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Why do small farmers have less access to credit? a microdata analysis of the Peruvian case

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ABSTRACT: Small farmers face many challenges regarding financial inclusion, which adversely affect farm productivity and reduce their income and welfare, especially in developing countries. An optimal comprehension of financial services in specific contexts is a significant challenge, especially for smallholders. So, the question is obvious: Why do small farmers have less access to credit? The main purpose of the present study is to estimate the impact of the determinants of credit access in the Peruvian agricultural sector from 2015 to 2019, considering farm size in different geographic areas, using an econometric methodology for cross-sectional data. The study used data extracted from the Peruvian National Agricultural Survey. The results reveal the probability of farmers accessing credit. However, it varies according to farm size, and was, on average, around 30% at the national level, whereas the size of the farms was identified as a crucial factor. Being a smallholder reduces farmers' probability of access to credit, while being a large-scale farmer nearly doubles this probability. Furthermore, the study estimated the trend in the odds ratios, which are associated with certain characteristics of the farming population in Peru.
Keywords: financial inclusion; agricultural finances; credit invisibility; smallholders.

Por que os pequenos agricultores têm menos acesso ao crédito? uma análise de microdados do caso Peruano

RESUMO: Os pequenos agricultores enfrentam muitos desafios com relação à inclusão financeira, que têm efeitos adversos sobre a produtividade agrícola e reduzem sua renda e seu bem-estar, especialmente nos países em desenvolvimento. A compreensão ideal dos serviços financeiros em contextos específicos é um desafio significativo, especialmente para os pequenos agricultores. Portanto, a pergunta é óbvia: Por que os pequenos agricultores têm menos acesso ao crédito? O principal objetivo do presente estudo é estimar o impacto dos determinantes do acesso ao crédito no setor agrícola peruano de 2015 a 2019, considerando o tamanho das fazendas em diferentes áreas geográficas, usando uma metodologia econométrica para dados transversais. O estudo usou dados extraídos da Pesquisa Agrícola Nacional do Peru. Os resultados revelam que a probabilidade de acesso ao crédito pelos agricultores, embora varie de acordo com o tamanho da fazenda, foi em média de cerca de 30% em nível nacional, enquanto o tamanho das fazendas foi identificado como um fator crucial. O fato de ser um pequeno produtor reduz a probabilidade de acesso ao crédito, enquanto o fato de ser um grande produtor quase dobra essa probabilidade. Além disso, o estudo estimou a tendência dos índices de probabilidade, que estão associados a determinadas características da população agrícola no Peru.
Palavras-chave: inclusão financeira; finanças agrícolas; invisibilidade do crédito; pequenos proprietários.

1. INTRODUCTION

Agricultural financial inclusion can boost the growth of the farming sector, which is key to ensuring food security and economic growth. Due to the heterogeneity of the agricultural sector, financial credit constraints can have important effects by making farmers' choice of crops and livestock production more complex, reducing access to markets, and increasing risks. Farmers face a lot of challenges regarding credit constraints, which have adverse effects on farm productivity and reduce their income and welfare, especially in developing economies (GUIRKINGER; BOUCHER, 2008; SIMTOWE et al., 2008; AMANULLAH et al., 2020; OKORUWA et al., 2020; Benni, 2022).

Conning; Udry (2005) proposed that rural financial options in most developing countries may affect decisions related to the scale of agricultural operations, crop choices, and investing in risky but profitable new technologies or infrastructure to prompt their economic development. In addition, Boucher; Guirkinger (2007) pointed out that informal and formal credit sectors coexist despite large interest rate differentials in developing countries, stating that informal lenders' better access to local information allows them to offer credit options to individuals excluded from the traditional financial sector.

Further, Phiri et al. (2019) found that information is essential for improved and sustainable agricultural productivity. However, some problems associated with smallholders' access to information in developing countries are related to farmers' lack of financial resources to purchase agricultural information. Therefore, an optimal comprehension of financial services in specific contexts is a significant challenge, especially for smallholder farmers in developing countries.

Khandker; Koolwal (2014), pointed out the importance of the expansion and strength of an ecosystem of financial institutional support that focuses more on reducing access to credit for smallholder farmers. Insufficient access to credit is a critical obstacle that influences the relatively low capitalization of the sector, as well as the low incorporation of technologies and technical models in small and medium-sized enterprises (SMEs) in the agricultural sector, leading to low productivity. Similarly, Benni (2022) pointed out that digital innovation in financial markets has the potential to alleviate most of the critical barriers that currently limit access to financial services for rural and vulnerable actors. Nonetheless, the benefits gained from expanding customer service channels offered by financial institutions might differ in urban and rural areas.

Hence, farmers in rural areas, especially low-income households in developing countries, still face difficulties in accessing credits to enhance their productivity and sustainable development of agriculture activities (BALANA; OYEYEMI, 2022; CHANDIO; JIANG, 2018; LINH et al., 2019; MOAHID; MAHARJAN, 2020). According to De Olloqui and Fernández (2017), interventions related to the financing of the primary agri-food sector and rural development in the Latin American region generate the capacity to address other major challenges related to the sector, such as risk management against the effects of climate change and the productive inclusion of the lower-income sectors of the rural population, thereby reducing poverty and inequality gaps.

Although, in most countries in Latin America, there is a limited capacity of the formal financial system to provide services to the agricultural sector (Alvarado; Pintado, 2017; Benni, 2022; Trivelli; Caballero, 2018), the impact of increasing credit accessibility in rural territories may have unexpected effects on small farmers in terms of improving their economic development. According to Schejtman; Berdegué (2004), in the rural sector, agricultural enterprises with land suitable for export production activities and capacities to access information and credits have competitive advantages, which, in the long term, lead to profit concentration arising from the production of a few exportable products.

However, Escobal et al. (2015) found that programs to prompt production and access to credit in Latin America, which focused on transforming small-scale grain production to export agriculture, did not necessarily stimulate family farming in rural territories; instead, the main beneficiaries of the process of product development in rural areas were large investors. Thus, credit affordability in the agricultural sector is an ongoing challenge, and there is still an important gap to be filled. However, the dynamics of the conditions in the geographically mega-diverse territories are not yet fully understood.

In the case of Peru, like many developing countries, in the last decades, the incorporation of a growing number of institutions and providers of financial services has developed rapidly, especially in urban areas, resulting in a sort of financial exclusion of rural territories, predominantly agriculture-based territories (JANVRY et al., 2003). The greatest challenge facing rural finances and financial institutions in Peru is to generate competitive mechanisms, products, and services that meet the financial demands of the rural population and agricultural SMEs in particular (TRIVELLI; VENERO, 2007). Additionally, Ghezzi (2021) pointed out that agricultural financing is still challenging in the Peruvian economy as less than 10% of rural family agriculture producers meet their credit demand through public or private entities. Trivelli (2021) pointed out that, in addition to the risks that characterize the agricultural SME sector in Peru, the problem of agricultural financing is a structural problem caused by administrative and operational costs.

In line with this, operational costs in rural areas could be related to the occupation of territory by formal Peruvian financial service providers and the rate of access to credit by Peruvian farmers (RAMOS-SANDOVAL; LARA, 2023). Thus, interventions in financing the agricultural sector must combine different instruments of entities of banking and nonbanking systems. This indicates that promoting investment in agricultural SMEs is especially relevant in resource scarcity and climate emergencies. Therefore, there should be a rethinking and adaptation of traditional practices that appeal to the resilience capacity of the agricultural sector. Developing countries should implement new technologies and capitalize on available assets and the rural environment. This requires a comprehensive knowledge of the role played by all actors in the sector (e.g., the state, private companies, and producers) to generate competitive mechanisms, products, and financial services, leading to the acquisition of greater knowledge of the supply and financial demand of the rural agricultural SME sector.

