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RESEARCH PAPER

Analysing credit risk in persons with disabilities as an instrument of financial inclusion

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Abstract

In many countries, the full financial inclusion of persons with disabilities remains to be achieved. Although researchers and international organisations observed that financial inclusion would be facilitated by analysis of solvency, the causes of default risk among this population have yet to be established. Our study, applied to loans made by a Spanish bank to 785 persons with disabilities, identifies several factors relevant to the default risk of this population. The findings show that the purpose of the loan, the borrower's degree of liquidity and financial leverage, economic context of GDP and risk premium all influence the probability of default of persons with disabilities. These risk factors have a similar impact to that observed in persons without disabilities. Our conclusions can be interesting in the negotiation of bank loans for persons with disabilities and also for bank managers, politicians, government managers, international organisations and other stakeholders concerned about financial inclusion. For developing countries our findings can have a high favourable impact on the financial inclusion of these people, due to their high number in these countries. Furthermore, our conclusions raise the usefulness of adopting political measures such as tax advantages or regulation of specific criteria to evaluate the default risk of these people.

Keywords Disability · Financial inclusion · Credit risk · Logit · Neural network · Basel III

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Introduction

Several international organisations (OECD, UN, WHO, WBG, CFI) and Singh (2018) indicate that 650 million people in the world (almost 15% of humanity) have some type of disability. Following European Disability Strategy 2010–2020 (European Union (EU), 2019), by 2020 one-fifth of the EU population is expected to have some form of disability. However, many people with disabilities have limitations in accessing financial services for bank credit. Less than 1% of microfinance bank clients have a disability, which raises the need to study how to improve access to credit for this group (Center for Financial Inclusion 2020; World Health Organization 2019; World Bank Group, 2018; Organisation for Economic Co-operation and Development OECD, 2018a and 2018b; United Nations (UN), 2008).

Despite this low percentage of access to banking services, PWD's financial inclusion is considered a key element for sustainable socioeconomic development and for equal opportunities for societies. In fact, the 2030 Agenda for Sustainable Development (United Nations (UN), 2008) has considered that the financial assistance of PWDs is an essential factor to improve social sustainability, the reduction of inequalities and the quality of life of citizens. SDG No. 8 (Decent Work and Economic Growth) has included in its goal 8.3 the promotion of access to financial services for micro-enterprises, while SDG No. 10 (Reduction of Inequalities) has chosen in its goal 10.2 to promote the economic inclusion of all people, regardless of age, gender, race or disability.

In this context, some international initiatives have tried to enhance PWD's financial inclusion, such as the creation of the World Bank Group Commitments on Disability-Inclusive Development (World Bank Group, 2018), the European Disability Strategy 2010–2020 (European Union (EU), 2019) and the Directive (EU) 2019/882 of the European Parliament and of the Council of 17 April 2019 on the accessibility requirements for products and services.

Despite these advances, the difficulties of access to bank credit for the PWD continue to be a social problem whose solution has not been sufficiently studied. Indeed, the financial exclusion of these people represents a major challenge that financial systems in developed western economies have yet to properly address (Lakshmi & Sreedhar 2020; Galera et al., 2017; Worldwide Bank Group, 2018; World Health Organization 2019).

Beisland & Mersland (2012) conclude that the financial exclusion of PWD is due to the lack of financial products and services specifically aimed at this group. They also report that 22% of economically active PWD do not request services from microfinance institutions for fear that their credit application will be rejected due to their disability. In this respect, Cramm & Finkenflügel (2008) and Mersland et al. (2009) find that the staff of microfinance institutions discriminate against PWD, as a result of which these persons often resort to informal sources of finance. However, Beisland & Mersland (2017) conclude that young staff members are generally more optimistic about PWD's access to financial services. In addition, Nelson et al. (2013) found that default on mortgage loans reveals special difficulties in households with PWD. These findings motivate the interest and opportunity to investigate the causes and possible solutions to this default, as an instrument to improve PWD's financial inclusion, equal opportunities and quality of life.

Our review of previous work regarding the measurement of credit risk and financial insolvency shows that it can be classified into three sectors: a) the private banking sector, where important work has been done by Blanco et al. (2013), Lee and Chen (2005) and Malhotra and Malhotra, (2002); b) microfinance, which is the area closest to our study focus, with papers by Vigano (1993), Sharma & Zeller (1997), Reinke (1998), Zeller

(1998), Vogelgesang (2003), Dinh & Kleimeier (2007), Rayo et al. (2010) and Blanco et al. (2013); c) public administration, with research by Lara-Rubio et al. (2017) and Navarro-Galera et al. (2017, 2015).

However, no previous studies have been conducted to measure the credit risk in PWD compared to persons with no disabilities, despite the fact that both the previous investigation and the aforementioned international organisations recognise the need to know the causes of default in this group to design policies aimed at full financial inclusion. Indeed, Moody's (2013), the United Nations (UN) (2006) and researchers such as Lakshmi & Sreedhar (2020), Villacorta & Reyes (2012) and Armendáriz (2011) have highlighted the need to develop strategies aimed at achieving the complete financial inclusion of PWD.

