefficient from the OLS results. The lagged GVA is inelastic in the Lasso estimation. This means that a 1% change in GVA leads to a relatively smaller change in loan demand. Accordingly, H2 can be rejected, because we expected a statistically significant positive association of the lagged GVA on the granted loan amount. Our result indicates an inverse relationship. This result is in contrast to the association that Fecke et al. (2016) find for the loan demand in the German agricultural sector.

Lasso selects the postharvest period in the final estimation model. The effect of the postharvest period on the loan demand remains, on average, positive and statistically significant. However, the coefficient in the post-Lasso estimation is twice as large compared to the coefficient obtained from the OLS. Lasso also selects and confirms the negative relationship between the lean season and the loan demand. However, the coefficient in the post-Lasso estimation is slightly smaller compared to the coefficient from the OLS results. Because of that, we cannot reject H3 and H4. This indicates a statistically significant relationship between the different stages of the harvest cycle and loan demand. Focusing on H5, gender was also included in the Lasso estimation. The effect size is smaller in comparison to the OLS regression, but leads to statistically significant negative results. Hence, the hypothesis cannot be rejected. This result provides evidence of gender discrimination in Mali. Nevertheless, more efforts are needed to get a better understanding and to adjust the gender inequalities that harm economic activity in developing countries.

In summary, while not a causal analysis, our main results suggest that the interest rate, the harvest period, the macroeconomic environment, measured as GVA in the agricultural sector, as well as the gender of the farmer are determinants of farmers loan demand in the Malian agriculture sector. Although we cannot completely rule out other mechanisms, the relationships of our five hypotheses are reasonable and consistent with the economic theory. Nevertheless, when drawing conclusions from the results in this study, the fact that we are here dealing with an observational study should be kept in mind.

6 | CONCLUSION

The formal credit sector continues to play an important role in financing the development toward a resilient and sustainable development. However, the determinants of loan demand in the agricultural sector are of interest to adjust market failures and improve the provision of liquidity to the agricultural sector. Therefore, the paper investigates the determinants of loan demand in agriculture in Mali by using a unique and comprehensive data set of granted loans for agricultural farmers covering the period from 2010 to 2020 and consisting of 28,746 observations.

Following the current literature, first, an OLS regression is estimated. The explanatory variables are selected based on theoretical considerations and the literature on credit demand. Second, the ML method Lasso is applied. The selection of explanatory covariates is data-driven and is a further literature extension. Lasso selected 17 out of potential 33 variables in the postestimation, including all five variables related to our hypotheses. The OLS and Lasso results yield qualitatively the same results. Lasso reduce multicollinearity and p-hacking concerns and strengthen the selection of our hypotheses. Focusing on the five hypotheses, we find evidence that interest rates, the GVA of the agricultural sector, the seasonal period as well as the gender of the farmer have a statistically significant effect on loan demand. We find evidence that the interest rate is highly elastic, farmers' loan decisions depend on the agricultural cycle, and that female farmers receive a smaller amount of credit compared to men.

By analyzing the determinants of loan demand in agriculture based on a detailed large data set at the farm level, we contribute to the existing literature. Our results are based on one empirical example from Mali but could have several practical implications for banks in the agricultural sector of the Global South. The interest rate elasticities of loan demand could serve as decision support for banks as well as the decision-making process for monetary policy. This is relevant, for example, when quantifying the effects of interest rate changes on the agricultural sector. Hence, previous studies that argued against a credit policy due to low inelasticity of demand (e.g., Bell et al., 1997; Kochar, 1997) do not hold universally, as the example of Mali shows. Moreover, the gender of the farmer plays an important role in the amount of the granted loan. On the one hand, our result indicates that women receive smaller loans. Due to data limitation, we cannot take the effect of credit rationing into account. On the other hand, only about 4% of all clients who received credit in our data are female. This could indicate that many Malian farmers may still have difficulties accessing credit in general. This implies that gender-based targeting could improve access to agricultural credit, in particular.

Our findings have practical implications for banks operating in the agricultural sector. By incorporating this information into the design of future loan products, financial institutions can stimulate the demand for loans among farmers, particularly female farmers. The interest rate elasticity of loan demand can serve as a valuable decision-making tool for banks, enabling them to assess the potential impact of interest rate adjustments on agriculture ex ante. Furthermore, we have observed that macroeconomic factors such as the lean season, postharvest season, and GVA play an important role in determining Malian farmers' loan demand. By including these factors in the development of future loan products, financial institutions can further stimulate the demand for loans among farmers, with a specific focus on empowering female farmers. The considerable role of the Malian agricultural sector makes these results relevant for political leaders who seek to address market failures, strengthen economic development, and enhance the resilience of agricultural smallholders. Additionally, the development of

state-promoted loan programs can facilitate sustainable structural changes within the Malian agricultural sector. These initiatives have the potential to contribute to the overall economic development and resilience of the agricultural sector in Mali.