The main purpose of the present study is to estimate the determinants of credit demand in the Peruvian agricultural sector from 2015 to 2019, with a particular emphasis on the supply of financial services available in the geographical area at different scales using an econometric methodology for cross-sectional data. We used data extracted from the Peruvian National Agricultural Survey (ENA). Using a logit econometric model, this study estimates the probability that a family or entrepreneur farmer will be in a formal financial system after obtaining a loan. The research question is as follows: "Is the probability of access to credit in the Peruvian agricultural sector mainly explained by variables such as the type of farmer, the type of activity, the geographical domain, the geographical area, and the supply of financial services in the geographical area?" To the best of our knowledge, this is the first study that explores such a research question using microdata at the farmer level for an Andean country.

The next section presents a literature review with relevant evidence related to the research question, presenting further information about spatial considerations and financial access in rural areas. The third section presents the methodological approach with the national-level summary data of the Peruvian financial system, including variables from previous studies, correlations, and descriptive statistics. In the fourth section, we present the results of the cross-sectional logit and transitional models from 2015 to 2019. The fifth section presents the discussion and conclusions of the study.

2. TERRITORIAL CONSIDERATIONS OF CREDIT INVISIBILITY IN RURAL AREAS

According to Salazar (2023), there is a consensus in considering Latin America and the Caribbean (LAC) as the second most urbanized region in the world, where 80% of its population lives in cities and the remaining 20% in rural areas; this is based on the traditional dualistic classification that "if it is not urban, then it is rural." This classification is too general, raising the risk that some features relevant to the dynamics of various territories may be misunderstood or underestimated. Territorial analysis that considers geographic approximations and focuses on LAC countries should be carried out to better classify the dynamism of each territory in the last few years.

Petersen; Rajan (2002) proposed that variables such as proximity have become less relevant as a factor of non-accessibility to credit due to the rise of new technologies. However, many transactions still require physical proximity. In addition, Pedrosa (2008) pointed out that distance is a de facto risk for the portfolio of financial institutions. Therefore, they need to screen the demand for finance accordingly. On the other hand, Pal; Laha (2014) suggested that proximity to traditional financial institutions is expected to lead to better access to financial services. However, as transaction costs for these institutions are higher in rural areas, their presence is not primarily felt in agricultural areas.

Thus, credit invisibility and the proximity of financial institutions are potential causes of the invisibility of the territories, bearing in mind the limited or nonexistent presence of traditional institutions in the financial system and the financial inclusion gap (BREVOORT et al., 2018). However, Prieto et al. (2021) pointed out that the territory may be understood or analyzed in many ways based on the conceptual framework used. Therefore, rural areas conventionally experience credit constraints. Although large rural areas have very different characteristics, all rural areas face common challenges in accessing credit. We believe it is important to identify the territorial effect of this financial exclusion.

According to Brevoort et al. (2016), having a credit history and credit score is an important determinant of credit accessibility. They provided the first documented analysis regarding the characteristics of consumers, defined as "credit invisible" and consumers who may have "unscorable" credit files. However, Balana; Oyeyemi (2022) proposed that some small farmers do not participate in the credit system, thus becoming invisible to credit, which may not necessarily mean they are not eligible for credit. Still, they may not have access to adequate information. Consumers and small producers in rural areas may qualify as invisible credit as most do not have a credit history with one of the nationwide credit reporting companies. Therefore, farmers, especially those in rural areas, may have an unscorable credit file, meaning that they have a thin file and an insufficient credit history, or they have stale files and lack any recent credit history, which is the reason why they are denied access to credit because they do not have credit records that can be scored. Furthermore, credit costs are higher if credit is approved than in full-information situations.

This study proposes a comprehensive analysis of credit constraints in smallholder farming and enterprises in the Peruvian context, considering geographical distribution, farming type, and farm size as factors of credit constraints related to transaction cost rationing and risk rationing.

2.1. Peruvian agricultural sector credit demand and access to credit

In Peru, according to Del Castillo et al. (2000), the main activity of the population in rural areas is agriculture (about 95%). These people have a low level of capitalization in terms of heritage and financial resources. Food expenses represent more than 60% of their income. Human capital is low since the heads of households tend to have a low level of education. Rural customers and producers face a series of risks (e.g., climate shocks) that lead to neglect of their credit demands in the formal financial market (GUTIÉRREZ, 2004).

According to the results of the National Agricultural Census-CENAGRO 2012 (INEI, 2014), the demand for credits in the agricultural sector is mainly met by national banks (e.g., Agrobanco) and local financial institutions (e.g., microfinance institutions and cooperatives). However, as public intervention is the main formal provider, it has not fully covered financial services in the agricultural sector (WIENER, 2021). Meanwhile, other non-financial institutions (e.g., lenders and merchants) serve about a third of the sector's credit demand, which are mainly alternative sources to the formal financial sector, companies in the value chain, or informal loans (BOUCHER et al., 2009; DEMIRGÜÇ-KUNT et al., 2015). This type of financing is more expensive, thus reducing the attractiveness of credit to farmers.

Despite the increase in institutions that meet the financial demand of the sector, the proportion of the agricultural population that requests and accesses credit is still very small, which is only about 10% of the national agricultural population (INEI, 2014). However, the agricultural sector has achieved great economic prominence in the national economy. According to Trivelli (2021), the challenge of expanding access to credit for Peruvian farmers is a pending task as the solutions implemented in the rural financial markets in Peru have not managed to meet the demand of customers in the agricultural sector. Thus, besides the scarce supply of other financial services in the agricultural sector (e.g., FinTech), the shortcomings in rural areas regarding limited access to formal credit in the short, medium, and long term still prevail.

Focusing on the need, demand, and obtaining credit in the Peruvian agricultural sector, Alvarado; Pintado (2017) pointed out that the need for credit by agricultural producers is almost 70%, which demonstrates a potential market that needs to be served, making it vital to promote rural producers' access to financial services as the probability that an agricultural producer would obtain credit in the formal financial market is around 87%. However, they indicated that despite the high percentage of demand, the probability that agricultural producers will request financing is only 10.8%. Regarding this, Wiener (2021) concluded that many excluded agricultural producers are interested in obtaining credits and other financial services and far exceed producers who access these services. This is not due to risk aversion or low production expectations but to the neglect of rural financial service providers in the country. In this way, we aim to uncover the untapped potential of the agricultural sector by promoting various credit sources. In contrast, public and private financial institutions should collaborate to provide financing opportunities to SMEs in this sector. The lack of access to finance has been a significant challenge, resulting in low capitalization and productivity and inadequate adoption of technologies and technical models by SMEs. We aim to address this issue and support SMEs in the Peruvian agricultural sector.