In this respect, the Basel III regulations, issued by the Basel Committee on Banking Supervision (BCBS, 2010, 2017), provide an interesting means of measuring the risk of default by PWD, according to previous empirical research (Durango-Gutiérrez et al. 2021; Buendía-Carrillo et al., 2020; Lara et al., 2017: Navarro-Galero et al., 2017) about default risk in bank loans. Although these studies have yet been specifically undertaken to analyse the default risk in bank loans granted to PWD, its conclusions indicate the opportunity and relevance of incorporating the disability variable as a mechanism for financial inclusion of PWD.

Under this motivation, our study aim is to identify factors that influence the credit risk of PWD, doing so by analysing explanatory variables of the probability of default on bank loans granted to this population group. In our empirical work, logistic regression and the difficulties in accessing bank credit might be alleviated. Our conclusions provide valuable information for PWD interested in take-out bank loans, international organisations interested in inclusive finance, as well as for politicians, policymakers, analysts in financial institutions and other stakeholders seeking to promote financial inclusion for all, regardless of mobility and cognitive and sensory abilities.

Using basel committee standards to assess the default risk among PWD

The fact that large numbers of PWD are currently in a situation of financial exclusion is a matter of great concern for international organisations, associations, politicians, financial managers, financial institutions and other stakeholders, for whom the study of bank loans is very interesting (Organisation for Economic Co-operation and Development OECD, 2018a and 2018b; United Nations (UN), 2008; World Health Organization, 2011; International Monetary Fund. IMF, 2014; Moody's, 2013).

Because this population group is at risk of financial exclusion, it is useful and timely to analyse the idiosyncratic and systemic risk factors that may increase the probability of credit default or, on the contrary, mitigate this risk. In addition, taking into account that banks are the main lenders to citizens, the study of the risk of default in bank loans is particularly relevant in the current economic context, where the effects of the COVID-19 pandemic are causing a strong economic recession, seriously affecting PWD.

In order to measure these risks, the standards issued by the Basel Committee on Banking Supervision (BCBS) are considered the main benchmark in the international financial system (European Union (EU), 2015; International Monetary Fund. IMF, 2014; Navarro-Galera et al. 2017; Padovani et al. 2018). The Basel III regulation (Basel

Committee on Banking Supervision, BCBS, 2010, 2017) represents a major advance for the international financial system, helping ensure the solvency and stability of credit institutions by facilitating the assessment of financial risks associated with loan recipients, among whom are PWD. Specifically, the Basel III standard stipulates capital requirements for credit institutions and requires banks to apply new instruments to improve the capital requirements derived from their credit, market and operational activities.

The Basel regulations, with the corresponding updates Basel Committee on Banking Supervision, (2006) and Basel Committee on Banking Supervision, (2010, 2017), recommend that credit risk should be measured by quantifying the probability of default, using an internal ratings-based approach (IRB). Thus, the credit risk loss is calculated as the sum of expected loss (EL) and unexpected loss (UL), or capital requirements.

The following parameters are normally used to calculate the credit risk loss: exposure at default (EAD), probability of default (PD), conditional probability of default (CPD), correlation of the asset value with the state of the economy (ρ) and loss given default (LGD). Because BCBS (2006, 2010, 2017) defines various default scenarios, we follow previous research approaches in this respect (Lara-Rubio et al. 2017; Navarro-Galera et al. 2017; Padovani et al. 2018) and select a dependent variable that incorporates and unifies the above scenarios via the concept of ability-to-pay process (APP), i.e. the capacity of PWD to repay their credit liabilities.

Any analysis of the capital requirements of financial institutions must take into account that the credit extended to borrowers is a factor of major importance. In this respect, application of the Basel III regulations could provide PWD with a better understanding of their own credit risk status and thus equip them to negotiate loans with financial institutions on the basis of more accurate information, and hence obtain better terms, regarding maturity dates and interest rates in particular.

Credit risk model for persons with disabilities

Using the concept of default proposed in the Basel III regulation, we define the ability-to-pay process (APP) to pay credit liabilities (Bluhmy et al, 2003; Gordy 2003) as a factor of great importance in analysing borrowers' joint credit risk.

For any borrower in a portfolio that includes those with disabilities, the APP depends on their assets and financial resources, together with a series of qualitative variables, including a latent variable that is not directly observable but which must be defined and estimated. We do so by means of a nonlinear discrete choice model (logistic regression) since the question of payment or non-payment is a dichotomous variable, in association with a nonparametric technique (neural networks), which improves the estimation of parametric techniques.

According to Gordy (2003), a borrower is in default if his ability to pay at a certain point in time APP_i is below a certain level of liability or debt or credit liability (c_i). Therefore, the borrower's situation of default is a random dichotomous variable Y_i such that:

$$Y_i = \left\{ \begin{array}{ll} 1 \text{ if} & \text{no paymet is made} \\ 0 \text{ if} & \text{payment is made} \end{array} \right\} \tag{1}$$

And the probability of default on the loan is

$$\text{PD}_i = P(Y_i = 1) = P(\text{APP}_i \le c_i) \tag{2}$$

The idiosyncratic factors of credit risk (Z_i) correspond to the borrower's own or specific factors, as variables corresponding to the borrower or to the loan. The systemic factors of credit risk (X_i) include factors of the macroeconomic cycle.