Our paper contributes to a broader debate: the analysis of credit demand in the Global South and the use of ML techniques in agricultural economics. The analysis highlights that ML is a useful extension to the analysis of credit demand and the business decision-making process of a company. This paper is a contribution to previous studies that highlighted how ML is applied in business decision-making processes. However, one should also be aware of trends in nontraditional finance. Further research on nontraditional finance that takes advantage of novel data and uses causal methods is encouraged. Future research could focus on further dimensions of loan demand, such as clients' socioeconomic characteristics or farmers' risk attitudes. On the one hand, a strength of the study is the use of data from multiple years and production seasons. On the other hand, it would be of interest if the analysis also included rejected credit requests as well as the demanded loan amount to analyze credit rationing. As discussed in the Results section, we provide three potential explanations for the possible differences in loan volume between males and females (credit rationing, apply for smaller loan amounts, differences in creditworthiness). Future research could focus on providing causal evidence to determine the driving factors behind these differences in loan demand. Future research could also investigate the association between climate variables and loan demand, as climate serves as another exogenous variable for farmers. Weather events in different regions of Mali might have an adverse impact on productivity and, consequently, on loan demand. While we lack the necessary data to investigate the expected U-shaped relationship between GVA and loan demand, this question would be an interesting avenue for future research.

Our results being based on one commercial bank in Mali, our approach could be applied and replicated for other countries in the Global South to analyze if heterogeneous results exist.

AUTHOR CONTRIBUTIONS

Tim Ölkens: Conceptualization; data curation; formal analysis; methodology; software; writing—original draft. **Oliver Mußhoff:** Funding acquisition and Supervision. **Tim Ölkens and Oliver Mußhoff:** Writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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APPENDIX A

See Tables A1, A2, A3, A4, and A5.

TABLE A1 Explanatory variables included in Lasso selection.

	Mean	SD	Min.	Max.
Variables related to the hypothesis				
Interest rate (as logarithmic value)	2.350	0.424	0.000	2.773
GVA before tax (as logarithmic value)	22.360	0.147	22.110	22.541
Lagged GVA before tax (as logarithmic value)	22.323	0.152	22.064	22.541
Dummy if credit is granted in the lean season (0 = no, 1 = yes)	0.475	-	0.000	1.000
Dummy if credit is granted in the postharvest season (0 = no, 1 = yes)	0.132	-	0.000	1.000
Gender dummy (0 = female, 1 = male)	0.966	-	0.000	1.000
Control variables				
Amount of interest (as logarithmic value)	11.751	2.250	0.000	17.728
Number of granted credits by client (continuous variable)	9.009	20.147	1.000	217.000
Number of open granted credits by client (continuous variable)	0.178	0.594	0.000	6.000
Number of closed granted credits by client (continuous variable)	7.948	19.940	0.000	215.000
Dummy if client has only one granted credit (0 = no, 1 = yes)	0.102	-	0.000	1.000
Name of agency	20.912	15.617	1.000	49.000
Frequency of credit (as absolute value)	1.979	0.762	1.000	5.000
Number of due dates (continuous variable)	6.040	11.817	0.000	120.000
Dummy if objective of credit is rice (0 = no, 1 = yes)	0.011	-	0.000	1.000
Dummy if objective of credit is tractor (0 = no, 1 = yes)	0.026	-	0.000	1.000
Year credit was granted	2015.723	3.016	2010.000	2020.000
Dummy if credit granted 2010	0.052	-	0.000	1.000
Dummy if credit granted 2011	0.087	-	0.000	1.000
Dummy if credit granted 2012	0.053	-	0.000	1.000
Dummy if credit granted 2013	0.061	-	0.000	1.000
Dummy if credit granted 2014	0.075	-	0.000	1.000
Dummy if credit granted 2015	0.101	-	0.000	1.000
Dummy if credit granted 2016	0.121	-	0.000	1.000
Dummy if credit granted 2017	0.112	-	0.000	1.000
Dummy if credit granted 2018	0.112	-	0.000	1.000

TABLE A1 (Continued)

	Mean	SD	Min.	Max.
Dummy if credit granted 2019	0.121	-	0.000	1.000
Dummy if credit granted 2020	0.104	-	0.000	1.000
Month credit was granted	6.257	2.935	1.000	12.000
Dummy if credit granted in 1st quartal	0.172	-	0.000	1.000
Dummy if credit granted in 2nd quartal	0.378	-	0.000	1.000
Dummy if credit granted in 3rd quartal	0.285	-	0.000	1.000
Dummy if credit granted in 4th quartal	0.165	-	0.000	1.000
Observations	28,764			

Source: Authors' own calculations based on BNDA data.

TABLE A2 Subsample OLS regression results (one credit per client) for credit demand.