3. DATA AND METHODS

3.1. Data Characteristics

The data used are from the Peruvian National Farming Survey (ENA in Spanish) from 2015 to 2019 (INEI, 2016-2020). This survey belongs to the Peruvian National Official Statistics Repository, and it has been conducted yearly since 2014 by the Peruvian National Institute of Statistics and Informatics (INEI abbreviation in Spanish) to provide statistical information to build indicators of the Peruvian agricultural sector. The ENA data were collected through direct interviews conducted by INEI each year from May to October (cultivation and harvesting season). We focused on 2015 to 2019 (Table 1) as the survey was not conducted in 2020 because of the coronavirus mobility restrictions, and in the 2021 ENA, information was not collected on Chapter 900—"Financial Services." Regarding the total producer respondents, Table 1 shows the samples by year, of which around 95% were smallholders, who, according to the criteria of the INEI (2014), are those whose farms are below or up to 50 hectares.

Table 1. Number of farmers responded to Chapter 900 of the ENA survey - financial services.
Table 1. Vários agricultores responderam ao Capítulo 900 da pesquisa da ENA - serviços financeiros.

Year	Total	$N_{smallholders\_total}$	% (total)	N_{large_total}	% (total)
2015	28 005	26 848	95.9%	1 157	4.1%
2016	28 840	27 500	95.4%	1 340	4.6%
2017	28 797	27 442	95.3%	1 355	4.7%
2018	28 487	27 088	95.1%	1 399	4.9%
2019	28 364	26 937	95 %	1 427	5.0%

Notes: Nsmallholders_total is the total number of smallholders in the sample. Nlarge_total is the total number of large-scale farmers in the sample.
Source: Own elaboration from the ENA (INEI, 2016–2020).

The sampling method for the ENA's survey was based on the statistical and cartographic information of the CENAGRO 2012 (INEI, 2014), which is the available census of the Peruvian agricultural sector. This study focuses on Chapter 900: Financial Services, specifically question #901 of the survey, in which farmers were asked if they had applied for credit in the last 12 months, while question #902 asked if they got the credit requested (Table 2).

Table 2. Chapter 900 of the ENA survey: Financial Services (Questions #901 and #902).
Table 2. Capítulo 900 da pesquisa ENA: Serviços financeiros (Perguntas #901 e #902).

Question # 901. In the last 12 months, from. to… Have you applied for credit? (Yes = 1; No = 2)
Question # 902. Have you obtained the credit you applied for? (Yes = 1; No = 2)

3.2. Binary logistic regression

We employed the binary logistic regression model as the first model as the dataset allows testing a relationship between a set of independent variables and a binary dependent variable - access to credit (Yes = 1; No = 2). Based on the review of past studies, some explanatory variables - farmer type, agricultural activity, livestock activity, and geographic location (Table 3) - were considered, and their effect on farmers' access to credit was examined. The data exploration and analysis were executed in Python because of the data's size and the study's longitudinal approach. Additionally, the hypothetical independent variables were evaluated to identify statistical issues such as multicollinearity. Multicollinearity among variables was tested using all variables' variance inflation factors (VIFs). The VIF values for all variables do not exceed 10.0, suggesting no serious concern about multicollinearity (Hair et al., 2010).

Table 3. Description of variables hypothesized to affect farmers' credit access.
Table 3. Descrição das variáveis que afetam o acesso dos agricultores ao crédito.

Variable	Description	Value	Expected sign
Farmer type	Classification of the farming unit according to ENA	1 = smallholders 2=large-scale farmers	+
Agricultural activity	Whether the agricultural activity was performed in the last 12 months	0 = non-agrarian 1 = agrarian	+
Livestock activity	Whether livestock activity was performed in the last 12 months	0 = non-livestock 1 = livestock	+
Geographic location	Peruvian administrative division (departments = regions)	1 = Amazonas; 2 = Ancash; 3 = Apurímac; 4 = Arequipa; 5 = Ayacucho; 6 = Cajamarca; 7 = Callao; 8 = Cusco; 9 = Huancavelica; 10 = Huánuco; 11 = Ica; 12 = Junín; 13 = La Libertad; 14 = Lambayeque; 15 = Lima; 16 = Loreto; 17 = Madre de Dios; 18 = Moquegua; 19 = Pasco; 20=Piura; 21 = Puno; 22 = San Martin; 23 = Tacna; 24 = Tumbes; 25 = Ucayali	+ / -

According to Gujarati; Porter (2009), the binary logistic regression model predicts the probability P (Y = 1) as a function of the vector of explanatory variables X_i. The equation of the binary logistic model is a logistic function (1).

$$Y_i = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 \text{ Farmer type}_i + \beta_2 \text{ agriculture}_i + \beta_3 \text{ livestock}_i + \beta_4 \text{ Geographical location}_i + \varepsilon_i \quad (1)$$

, variablevariable. In the context of this study, we consider Y é $igual\ a$ 1 $when\ the\ armerasccess\ is\ to$redit
Since that is the event of interest, and Y=0 otherwise.

$i = 1; \ldots; k$ (farmer)

p_i = probability that $Y_i = 1$ given X_i

$\beta 1, \quad \beta 2, \quad \beta 3, \quad \beta 4$ = parameters of the model

ε_i = error term

4. RESULTS

4.1. Descriptive analysis

Table 4 presents the distribution of farmers with access to credit interviewed in the ENA from 2015 to 2019 (INEI, 2016-2020). According to the data in this table, the access ratio is constant throughout the research period, with an average of less than 15% for smallholders. Among agricultural entrepreneurs, we identified that the accessibility ratio is around 40% of the total number of respondents. Furthermore, regarding farm size, we found better access to credit among agricultural enterprises than small farmers.

Table 4. Distribution of access to credit among farmers from 2015 to 2019.
Table 4. Distribuição do acesso ao crédito entre os agricultores de 2015 a 2019.

Year	$N_{smallholders\_access}$	% (over smallholders*)	N_{large_access}	% (over large-scale*)
2015	3 758	14	464	40.1%
2016	4 155	15.1	557	41.6%
2017	3 724	13.6	531	39.2%
2018	3 328	12.3	508	36.3%
2019	2 864	10.6	495	34.7%

Notes: $\mathbf{N_{smallholders\_access}}$: The number of smallholders declared to have received credit. Nlarge_access: The number of large-scale farmers who declared to have received credit. (*) The total sample is in Table 1. Source: My own elaboration from the ENA (INEI, 2016–2020).

Using a disaggregated approach, the rates of credit access per year were explored based on the farm size, activity type (agrarian or livestock), and geographic location. Figure 1 depicts the rates of accessibility based on farm size by year, finding common patterns among smallholder farmers and agricultural entrepreneurs. For both smallholder farmers ($N_{small\_access\_2017}$ = 3 405; $N_{small\_access\_2018}$ = 3 057; $N_{small\_access\_2019}$ = 2 600) and agricultural entrepreneurs ($N_{large\_access\_2017}$ = 509; $N_{large\_access\_2018}$ = 486; $N_{large\_access\_2019}$ = 463), there was a sustained decrease in the number of farmers accessing credit from 2017 to 2019. However, from 2015 to 2016, there was an increase in the number of farmers accessing credit ($N_{small\_access\_2015}$ = 3 383; $N_{small\_access\_2016}$ = 3 738; $N_{large\_access\_2015}$ = 448; $N_{large\_access\_2016}$ = 524).

Furthermore, regarding the type of activity, we identified a divergent trend between farmers engaged in solely agricultural or livestock activities. In the case of small farmers and agricultural entrepreneurs, agrarian activities had an increasing participation rate during the research period. However, regarding livestock farming activities, there was a sustained decrease in participation by the respondents (Figure 2).