Assume, without loss of generality, (a) that PWD form a homogeneous segment within the private sector; (b) that there exists a single systemic credit risk factor *i* (a linear combination of multiple systemic factors) which affects all borrowers equally and which behaves as a continuous random variable; and (c) that the idiosyncratic risk factor *Zi* (*i* = *1*,…, *N*) affects each borrower individually.

Following common practice in the framework of the capital market theory, we assume that X_i and Z_i are distributed as standardised normal random variables and that the idiosyncratic and systemic factors are independent for each creditor in the portfolio and mutually so. In this context, Rösch (2003) and Bonfim (2009) showed that given the independence between the factors, the APP*i* is distributed as a standardised normal random variable as follows:

$$\text{APP}_i = \sqrt{\rho}\, X_i + \sqrt{1-\rho}\, Z_i \tag{3}$$

where the variables X_i and Z_i correspond respectively to the state of the economy in the time interval (*0, T*) and to the state of the idiosyncratic factor of the borrower in the same time interval. The parameter ρ represents the level of linear correlation between *APPt* and the state of the economy. The component $\sqrt{\rho}X_i$ measures the weight of the effect of the systemic factor (common to all clients) in its APP*i*, and the component $\sqrt{1-\rho}Z_i$ is the weight of the effect of the idiosyncratic factor. However, in the present context these assumptions may be too restrictive. First, because empirical evidence suggests that the single factor hypothesis is unrealistic, since there are multiple systemic and idiosyncratic factors. Second, because the idiosyncratic factor is not totally independent of the systemic one, as in an economic recession the borrowers' financial situation would also be affected, to a greater or lesser extent. Taking this into account, expression (3) can be modified to expression (4) and, generalising to *n* systemic and *m* idiosyncratic factors, to expression (5):

$$\text{APP}_i = \alpha + \beta X_i + \delta Z_i + u_i \tag{4}$$

$$\text{APP}_i = \alpha + \sum_{j=1}^{n} \beta_j X_j + \sum_{k=1}^{m} \delta_k Z_{\text{ki}} + u_i \tag{5}$$

where β_j and δ_k are the parameter vectors estimated and u_i is the random perturbation. Then, a borrower will be classified as being in default if his APP_i is below a certain level c_i:

$$\alpha + \sum_{j=1}^{n} \beta_j X_j + \sum_{k=1}^{m} \delta_k Z_{\text{ki}} + u_i \le c_i \Leftrightarrow Y_i = 1 \tag{6}$$

Although the variable APP_i is latent and not directly observable, the explanatory variables, the risk factors X_j and Z_{ki}, together with the independent variable, the default indicator Y_i, are directly observable from the sample data. Therefore, the relationship between PD and the risk factors can be established through a logit model, which allows us to estimate the borrower's default probability as a function of the systemic and idiosyncratic factors.

Methodology

Taking into account the pronouncements of international organisations (Center for Financial Inclusion 2020; World Health Organization 2019; World Bank Group, 2018; Organisation for Economic Co-operation and Development OECD, 2018a and 2018b; United Nations (UN), 2008), this empirical study focuses on a Spanish financial entity linked to social work, an institution that has initiated a pilot scheme to grant loans to PWD. The following research methodology is employed. First, we describe the study sample and define the dependent (default) and the independent variables (idiosyncratic and systemic).

The causes of credit default by the PWD group are then compared with that by the rest of the population, by estimating three logistic regression models (after confirming that the PWD variable is statistically significant). Of these, Model 1 is a joint model corresponding to the entire portfolio; Model 2 represents the PWD population; and Model 3 represents the non-PWD population. The aim addressed in constructing these three models is to identify the explanatory variables that are specific to the credit risk of PWD, as called for in our fundamental study goal.

Sample selection

According to the Park and Mercado (2018) research, Spain has the best indicator of financial inclusion at an international level. Therefore, carrying out the study with a database of people with disabilities registered in the Spanish financial system demonstrates the suitability and strength of the database selected for this study. The sample population was obtained from a branch of Caixabank, with information related to the idiosyncratic variables, both qualitative and quantitative. The sample used in this study was selected randomly but by means of targeted sampling, aiming for a minimum acceptable ratio between people with disabilities and people without disabilities, considering the difficulty of obtaining data from people with disabilities as they borrow less proportionally. In logistic regression it is recommended to have a reasonably balanced distribution of the two values in the dependent variable. In our case, we were able to analyse a total of 785 loan transactions granted to non-disabled people and, therefore, to achieve a minimum of one-third representativeness of this group in the sample (Durango-Gutierrez et al., 2021), 1565 loan transactions granted to non-disabled people were randomly selected. Therefore, our sample consists of a total of 2350 disabled and non-disabled clients. The idiosyncratic information was composed of: a) personal information (gender, marital status, etc.); b) the borrowers' financial and economic ratios; c) the characteristics of the financial operation in question (interest rate, amount of loan, etc.). Subsequently, we added variables related to the economic context, as suggested in previous research and by the aforementioned international organisations (systemic variables).