	(1) OLS	(2) OLS with time FE	(3) OLS with regional FE	(4) OLS with time & regional FE
Variables related to the hypothesis				
Interest rate (logarithmic value)	-3.415*** (0.083)	-3.488*** (0.078)	-3.409*** (0.084)	-3.480*** (0.078)
GVA before tax (logarithmic value)	0.559*** (0.152)	5.022*** (0.584)	0.551*** (0.153)	4.984*** (0.579)
Lagged GVA before tax (logarithmic value)	-1.753*** (0.151)	-5.457*** (0.507)	-1.760*** (0.154)	-5.434*** (0.504)
Dummy if credit is granted in the post-lean season (0 = no, 1 = yes)	0.052*** (0.020)	0.053*** (0.020)	0.050** (0.021)	0.050** (0.020)
Dummy if credit is granted in the lean season (0 = no, 1 = yes)	-0.065*** (0.011)	-0.078*** (0.011)	-0.063*** (0.011)	-0.076*** (0.011)
Gender dummy (0 = female, 1 = male)	0.216*** (0.050)	0.216*** (0.049)	0.219*** (0.049)	0.220*** (0.048)
Control variables				
Amount of interest (logarithmic value)	0.766*** (0.010)	0.778*** (0.010)	0.766*** (0.011)	0.777*** (0.001)
Number of due dates (continuous variable)	-0.003*** (0.000)	-0.003*** (0.000)	-0.003*** (0.001)	-0.002*** (0.001)
Number of granted credits by client (continuous variable)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.006*** (0.001)

(Continues)

TABLE A2 (Continued)

	(1)	(2)	(3)	(4)
	OLS	OLS with time FE	OLS with regional FE	OLS with time & regional FE
Regional FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
R ²	0.766	0.774	0.768	0.775
Observations	9,246	9,246	9,246	9,246

Note: Standard errors in parentheses. Independent variable is credit amount disbursed (as logarithmic value).

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Source: Authors' own calculations based on BNDA data.

TABLE A3 OLS results for credit demand: Romano-Wolf step-down adjusted p values.

	p Value	Resample p value	Romano-Wolf p value
Variables related to the hypothesis			
Interest rate (as logarithmic value)	0.000	0.010	0.010
GVA before tax (as logarithmic value)	0.000	0.010	0.010
Lagged GVA before tax (as logarithmic value)	0.000	0.010	0.010
Dummy if credit is granted in the postharvest season (0 = no, 1 = yes)	0.009	0.010	0.010
Dummy if credit is granted in the lean season (0 = no, 1 = yes)	0.000	0.010	0.010
Gender dummy variable (0 = female, 1 = male)	0.000	0.010	0.010
Interest rate (as logarithmic value)	0.000	0.010	0.010
Control variables			
Number of due dates (continuous variable)	0.000	0.010	0.010
Amount of interest (as logarithmic value)	0.000	0.010	0.010
Number of granted credits by client (continuous variable)	0.000	0.010	0.010
Observations	28,764	28,764	28,764

Note: Number of resamples: 100. Independent variable is credit amount disbursed (as logarithmic value).

Source: Authors' own calculations based on BNDA data.

TABLE A4 Unbalanced panel estimation.

	(1)	(2)	(3)
	Panel	Panel with time FE	Panel with time and individual FE
Variables related to the hypothesis			
Interest rate (as logarithmic value)	-3.069*** (0.046)	-3.176*** (0.042)	-1.454*** (0.045)
GVA before tax (as logarithmic value)	1.350*** (0.094)	6.371*** (0.295)	3.031*** (0.214)
Lagged GVA before tax (as logarithmic value)	-2.495*** (0.100)	-6.519*** (0.258)	-2.693*** (0.186)
Dummy if credit is granted in the postharvest season (0 = no, 1 = yes)	0.0145 (0.013)	0.027** (0.013)	-0.88*** (0.14)
Dummy if credit is granted in the lean season (0 = no, 1 = yes)	-0.137*** (0.010)	-0.150*** (0.009)	-0.143*** (0.01)
Gender dummy (0 = female, 1 = male)	0.360*** (0.032)	0.352*** (0.031)	-
Control Variables			
Amount of interest (as logarithmic value)	0.777*** (0.005)	0.789*** (0.005)	0.391*** (0.01)
Number of due dates (continuous variable)	-0.010*** (0.000)	-0.005*** (0.000)	0.026*** (0.001)
Number of granted credits by client (continuous variable)	0.004*** (0.000)	0.003*** (0.000)	-
Individual FE	No	No	Yes
Year FE	No	Yes	Yes
R ²	0.754	0.762	0.932
Observations	27,385	27,385	27,385

Note: Standard errors in parentheses. Dependent variable is the credit amount disbursed (log).

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Source: Authors' own calculations based on BNDA data.

TABLE A5 Lasso—Postselection coefficients.

Name	MSE	R ²	Observations
OLS			
Sample 1	0.439	0.786	14,382
Sample 2	0.419	0.798	14,382
cv			
Sample 1	0.439	0.786	14,382
Sample 2	0.435	0.791	14,382
minBIC			
Sample 1	0.439	0.786	14,382
Sample 2	0.435	0.791	14,382
Adaptive			
Sample 1	0.428	0.791	14,382
Sample 2	2.319	-0.116	14,382

Abbreviations: cv, the Lasso specification based on the cross validation mean; MSE, mean squared error. minBic, the lambda that led to the lowest BIC.

Source: Authors' own calculations based on BNDA data.

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