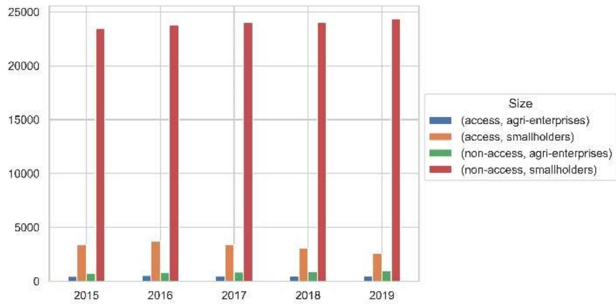

Figure 1. Rates of access based on farm size (agri-enterprises & smallholders) by year, 2015-2019. Source: Own elaboration from the ENA (INEI, 2016–2020).
Figure 1. Taxas de acesso com base no tamanho da exploração agrícola (agroempresas e pequenos proprietários) por ano, 2015-2019. Fonte: Elaboração própria a partir do ENA (INEI, 2016-2020).

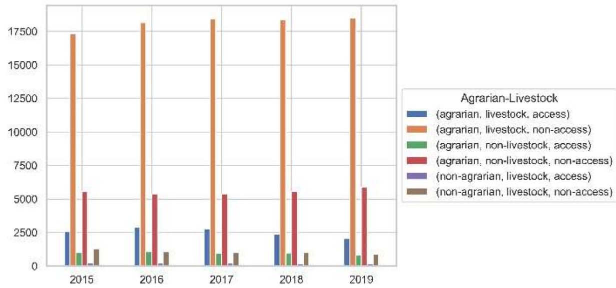

Figure 2. Rates of access based on the type of activity by year, 2015-2019. Source: Own elaboration from the ENA (INEI, 2016–2020).
Figure 2. Taxas de acesso com base no tipo de atividade por ano, 2015-2019. Fonte: Elaboração própria a partir do ENA (INEI, 2016-2020).

Table 5 (Appendix 1a) summarizes the percentages of farmers' access to credit by region. Overall, from a territorial perspective, access to credit decreased from 2015 to 2019. The difference between respondents with access to credit in urban and rural areas is remarkable.

We found that, in the coastal regions, which are predominantly urban, 15% to 25% of farmers accessed credit throughout the research period. The exception is the La Libertad region, which had a ratio of less than 10% and a decreasing trend from 2015 to 2019. In contrast, in territories in the Andean region, where the population distribution is mostly rural (some places had a proportion of more than 50% of the population in rural areas (Apurimac = 54.2%,

Cajamarca = 64.6%, Ayacucho = 58.1%, Huancavelica = 69.5%)), the average accessibility ratios ranged from 6% to 10%, which is quite low. Even in urban departments, the accessibility ratios were relatively lower than those in the coastal areas, except for farmers in the Junín, which had an accessibility ratio ranging from 16% to 11%, although it was decreasing. Finally, in the Amazonian region, the lowest credit accessibility ratio was in Loreto, with a ratio of 2% of access to credit in 2019. Although the regions are predominantly urban, the ratio of access to credit was not more than 20%, and there was a declining trend of credit accessibility in the last few years of the research period.

Table 5. Access to credit of farmers, by region, from 2015 to 2019.
Table 5. Acesso ao crédito por região de agricultores de 2015 a 2019.

Region	Population distribution*		2015	2016	2017	2018	2019
	Urban	Rural	access %	access %	access %	access %	access %
Arequipa[a]	91.8	8.2	21	21	17	16	14
Ica[a]	92.4	7.6	19	16	14	18	15
La Libertad[a]	78.9	21.1	10	9	9	6	8
Lambayeque[a]	81.1	18.9	21	24	27	21	22
Lima[a]	98.3	1.7	17	20	20	18	24
Piura[a]	79.3	20.7	17	19	19	17	16
Tacna[a]	90.1	9.9	22	22	16	17	15
Tumbes[a]	93.7	6.3	34	41	31	29	12
Ancash[b]	63.4	36.6	8	6	6	6	9
Apurímac[b]	45.8	54.2	13	14	14	11	11
Ayacucho[b]	41.9	58.1	10	9	8	9	6
Cajamarca[b]	35.4	64.6	11	10	8	10	9
Cusco[b]	60.7	39.3	8	13	11	6	8
Huancavelica[b]	30.5	69.5	6	10	8	8	7
Huánuco[b]	52.1	47.9	10	10	11	11	6
Junín[b]	71	29	16	14	15	15	11
Moquegua[b]	86.9	13.1	10	13	9	9	6
Pasco[b]	63.1	36.9	13	17	16	10	10
Puno[b]	53.8	46.2	7	4	8	10	10
Amazonas[c]	41.5	58.5	14	16	13	13	9
Loreto[c]	68.7	31.3	5	4	3	4	2
Madre de Dios[c]	82.8	17.2	20	18	19	18	8
San Martín[c]	68.1	31.9	14	19	17	14	19
Ucayali[c]	81	19	12	17	16	14	12

Notes: For each region, the percentages disclosed represent the proportion of farmers declared to have received credit from the overall respondents. [a]Coastal region. [b]Andean region. [c]Amazonia region. *Population distribution estimates based on the Peruvian National Census (INEI, 2017). Some regions may include territories in multiple locations; the table considers the main location in those cases. Source: Own elaboration from the ENA (INEI, 2016–2020).

We found that, in the coastal regions, which are predominantly urban, 15% to 25% of farmers accessed credit throughout the research period. The exception is the La Libertad region, which had a ratio of less than 10% and a decreasing trend from 2015 to 2019. In contrast, in territories in the Andean region, where the population distribution is mostly rural (some places had a proportion of more than 50% of the population in rural areas (Apurimac = 54.2%, Cajamarca = 64.6%, Ayacucho = 58.1%, Huancavelica = 69.5%), the average accessibility ratios ranged from 6% to 10%, which is quite low. Even in urban departments, the accessibility ratios were relatively lower than those in the coastal areas, except for farmers in the Junín, which had an accessibility ratio ranging from 16% to 11%, although it was decreasing. Finally, in the Amazonian region, the lowest credit accessibility ratio was in Loreto, with a ratio of 2% of access to credit in 2019. Although the regions are predominantly urban, the ratio of access to credit was not more than 20%, and there was a declining trend of credit accessibility in the last few years of the research period.

4.2. Logistic regression analysis

The coefficient estimates of the model for each year are presented in Table 6 (Appendix 1b). Furthermore, the significance of each model is presented along with information on the model's predictability and likelihood. Regarding the predictability measures, the overall Pseudo R-squared values suggest limited predictive values, but with predictive ability further supported by the AUC-ROC (>0.5) curve rates to denote the diagnostic ability of binary classifiers (Berge; Jordà, 2011), by each year in the study. For example, the AUC in 2015 was 0.64, meaning a 64% chance that the model this year will be able to distinguish between positive and negative classes. This ratio remained fairly constant over the years of evaluation. The goodness-of-fit measures (log-likelihood) indicate high variability of the models, although with representative significance for each model ($p > 0.001$). This indicates that the models are statistically significant, with some predictive value for farmers' access to credit in Peru.