The dependent variable

Our analysis of credit risk was conducted from the perspective of financial institutions, which are the largest providers of bank credit and microcredit. The definition of default used is in accordance with paragraph 90 of the Basel Committee on Banking Supervision BCBS, (2017) regulations, on defaulted exposures. Thus, a loan is considered in default when at least one of the following conditions is met:

- *Default variable 1* $Y_i(k_1)\epsilon\{0,1\}$. The bank considers it probable that the debtor will not pay all his credit obligations to the banking group, without the bank taking recourse to means such as the enforcement of guarantees (if applicable);
- *Default variable 2* $Y_{it}(k_2)\epsilon\{0,1\}$. The debtor has been in arrears for over 90 days concerning a significant credit obligation to the banking group. The overdraft is considered to be in arrears when the client exceeds a stipulated limit or when the limit imposed is lower than the current debit balance.

Taking these observations into account, the dependent variable that we use, as an indicator of the borrower's default, is $Y_{it}(k_{1,}k_2)\epsilon\{0,1\}$, where 0 indicates no default and 1 indicates default.

$$Y_{\mathrm{it}}(k_1,k_2) = \max\left\{0, \max\left(k_1,k_2\right)\right\} \tag{7}$$

Independent variables

Table 1 shows the idiosyncratic variables and systemic variables used in this study. The table also shows the expected sign of the estimator according to the relationship between each independent variable and the probability of default. The variables that we propose in order to identify factors which influence the credit risk of borrowers through their probability of default are derived from previous research in the fields of finance and microfinance. Furthermore, these variables are in line with the factor classification established by the rating agencies Standard & Poor's (2011) and Moody's Investors Service (2008, 2013).

The variable *HISTORY* refers to the client's standing as a borrower. Based on Gutierrez-Nieto et al. (2016) and Rayo et al. (2010), the expected sign is negative in the estimator, in the view that a long-standing customer will have correctly repaid previous loans and remains creditworthy. With respect to the credits previously granted to the client (*LOAN_GRANT*), a negative sign is also expected in the estimator, for the same reasons as for the previous variable (Kiruthika & Dilsha, 2015). For previous credit applications denied to the client (*LOAN_DENY*), a positive sign is expected in the estimator because in this case the applicant's past reflects a risk of default.

Regarding *SECTOR*, no specific criterion was adopted regarding the activity sector that might present greater risk (Vega et al., 2013; Rayo et al. 2010). For the indicator reflecting the purpose of the credit requested, *LOAN_AIM*, we propose a positive sign, in the understanding that a loan intended for the acquisition of a fixed asset implies greater risk than one intended to provide working capital, because recovery of the fixed asset by means of technical amortisation takes longer (Blanco et al. 2013). Regarding the number of periodic repayments made in the client's credit history (*TOT_PMTS*), we expect a negative sign in the corresponding estimator because a customer with a higher number of payments is assumed to have been granted, on average, a larger number of loans, which also reflects greater experience as a borrower (Kiruthika & Dilsha, 2015; Abdou et al. 2008). Likewise, information is included on the client's arrears record, coded with the variables *TOTAL_ARRS*, *AVG_ ARRS* and *MAX_ARRS*, which represent, respectively, the total number of payments missed, the average number of days in this situation and the number of days at the highest level of arrears. We expect a positive sign for each of these estimators in the model, since a borrower who presents a history of large values for any of these variables will have had greater difficulty in making loan repayments.

Table 1 Idiosyncratic and systemic variables

Variable	Concept	Expected sign of β
Idiosyncratic variables		
Non-financial information		
HISTORY	How long the borrower has been a client. Numerical variable	–
LOAN_GRANT	Loans granted previously. Numerical variable	–
LOAN_DENY	Loans denied previously. Numerical variable	+
SECTOR	Activity sector of the microenterprise. Categorical variable: (0) trade (1) agriculture (2) production (3) service	+/–
LOAN_AIM	Purpose of the microcredit. Dichotomous variable: (0) working capital; (1) fixed asset	+
TOT_PMTS	Total number of repayment instalments made in the client's credit history. Numerical variable	–
TOT_ARRS	Number of repayment instalments paid in arrears. Numerical variable	+
AVG_ ARRS	Average (days) duration of arrears. Numerical variable	+
MAX_ ARRS	Number of days in a situation of maximum arrears. Numerical variable	+
SEX	Borrower's gender. Dichotomous variable: (0) male; (1) female	–
AGE	Borrower's age when requesting the loan. Numerical variable	+
MAR_STAT	Marital status. Dichotomous variable: (0) Unattached; (1) family relationship	–
Financial ratios		
EMPT_STAT	Client's employment situation. Dichotomous variable: (0) Owner; (1) Employed	+
R1	Asset rotation = Sales income/Total assets	–
R2	Productivity = Gross profit/Operating costs	–
R3	Liquidity = Payment capacity/Total assets	–
R4	Liquidity rotation = Payment capacity/Sales income × 360	+
R5	Dependence or debt = Total liabilities/(Total liabilities + Total equity)	+
R6	Leverage = Total liabilities/Total equity	+
R7	ROA = Net profit/Total assets	–
R8	ROE = Net profit/Total equity	–