Variables representing the type of activities carried out by farmers, whether rural or livestock, significantly explain the farmers' accessibility to credit. We found that performing agrarian activities has a positive coefficient while performing livestock activities has a negative coefficient. Although relatively conservative, the coefficient for agrarian activities increased yearly despite the significance of both activities. The criteria for the size of the agricultural exploitation is based on the classification of the INEI (2014), which pointed out those smallholders are farms below or up to 50 hectares. Regarding farm size, the results indicate that being a smallholder decreases the likelihood of accessing credit.

The geographic variable was recategorized as binary for each region, so the evaluation was independent of each region as a predictor. The results are significant for the geographical variable ($p < 0.001$). Furthermore, the modeling coefficients provide the change in the logarithm of the probability of access to credit due to changes in the predictor variables. A positive coefficient was found for almost all regions, except for Loreto, which had a negative and insignificant coefficient in 2015 (Loreto_{2015} : p-value=0.0737), while for the remaining years, that is, from 2016 to 2019, the coefficients were significant and negative. This indicates a reduction in farmers' likelihood of accessing credit in Loreto. Although not sustainable, negative coefficients were found, especially in regions such as La Libertad, Ancash, Huancavelica, Huánuco, Moquegua, and Puno. However, farmers had a positive coefficient of the probability of accessing credit in regions previously highlighted as predominantly urban (Table 5) in the Coastal and Amazonian areas.

The odd ratios (Figure 3) are interpreted as the likelihood of farmers' access to credit when the predictor variables increase, which also enables us to obtain the probability values derived from the variables as predictors. We obtained the probabilities according to the predictors' characteristics from the odd ratios' results (see Appendix 1). Because the odd ratio was found to be negatively associated with smallholders, being a smallholder farmer decreased the probability of obtaining credit during the research period by 20%–30%. However, under the same parameters, focusing on rural activities leads to a higher probability of getting credit than those solely dedicated to livestock farming, which is negatively associated with farmers' access to credit.

Figure 3. Odds ratios for farm size and type of activities from 2015 to 2019 were estimated from the cross-sectional models. Note: Odds ratio-OR= ($p_{access}/p_{non-access}$); OR confidence interval at 95%.
Figure 3. Odds ratios estimados a partir dos modelos transversais para tamanho da exploração agrícola e tipo de atividades de 2015 a 2019. Observação: Odds ratio-OR= (p_{access} / $p_{non-access}$); intervalo de confiança de OR a 95%.

Regarding the geographic variables, we found that most of the regions were positive predictors of the probability of farmers' access to credit (Figure 4). We also found that higher probabilities were associated with these regions in 2015. This confirms the trend previously found for the coastal regions (e.g., Arequipa, Lambayeque, and Ica) because, for farmers in these regions, the probability of accessing credit increased by 70%–80% during the research period. As an exception, La Libertad began with a positive coefficient in 2015. Still, from 2016 to 2019, it had a negative coefficient ranging from 30% to 50%, indicating that farmers in this department are less likely to access credit. The departments of the Andean zone, such as Cusco, Huánuco, and Puno, had this same tendency. These departments had a positive association as predictors of access to credit for farmers in 2015 and 2016. Still, from 2017 to 2019, the prediction coefficients became negatively associated with accessing credit, decreasing the probability of farmers in these regions accessing credit by 30%–40%. In addition, most of the regions in Amazonia had a positive and significant coefficient as a predictor of access to credit. However, Loreto consistently had a negative coefficient throughout the research period (2015–2019), i.e., farmers in Loreto are less likely to access credit compared with those in other regions in Peru.

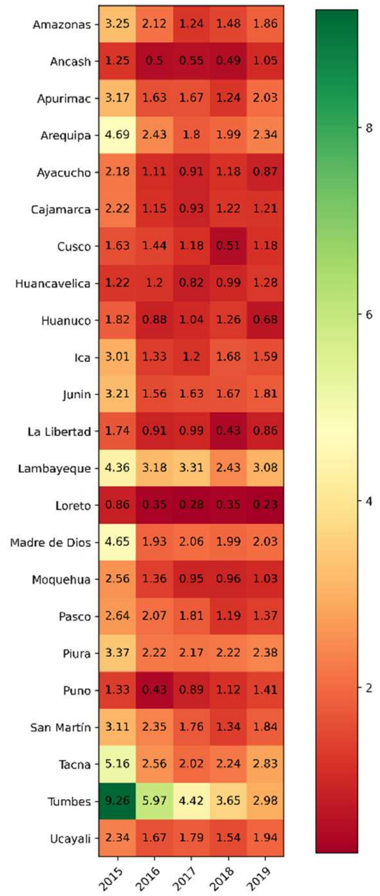

Figure 4. Odds ratios were estimated from the cross-sectional models from 2015 to 2019 based on geographic distribution. Note: Odds ratio-OR= ($p_{access}/p_{non-access}$); OR confidence interval at 95%.
Figure 4. Odds ratios foram estimados a partir dos modelos transversais de 2015 a 2019 com base na distribuição geográfica. Observação: Odds ratio-OR= ($p_{access}/p_{non-access}$); intervalo de confiança OR de 95%.

4. DISCUSSION

The basic statistics of the sample presented in the results section indicate that farm size and geographic region are important factors. The results of our study regarding the lower percentage of access to credit in the agricultural sector are consistent, which is approximately 70% of the potential demand for credit, as identified by Alvarado; Pintado (2017), representing a significant population of excluded agricultural producers who may be interested in obtaining credits and other financial services (WIENER, 2021). However, according to the data presented in this study, which is the first that explores credit access at the farmer level for several years in an Andean country, although the proportion of Peruvian farmers who have access to credit varies according to farm size, on average, it was approximately 30% of the population of farmers at the national level. Smallholders were the least represented population because, on average, 10% of the population accessed credit from the total population of smallholders, which, according to INEI (2014), represents 95% of the total population of agricultural producers in Peru. This characteristic is particularly relevant because, based on the results of this study, being a smallholder farmer significantly reduces the likelihood of accessing credit.

As better classifications of farmers according to territory characteristics can improve the financial inclusion gaps in the Peruvian agricultural sector, previous studies have focused on the impacts of geographic characteristics, pointing out that proximity to financial institutions is expected to lead to better access to financial services (PAL; LAHA, 2014). In contrast, Prieto et al. (2021) proposed that territory may be understood or analyzed in many ways based on the context.

This study reveals that the geographical variable is a significant predictor of Peruvian farmers' credit access probability because the regions had special characteristics. Our empirical findings on the geographic location, whether rural or urban, revealed that Coastal and Amazonian areas are mainly urban territories, and farmers in these areas had a positive coefficient of the probability of accessing credit. Rural territories, especially farmers in the Andean region, have the lowest ratios of access to credit, which is consistent with the finding of Trivelli (2021), who stated that the unresolved issue in Peru concerning financing in the agricultural sector is concentrated mainly in rural territories. This is valid, except for Loreto, located in the Amazonia region, a moderately urban territory with approximately a third of its area considered rural (Table 4). In contrast, farmers in Loreto are the least likely to have access to credit in the country.

Regarding the territory effect, previous work proposed that proximity has become less relevant as a factor of non-accessibility to credit (Petersen; Rajan, 2002) due to the rise of new technologies. However, a specific context requires physical proximity because of the credit invisibility characteristics of a territory (BREVOORT et al., 2018). However, the trend observed, especially in rural areas, does not necessarily reflect better access to financial services associated with improved accessibility due to the increase in technological customer service channels, as access to technological services is affected by the availability of communication networks. Therefore, for some territories, the proximity to financial service providers will be less relevant due to the services' virtualization. However, for rural territories, it can be a factor of exclusion, reducing the probability of farmers accessing credit.

This study explores farm size as a credit constraint in the Peruvian farming context while considering its geographical distribution, finding that particularities in the territory can define these variables' predictability power and direction. At the same time, the size of the farm was also important as being a smallholder reduces farmers' probability of accessing credit and being a large-scale farmer improves this probability. Regarding farmers´ activities, agricultural activities are more likely than livestock to be eligible for access to credit. Therefore, regarding the temporality approach concerning the years in which farmers were assessed through the ENA survey, the study observes a generally uneven trend in participation frequencies, which are also based on the decrease in positive probabilities associated with certain characteristics of the farming population in Peru.

5. CONCLUSIONS

This paper presents the findings of assessing farmers' access to credit in Peru from 2015 to 2019, employing factors such as farm size, type of activity, and geographical location to predict the likelihood of accessing credit. Based on preliminary findings, we identified factors that consistently influence farmers' access to credit. The size of farms, which is an influential factor particularly associated with smallholders, and exclusive dedication to livestock negatively influence the likelihood of farmers accessing credit. However, being a large-scale farmer dedicated solely to agricultural activities was found as a predictor variable with a positive likelihood ratio across farmers who accessed credit during the research period. Nonetheless, the predictors' value and probability ratio are influenced by other factors included in the model, such as geographic consideration.

The geographical location of farmers can be considered as a contextual variable of the other variables that influence the model. However, as the location and characteristics of the territories may be either an advantage or disadvantage, the analysis is based on factors such as the supply of financial services, proximity, and connectivity. Therefore, it is important to explore factors related to the territory, that is, factors that, according to previous literature, may reduce the cost of adopting the financing model in the agricultural sector. The low access to financial services in rural areas and to finance in the agricultural sector may be considered a potential market failure as the demand is high, but the supply is insufficient. This study used geographic data to provide a geospatial overview of the density of agricultural producers in each Peruvian region.

Our findings are limited by the variables included in the dataset, which is based on the ENA survey. As this data source offers limited information regarding mobility costs in the economic environment in rural areas, further research can benefit from conducting financial surveys at the farm level and matching both data sources with georeferenced data.

6. REFERENCES

ANTROP, M. Why landscapes of the past are important for the future. **Landscape and Urban Planning**, v. 70, n. 1-2, p. 21-34, 2005. https://doi.org/10.1016/j.landurbplan.2003.10.002

ALVARADO, J.; PINTADO, M. Necesidad, demanda y obtención de crédito en el sector agropecuario en el Perú. In: **Censo Nacional Agropecuario 2012: Investigaciones para la toma de decisiones en políticas públicas, IV**. Organización de las Naciones Unidas para la Alimentación y la Agricultura (FAO). 2017. 100p. http://www.fao.org/3/a-i6713s.pdf

AMANULLAH, G.; CHANNA, S.; MAGSI, H.; KOONDHER, M.; WANG, J.; CHANNA, N. Credit constraints and rural farmers' welfare in an agrarian economy. **Heliyon**, v. 6, n. 10, e05252, 2020. https://doi.org/10.1016/j.heliyon.2020.e05252

BALANA, B.; OYEYEMI, M. Agricultural credit constraints in smallholder farming in developing countries: Evidence from Nigeria. **World Development Sustainability**, v. 1, e100012, 2022. https://doi.org/10.1016/j.wds.2022.100012

BENNI, N. **El fortalecimiento de la inclusión financiera digital en zonas rurales y agropecuarias**.

Organización de las Naciones Unidas para la Alimentación y la Agricultura (FAO). 2022. https://doi.org/https://doi.org/10.4060/cc2877es

BOUCHER, S.; GUIRKINGER, C. Risk, wealth, and sectoral choice in rural credit markets. **American Journal of Agricultural Economics**, v. 89, n. 4, p. 991-1004, 2007. https://doi.org/10.1111/j.1467-8276.2007.01009.x

BOUCHER, S.; GUIRKINGER, C.; TRIVELLI, C. Direct elicitation of credit constraints: Conceptual and practical issues with an application to Peruvian agriculture. **Economic Development and Cultural Change**, v. 57, n. 4, p. 609-640, 2009. https://doi.org/10.1086/598763

BREVOORT, K.; CLARKBERG, J.; KAMBARA, M.; LITWIN, B. **The Geography of Credit Invisibility**. Consumer Financial Protection Bureau Office of Research Reports Series No. 18-6, 2018. https://ssrn.com/abstract=3288848.

BREVOORT, K.; GRIMM, P.; KAMBARA, M. Credit Invisibles and the Unscored. **SSRN Electronic Journal**, v. 18, n. 2, p. 9-34, 2016. https://doi.org/10.2139/ssrn.2743007

CHANDIO, A.; JIANG, Y. Determinants of Credit Constraints: Evidence from Sindh, Pakistan. **Emerging Markets Finance and Trade**, v. 54, n. 15, p. 3401-3410, 2018. https://doi.org/10.1080/1540496X.2018.1481743

CONNING, J.; UDRY, C. Rural financial markets in developing countries. **Yale University Economic Growth Center Discussion Paper**: v. No. 914, 2005. https://doi.org/10.2307/3324578

DEMIRGÜÇ¸-KUNT, A., KLAPPER, L., SINGER, D., VAN OUDHEUSDEN, P. **The Global Findex Database 2014. Measuring Financial Inclusion Around the World**. Policy Research Working Paper No. 7255. The World Bank, Washington, DC. 2015. 97p. https://documents1.worldbank.org/curated/en/187761468179367706/pdf/WPS7255.pdf

ESCOBAL, J.; FAVARETO, A.; AGUIRRE, F.; PONCE, C. Linkage to dynamic markets and rural territorial development in Latin America. **World Development**, v. 73, p. 44-55, 2015. https://doi.org/10.1016/j.worlddev.2014.09.017

GHEZZI, P. **Cómo fortalecer el agrobanco y el financiamiento agropecuario: una visión productivista. Instituto Interamericano de Cooperación para la Agricultura**. IICA, 2021. 40p. https://repositorio.iica.int/handle/11324/18625

GUIRKINGER, C.; BOUCHER, S. Credit constraints and productivity in Peruvian agriculture. **Agricultural Economics**, v. 39, n. 3, p. 295-308, 2008. https://doi.org/10.1111/j.1574-0862.2008.00334.x

GUJARATI, D. N.; PORTER, D. **Basic Econometrics**. 5 th Ed. New York: McGraw Hill Inc., 2009. 922p. https://search.worldcat.org/es/title/226356768

HAIR, J.; BLACK, B.; BABIN, B.; ANDERSON, R. **Multivariate Data Analysis: Global Edition**. 7th ed. Harlow: Pearson Education, 2010. 665p. https://search.worldcat.org/es/title/855545532

INEI. **IV Censo Nacional Agropecuario 2012**. 2014. http://inei.inei.gob.pe/microdatos/

INEI. **Encuesta Nacional Agropecuaria 2015**. 2016. Retrieved from http://iinei.inei.gob.pe/microdatos/

INEI. **Encuesta Nacional Agropecuaria 2016**. 2017. Retrieved from http://iinei.inei.gob.pe/microdatos/

INEI. **Encuesta Nacional Agropecuaria 2017**. 2018. Retrieved from http://iinei.inei.gob.pe/microdatos/