Table 1 (continued)

Variable	Concept	Expected sign of β
Loan variables		
GUARANT	Type of guarantee supplied by the client. Dichotomous variable: (0) None (1) Real guarantee (surety, pledge, mortgage, etc.)	–
DISABILITY	The client has some type of disability. Dichotomous variable: (0) Known disability; (1) No known disability	–
NOMINAL	Value of the microcredit. Numerical variable	–
DURATION	Number of monthly instalments of the microcredit applied for. Numerical variable	+
INT_RATE	Monthly rate of interest of the microcredit. Numerical variable	+
Systemic variables		
ECO_CYCLE	Phase of the economic cycle. Dummy variable: (0) Observation after the economic crisis (20,016–2017); (1) Observation during the economic crisis (2014–2016)	+
GDP	Growth rate of the national economy. Numerical variable	–
UNEMPT	National rate of unemployment. Numerical variable	+
RISK_PREM	Risk premium: difference between the price of Spanish and German treasury bonds. Numerical variable	+

Source: Authors based on previous literature

On the other hand, in microfinance, women are said to be more creditworthy than men, since they are considered to have a greater sense of family responsibility, a fact that is reflected in patterns of loan repayment. For this reason, we expect to obtain a negative sign for the *SEX* variable, according to Govindapuram et al. (2023), Beisland et al. (2019), Dorfleitner et al. (2021) and Cozarenco & Szafarz (2018). The sign for the estimator of the *AGE* variable is expected to be positive, because a younger client will have greater economic potential and be better able to repay credits than an older person (Kiruthika & Dilsha, 2015; Van Gool et al. 2012). Regarding the client's marital status, *MAR_STAT*, the credit risk posed by unattached clients is expected to be greater than that of clients who undertake the responsibility of a family unit, since family and household responsibilities are, in general, associated with a more reliable pattern of debt repayment (Beisland et al. 2019; Cozarenco & Szafarz 2018). Therefore, the sign of this statistical estimator is expected to be negative. Likewise, we expect to obtain a positive estimator for the employment status, *EMPT_STAT*, variable, since clients whose economic activity is already consolidated in the management of a small business will have a lower probability of credit default than those who have previously worked as employees and now seek to obtain a microcredit to set up a microenterprise (Rayo et al. 2010). Finally, the expected signs for the estimators of the R_i ratios of equity, liquidity, debt and profitability were adopted taking into account previous research practice in credit scoring models for commercial banking. Authors such as Blaylock (2018) or Beisland & Mersland (2017) concluded that in the PWD the lower income levels have less access to microfinance services and, in addition, the PWD that work in agriculture and manufacturing have less financial access than the PWD who work in the service sector. Depending on the selected ratios, the higher the payment capacity, the lower the default probability, which justifies the signs assigned to the estimator. In parallel, Hemingway (2010) indicates that the increase in risk in mortgage loans hurts PWD.

In microfinance, the approach taken to the guarantors, *GUARANT*, of a microcredit is different from that for credits awarded by large banking corporations (Maes & Reed; 2012; Rayo et al. 2010; Abdou et al. 2008). We expect a negative sign for this variable. By analogy with borrowers who are not disabled, collateral reduces credit risk. Similar to the microfinance industry, regarding the variable *DISABILITY*, the client's own reputation or moral solvency becomes the main guarantee requested and supplied. Accordingly, we expect the presence of disability to mitigate the applicant's credit risk. Thus, the bank will request an affidavit of assets from borrowers who do not usually have significant problems in meeting their payment obligations. In the institution's experience, PWD are often regarded as being more creditworthy and reliable than clients not affected by disability. On the contrary, solid guarantees are required of customers who, in the past, have habitually failed to meet their repayment obligations. Accordingly, we expect to find a negative sign for this estimator. Furthermore, the request for a large loan, within the limits imposed in the definition of microcredit, is usually accepted if the client has a good repayment record with respect to previous credits. In addition, the loan of a large sum is usually made with respect to well-established, secure economic activities. Therefore, based on Kiruthika & Dilsha (2015) and Vega et al. (2013), we would expect a larger loan to be less inherently risky than one for a smaller amount. In consequence, we expect to obtain a negative sign for the estimator of the *NOMINAL* variable. Based on Blanco et al. (2013) and Abdou et al. (2008) the greater the *DURATION* of the loan, the greater the probability of default. Hence, we expect to see a positive estimator for this variable. Similarly, the higher the rate of interest, *INT_ RATE*, of the operation, the more difficulty the client will have in meeting the repayment schedule. For this reason, we expect this estimator to be positive.