INEI. **Encuesta Nacional Agropecuaria 2018**. 2019. Retrieved from http://iinei.inei.gob.pe/microdatos/

INEI. **Encuesta Nacional Agropecuaria 2019**. 2020. Retrieved from http://iinei.inei.gob.pe/microdatos/

JANVRY, A.; DE SADOULET, E.; MCINTOSH, C.; WYDICK, B.; LUOTO, J.; GORDILLO, G.; SCHUETZ, G. **Credit bureaus and the rural microfinance sector: Peru, Guatemala, and Bolivia**. Collaborative Research Support Program. The University of California and The FAO Office for Latin America. 2003. 129p. http://crsps.net/wp-content/downloads/BASIS/Inventoried 2.27/13-2003-7-115.pdf

KHANDKER, S.; KOOLWAL, G. Does institutional finance matter for agriculture? evidence using panel data from Uganda. **Policy Research Working Papers**, 2014. https://doi.org/10.1596/1813-9450-6942

LINH, T.; LONG, H.; CHI, L.; VAN, L.; LEBAILLY, P. Access to rural credit markets in developing countries, the case of Vietnam: A literature review. **Sustainability**, v. 11, n. 5, p. 1-18, 2019. https://doi.org/10.3390/su11051468

MOAHID, M.; MAHARJAN, K. Factors affecting farmers' access to formal and informal credit: Evidence from rural Afghanistan. **Sustainability**, v. 12, n. 3, p. 1-16, 2020. https://doi.org/10.3390/su12031268

OKORUWA, V.; ABASS, A.; AKIN-OLAGUNJU, O.; AKINOLA, N. Does institution type affect access to finance for cassava actors in Nigeria? **Journal of Agriculture and Food Research**, v. 2, e100023, 2020. https://doi.org/10.1016/j.jafr.2020.100023

PAL, D.; LAHA, A. Credit off-take from formal financial institutions in rural India: quantile regression results. **Agricultural and Food Economics**, v. 2, n. 1, a9, 2014. https://doi.org/10.1186/s40100-014-0009-y

PEDROSA, J.; DO, Q. **How does geographic distance affect credit market access in Niger**. Policy Research working paper ; no. WPS 4772 Washington, D.C. : World Bank Group. 2008. http://documents.worldbank.org/curated/en/534711468288946769/How-does-geographic-distance-affect-credit-market-access-in-Niger.

PETERSEN, M.; RAJAN, R. Does distance still matter? The information revolution in small business lending. **Journal of Finance**, v. 57, n. 6, p. 2533-2570, 2002. https://doi.org/10.1111/1540-6261.00505

PHIRI, A.; CHIPETA, G.; CHAWINGA, W. Information behaviour of rural smallholder farmers in some selected developing countries: A literature review. **Information Development**, v. 35, n. 5, p. 831-838, 2019. https://doi.org/10.1177/0266666918804861

PRIETO, G.; TORERO, D.; RONDÓN, G.; HUAIRE, C. Nuevas herramientas para analizar la ocupación del territorio peruano: hacia un cambio de paradigma en la gestión pública. **Espacio y Desarrollo**, v. 38, p. 1-32, 2021. https://dialnet.unirioja.es/descarga/articulo/8617550.pdf

RAMOS-SANDOVAL, R.; LARA, R. Geographic Data Science for Analysis in Rural Areas: A Study Case of Financial Services Accessible in the Peruvian Agricultural Sector. In: Silhavy, R., Silhavy, P. (eds) Artificial

Intelligence Application in Networks and Systems. CSOC 2023. **Lecture Notes in Networks and Systems**, v. 724, p. 246-259, 2023. https://doi.org/10.1007/978-3-031-35314-7_24

SCHEJTMAN, A.; BERDEGUÉ, J. **Rural Territorial Development.** Programa Dinámicas Territoriales Rurales, Issue March, 2004. https://rimisp.org/wp-content/files_mf/13663830272004_schejtman_berdegue_rural_territorial_development.pdf (Documento de Trabajo, 4)

SIMTOWE, F.; DIAGNE, A.; ZELLER, M. Who is credit constrained? Evidence from rural Malawi. **Agricultural Finance Review**, v. 68, n. 2, p. 255-272, 2008. https://doi.org/10.1108/00214660880001229

TRIVELLI, C.; IEP. **Finanzas agropecuarias: Desafío pendiente en la agenda agraria en Perú**. LAC Working Paper 15. Washington, DC: International Food Policy Research Institute (IFPRI), 2021. 35p. https://doi.org/10.2499/p15738coll2.134248

TRIVELLI, C.; CABALLERO, E. **¿Cerrando brechas?: las estrategias nacionales de inclusión financiera en América Latina y el Caribe**. Instituto de Estudios Peruanos. 2018. 110p. http://repositorio.iep.org.pe/handle/IEP/1132

TRIVELLI, C.; VENERO, H. **Banca de desarrollo para el agro: experiencias en curso en América Latina** (Vol. 25). Instituto de Estudios peruanos-IEP. 2007. 375p. http://repositorio.iep.org.pe/handle/IEP/543

WIENER, H. Perú: un mercado incompleto de servicios financieros al agro. **Pensamiento Crítico**, v. 26, n. 1, p. 5-38, 2021. https://doi.org/10.15381/pc.v26i1.20222

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APPENDIX

Appendix 1a: Table 5. Access to credit by region of farmers from 2015 to 2019.
Anexo 1a: Tabela 5. Acesso ao crédito por região dos agricultores de 2015 a 2019.

Region				2015		2016		2017		2018		2019	
Name	Location	Population distribution[a]		N_{access} = 3 831	%	N_{access} = 4 262	%	N_{access} = 3 914	%	N_{access} = 3 543	%	N_{access} = 3 063	%
		Urban	Rural										
Arequipa	Coast	91.8	8.2	254	21	255	21	202	17	200	16	195	14
Ica	Coast	92.4	7.6	227	19	198	16	169	14	206	18	168	15
La Libertad	Coast	78.9	21.1	131	10	128	9	131	9	81	6	101	8
Lambayeque	Coast	81.1	18.9	239	21	281	24	323	27	239	21	221	22
Lima	Coast	98.3	1.7	216	17	261	20	258	20	220	18	176	24
Piura	Coast	79.3	20.7	220	17	260	19	254	19	239	17	194	16
Tacna	Coast	90.1	9.9	245	22	248	22	178	16	188	17	171	15
Tumbes	Coast	93.7	6.3	292	34	346	41	265	31	233	29	168	12
Ancash	Andean	63.4	36.6	105	8	84	6	86	6	83	6	107	9
Apurímac	Andean	45.8	54.2	156	13	166	14	172	14	128	11	144	11
Ayacucho	Andean	41.9	58.1	126	10	114	9	95	8	114	9	71	6
Cajamarca	Andean	35.4	64.6	132	11	131	10	109	8	127	10	113	9
Cusco	Andean	60.7	39.3	102	8	166	13	144	11	73	6	103	8
Huancavelica	Andean	30.5	69.5	78	6	123	10	97	8	95	8	89	7
Huánuco	Andean	52.1	47.9	119	10	125	10	139	11	140	11	74	6
Junín	Andean	71	29	183	16	178	14	179	15	169	15	124	11
Moquegua	Andean	86.9	13.1	116	10	146	13	103	9	109	9	80	6
Pasco	Andean	63.1	36.9	140	13	203	17	190	16	116	10	112	10
Puno	Andean	53.8	46.2	92	7	58	4	117	8	134	10	118	10
Amazonas	Amazonia	41.5	58.5	166	14	195	16	157	13	161	13	135	9
Loreto	Amazonia	68.7	31.3	56	5	40	4	31	3	43	4	21	2
Madre de Dios	Amazonia	82.8	17.2	142	20	146	18	147	19	132	18	89	8
San Martín	Amazonia	68.1	31.9	164	14	235	19	198	17	158	14	156	19
Ucayali	Amazonia	81	19	130	12	175	17	167	16	155	14	132	12

Notes: For each region, the percentages disclosed represent the proportion of farmers that were declared to have received credit to the overall respondents. [a]Population distribution estimates based on the Peruvian National Census (INEI, 2017). Some regions may include territories is more than one location, in those cases the table considers the main location. Source: Own elaboration from the ENA (INEI, 2016–2020).