Turning to the macroeconomic variables (systemic variables related to country as a whole), according to Benito et al. (2015) and Balaguer-Coll et al. (2016), the situation of the economic cycle, *ECO_CYCLE*, could influence the volume of debt and, therefore, problems insolvency. In an upward cycle, people generate more income and, therefore, have more ability to pay. In a recession cycle, the opposite occurs. Accordingly, we included this variable as a possible determinant of the probability of default, assigning it an expected positive sign. In parallel, the conclusions of Navarro-Galera et al. (2017) and Balaguer-Coll et al. (2016) suggest that an increased level of economic activity and of the national rate of unemployment are both associated with higher levels of borrowing. Therefore, we also included the macroeconomic variables *GDP* and *UNEMPT*, expecting a negative effect of the first and a positive effect of the second on the default probability (Lara-Rubio et al. 2017). The selection of the national unemployment rate can influence the credit risk of people with disabilities for two reasons. First, if the borrower with a disability has borrowed for a business project, a rise in the unemployment rate may harm the borrower's income and thus undermine his or her ability to repay and creditworthiness. Second, when the unemployment rate rises, financial institutions adopt more stringent lending policies, which could limit access to credit for people with disabilities. Finally, pronouncements made by organisations such as the International Monetary Fund. IMF (2014) and the European Union (EU) (2015), together with previous research findings (Mackey 2014), led us to incorporate the variable *RISK_PREMIUM*, for which a positive sign is expected.

The statistical model

As mentioned in the section dedicated to the dependent variable, to measure the probability of default we assign a value of 1 to borrowers that meet one or more of the conditions for the two indicators selected, and a value of 0 otherwise, according to our analysis of 2350 loan portfolio clients, including 785 PWD. These data reflect the values of the dependent, or explained, variable (the probability of default as an indicator of financial credit risk) and of 30 independent, or explanatory, variables, which reflect idiosyncratic and systemic factors.

Our empirical results were obtained by means of logistic regression, a parametric technique for calculating the probability of credit default, and a nonparametric technique consisting of a multilayer perceptron (MLP) artificial neural network.

We decided to use binary logistic regression for the following reasons: (a) the analysis of the study sample characteristics identified a large number of categorical explanatory variables; (b) in logit models, the coefficients are interpreted in terms of odds ratios, which are relatively easier to understand compared to the coefficients of Probit regression (Hosmer et al. 2013). Odds ratios indicate how much the odds (odds ratio) of the event occurring changes for a unit change in the independent variable; (c) the optimisation algorithms used in logistic regression tend to converge quickly, highlighting greater computational efficiency (Garson 2014); and (d) logistic regression is robust to violations of the assumption of normality of errors (Fox 2015).

The main purpose of our logistic regression model is to predict the result category for individual cases, using the most parsimonious model. To achieve this goal, the model created includes all the predictor variables considered useful for predicting the dependent variable. These variables can be introduced into the model by stepwise regression, following the order proposed in previous studies, testing the fit of the model after the integration of each coefficient.

First, we consider the parametric model (logistic regression) and then the MLP neural network, comparing it with classical parametric techniques. Neural networks are particular, implicitly limited, implementations of ordinary smoothers, which are nonlinear, not necessarily additive extensions of the logistic regression model, according to Blanco et al. (2013) and Cubiles-de-la-Vega et al. (2013). Finally, the statistical characteristics of the best credit scoring models are described.

Logistic regression

Starting from Eq. 6 (see Sect. "Credit risk model for persons with disabilities"), the logistic regression model estimates the probability of default of borrower i as a function of systematic and idiosyncratic factors according to:

$$\mathrm{PD}_i = \mathrm{PD}\left(\mathrm{APP}_i \le c_i | X_j, Z_{ki}\right) = \frac{e^{\left(\widehat{\alpha}+\sum_{j=1}^{n}\widehat{\beta}_j X_j+\sum_{k=1}^{m}\widehat{\delta}_k Z_{ki}\right)}}{1+e^{\left(\widehat{\alpha}+\sum_{j=1}^{n}\widehat{\beta}_j X_j+\sum_{k=1}^{m}\widehat{\delta}_k Z_{ki}\right)}} \tag{8}$$

The parameters $\widehat{\alpha}$,$\widehat{\beta}_j$ and $\widehat{\delta}_k$ in the logit can be estimated by maximising the value of the likelihood function.

The credit risk model we propose was chosen for several reasons. First, according to the literature, discrete choice models are appropriate when the study goal is to analyse the factors that influence the probability of an individual defaulting (Jacobson et al. 2013; Kukuk & Rönnberg 2013; Hwang et al. 2013). Second, this model meets the statistical requirements established in the Basel III regulations for calculating the probability of default. Third, international organisations such as the European Union (EU) (2015), the International Monetary Fund. IMF (2014), the Worldwide Bank Group (2015) and the World Health Organization (2011) have highlighted the need to study the combined effect of idiosyncratic and systemic factors in the measurement of credit risk.

Artificial neural network

According to Blanco et al. (2013), artificial neural networks constitute a computational paradigm from which many nonlinear mathematical models can be derived, providing solutions to a broad range of statistical problems.

A MLP or radial base function (RBF) network is a function of predictors (independent variables or inputs) that minimises the prediction error of the destination variables (or outputs). Theoretical investigations have shown that a particular architecture, the MLP, provides a reference procedure in the family of nonparametric models (Bishop 1995). Currently, this type of neural network is most commonly used in commercial studies (Vellido et al. 1999; Zhang et al. 1998). Taking into account these considerations, we use a three-layer MLP in which the output layer is formed of a node that provides the probability of default by PWD. In this calculation, we use a sigmoid activation function calculated by the logistic activation function g (u) = $e_u/(e_u + 1)$, which is also used in the hidden layer of the MLP, taking arguments of real value which are later transformed to the rank (0, 1).

The output layer contains the destination (dependent) variables. In this case, the activation function relates the weighted sum of units of a given layer with the values of units in the correct layer. This function takes the following form: $\gamma(c_h) = \exp(c_h)/\Sigma j \exp(c_j)$ and the output of the neural network from a vector of inputs $(x_1,\ldots,x_p)$ is:

$$\hat{y} = g\left(w_0 + \sum_{h=1}^{H} w_0\, g\left(v_{0h} + \sum_{j=1}^{p} v_{\text{ih}}\, x_j\right)\right) \tag{9}$$

The output from this model provides an estimate of the probability of default by PWD for the corresponding input vector. The final decision can be obtained by comparing this result with a threshold, usually set at 0.5. Therefore, default is expected when the result obtained is the cut-off point associated with the values of sensitivity and specificity that are most proximal to each other and which present the highest percentage of correct classification.

A major drawback of MLP is the fact that there is no known procedure to ensure that a global solution can be found to the problem of finding a synaptic weight configuration that minimises the usual error criteria, and therefore, the choice of any one criterion among the many possible is often taken by applying the many learning rules that have been proposed. Another drawback is its black box nature, which makes it difficult to interpret the resulting model, although certain interesting proposals in this respect have been made, such as Bayesian neural networks (Neal 1996).

There is no general rule for determining the optimal number of hidden nodes, a parameter that is necessary for best network performance. The most common way to determine the size of the hidden layer is through experiments, or trial and error (Tang and Fishwick 1993; Wong 1991). Figure 1 shows the typical structure of an MLP model. The number of hidden nodes determines the complexity of the final model, but the creation of a more complex network does not guarantee a better generalisation capability.

We decided to use an MLP-type neural network for several reasons: a) previous investigations have done so, to complement and advance parametric techniques, which in most cases improves performance (Viswanathan & Shanthi 2017; Blanco-Oliver et al. 2016); b) MLP neural networks take into account nonlinear relationships that are not considered in classical parametric techniques (Blanco et al. 2013; Cubiles-de-la-Vega et al. 2013; Liébana-Cabanillas & Lara-Rubio 2017); c) this explanatory, predictive artificial intelligence technique is often used to solve financial problems arising in the calculation of default probability in the private sector (Adewusi et al. 2016; Yeh & Lien 2009) and in the financial field (Abbasi and Hanandeh, 2016; Wu & Wu 2016).

Analysis of results

Our empirical results show that loan default occurred in 344 cases of 1565 persons with no disability (21.98%) and in 62 cases of 785 PWD (7.89%). Table 2 presents the coefficients estimated by maximum likelihood and their transformation into odds ratios (*OR*) or *Exp (β)* for the three models considered and described in previous sections. The OR information for each variable enables us to determine the influence of the statistically significant variables. The OR is interpreted as the variation in the odds of the occurrence of the event (default) in response to a unit variation in the explanatory variable considered. Figures 2, 3 and 4 show the normalised importance for each variable versus the explanation of the probability of default among all borrowers in the portfolio. These results show that greater weights are assigned to the variables found to be significant in the logistic regression model, which means that the significant variables discussed above best explain the phenomenon of default by PWD.