Appendix 1b: Table 6. Estimated coefficients for cross-sectional models from 2015 to 2019.

Apêndice 1b: Tabela 6. Coeficientes estimados para modelos transversais de 2015 a 2019.

Variables	2015		2016		2017		2018		2019	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Amazonas	1.1779	0.0000	0.7526	0.0000	0.2191	0.0016	0.3902	0.0000	0.6184	0.0000
Ancash	0.2265	0.0024	−0.6875	0.0000	−0.5964	0.0000	−0.7159	0.0000	0.0473	0.4889
Apurimac	1.1524	0.0000	0.4891	0.0000	0.5146	0.0000	0.2183	0.0019	0.7071	0.0000
Arequipa	1.5457	0.0000	0.8865	0.0000	0.5867	0.0000	0.6900	0.0000	0.8512	0.0000
Ayacucho	0.7788	0.0000	0.1050	0.1568	−0.0952	0.1947	0.1685	0.0155	−0.1402	0.0655
Cajamarca	0.7974	0.0000	0.1368	0.0571	−0.0690	0.3336	0.1956	0.0036	0.1937	0.0053
Cusco	0.4870	0.0000	0.3669	0.0000	0.1613	0.0203	−0.6730	0.0000	0.1646	0.0218
Huancavelica	0.1981	0.0175	0.1833	0.0127	−0.2031	0.0084	−0.0146	0.8428	0.2461	0.0008
Huánuco	0.5978	0.0000	−0.1245	0.0889	0.0371	0.5928	0.2302	0.0006	−0.3814	0.0000
Ica	1.1007	0.0000	0.2838	0.0000	0.1815	0.0058	0.5195	0.0000	0.4631	0.0000
Junín	1.1651	0.0000	0.4422	0.0000	0.4890	0.0000	0.5136	0.0000	0.5915	0.0000
La Libertad	0.5528	0.0000	−0.0990	0.1547	−0.0098	0.8814	−0.8350	0.0000	−0.1542	0.0227
Lambayeque	1.4731	0.0000	1.1554	0.0000	1.1955	0.0000	0.8873	0.0000	1.1255	0.0000
Loreto	−0.1552	0.0737	−1.0417	0.0000	−1.2790	0.0000	−1.0466	0.0000	−1.4873	0.0000
Madre de Dios	1.5371	0.0000	0.6594	0.0000	0.7250	0.0000	0.6893	0.0000	0.7098	0.0000
Moquegua	0.9384	0.0000	0.3089	0.0000	−0.0563	0.4427	−0.0435	0.5466	0.0326	0.6564
Pasco	0.9699	0.0000	0.7263	0.0000	0.5909	0.0000	0.1699	0.0159	0.3154	0.0000
Piura	1.2163	0.0000	0.7969	0.0000	0.7757	0.0000	0.7991	0.0000	0.8680	0.0000
Puno	0.2848	0.0002	−0.8531	0.0000	−0.1218	0.0836	0.1128	0.0960	0.3424	0.0000
San Martin	1.1359	0.0000	0.8528	0.0000	0.5637	0.0000	0.2893	0.0000	0.6073	0.0000
Tacna	1.6404	0.0000	0.9382	0.0000	0.7009	0.0000	0.8044	0.0000	1.0400	0.0000
Tumbes	2.2258	0.0000	1.7867	0.0000	1.4853	0.0000	1.2950	0.0000	1.0912	0.0000
Ucayali	0.8516	0.0000	0.5149	0.0000	0.5816	0.0000	0.4331	0.0000	0.6627	0.0000
Smallholders	−1.3799	0.0000	−0.7677	0.0000	−0.7848	0.0000	−0.8117	0.0000	−0.9202	0.0000
Agrarian	0.4942	0.0000	0.4755	0.0000	0.5551	0.0000	0.7412	0.0000	0.6311	0.0000
Livestock	−0.3035	0.0000	−0.3299	0.0000	−0.2788	0.0000	−0.4368	0.0000	−0.3657	0.0000
N	26 848		27 500		27 442		27 088		26 937	
Pseudo R-squared	0.072		0.068		0.058		0.067		0.055	
Log Likelihood	−21719 (0.000)		−22225 (0.000)		−22709 (0.000)		−22573 (0.000)		−23224 (0.000)	
AUC-ROC Curve	0.64		0.64		0.62		0.64		0.61	

Note: correlation is significant at $p < 0.001$ level. Source: Own elaboration from the ENA (INEI, 2016–2020).

Appendix 1c: Probabilities estimated from the cross-sectional models from 2015 to 2019 for exploitation size and type of activities.
Apêndice 1c: Probabilidades estimadas a partir dos modelos transversais de 2015 a 2019 para o tamanho da exploração e tipo de atividades.

Variables	2015	2016	2017	2018	2019
	Prob[a] (%)	Prob[a] (%)	Prob[a] (%)	Prob[a] (%)	Prob[a] (%)
Smallholders	20%	32%	31%	31%	28%
Agrarian	62%	62%	64%	68%	65%
Livestock	42%	42%	43%	39%	41%

[a]odds to probability = odds / (1 + odds)

Appendix 1d: Probabilities estimated from the cross-sectional models from 2015 to 2019 by geographic distribution.
Apêndice 1d: Probabilidades estimadas a partir dos modelos transversais de 2015 a 2019 por distribuição geográfica.

Variables	2015	2016	2017	2018	2019
	Prob[a] (%)	Prob[a] (%)	Prob[a] (%)	Prob[a] (%)	Prob[a] (%)
Amazonas	76	68	55	60	65
Ancash	56	33	36	33	51
Apurimac	76	62	63	55	67
Arequipa	82	71	64	67	70
Ayacucho	69	53	48	54	46
Cajamarca	69	53	48	55	55
Cusco	62	59	54	34	54
Huancavelica	55	55	45	50	56
Huánuco	65	47	51	56	41
Ica	75	57	55	63	61
Junín	76	61	62	63	64
La Libertad	63	48	50	30	46
Lambayeque	81	76	77	71	75
Loreto	46	26	22	26	18
Madre de Dios	82	66	67	67	67
Moquegua	72	58	49	49	51
Pasco	73	67	64	54	58
Piura	77	69	68	69	70
Puno	57	30	47	53	58
San Martin	76	70	64	57	65
Tacna	84	72	67	69	74
Tumbes	90	86	82	78	75
Ucayali	70	63	64	61	66

[a]odds to probability = odds / (1 + odds)