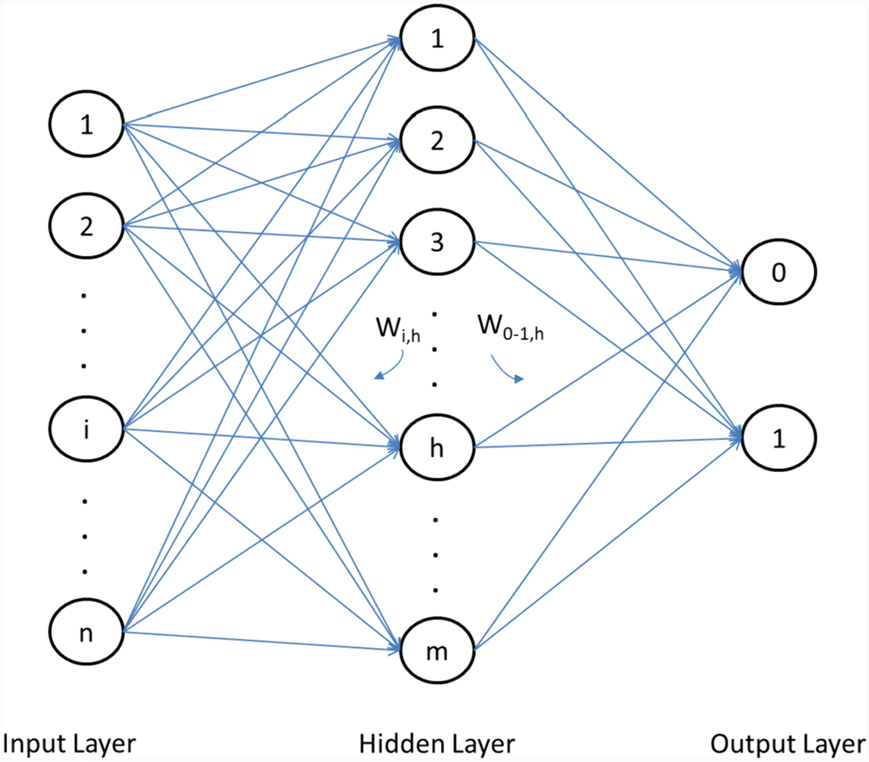

Fig. 1 Three-layer multilayer perceptron Source: own elaboration

The classification matrix, i.e. the table of observed vs. estimated cases (Table 3), shows the percentage of correct classification obtained by each of the three models using the two statistical techniques we consider. This table shows that model 2, designed for PWD, achieves higher percentages of correct classification (80.89% and 77.83% for the neural network and for logistic regression, respectively) than the other models. Therefore, we conclude that this model presents a better fit to the variables, although the two groups have similar payment profiles. In addition, according to previous research, models estimated using nonparametric techniques significantly improve the predictive power of the probability of default in PWD.

The results obtained also show that the probability of default, for all clients in the study sample, with and without disabilities, is 23.81%. For PWD, the mean probability of non-payment is 19.53%, while for clients without disabilities, the figure rises to 24.95%. These initial findings extend our understanding of the question, showing that PWD present less risk of default than persons without disabilities.

In the full model (Model 1), the results show that the variable *DISABILITY* is strongly significant. This observation justifies the development of models 2 and 3, to perform two separate studies of the factors that influence PD, according to the presence or absence of disabilities in the applicant. In this regard, we find that the stated purpose of the loan is relevant to the client's PD, this association being stronger in the case of PWD. On the contrary, the number of repayments made previously, according to the client's credit record, is

Table 2 Significant variables for the models estimated with logistic regression

Variable	Model 1		
	Coef. (β)	Std. err	Exp (β)
Loan_AIM	– 0.0735494 (*)	0.0398241	0.929090
TOT_PMTS	– 0.1305842 (***)	4.79959	0.8775826
R2	– 0.795266 (***)	0.3254843	0.451461
R4	0.1042556 (**)	0.0651658	1.109884
R6	0.4688818 (*)	0.3164849	1.598206
Disability	– 0.3942798 (***)	0.1945397	0.674165
GDP	– 0.165963 (***)	3.639751	0.8470775
Risk_Premium	0.4207524 (***)	7.273572	1.5231071
CONS	4.893446 (***)	1.504701	
Variable	Model 2		
	Coef. (β)	Std. err	Exp (β)
LOAN_AIM	– 0,270,232 (***)	0.0768787	0.7632023
TOT_ PMTS	– 21.59687 (***)	7.266459	4.1744E-10
R2	– 1.757557 (***)	0.3756014	0.1724656
R4	0.0883237 (**)	0.0466876	1.092341
R6	0.444984 (***)	0.1428	1.560465
GDP	–0.225793(**)	3.96547	0.79788325
Risk_Premium	0,270,232 (***)	0.0768787	1.31022
CONS	3.267 (***)	1.618851	
Variable	Model 3		
	Coef. (β)	Std. err	Exp (β)
LOAN_AIM	– 0.130232 (**)	0.054678	0.87789174
R4	0.123671(**)	0.0951357	1.1316435
R6	0.691347(***)	0.12894	1.99640288
GDP	–0.145632(**)	3.845266	0.8644757
RISK_PREMIUM	0.13544(*)	0.63247	1.14504049
CONS	5.2567(***)	1.00954	

Source: Authors' computations using the dataset

(*), (**) and (***) represent significance at the 10%, 5% and 1% levels

significant in the complete model and in the model for PWD, but not for persons without disabilities. For both of these factors, our study results represent an advance on previous research findings.

Our results find a negative sign in the estimator of the LOAN_AIM variable, in contrast to previous research findings in the microfinance sector (Blanco et al. 2013). We suggest that since the fixed asset investment is not too large, the associated volatility is lower assuming that the evolution of the debt is known as it is repaid through an established repayment procedure. Thus, the risk of acquiring a fixed asset is lower with respect to financing working capital needs, which justifies the sign obtained in our estimator.

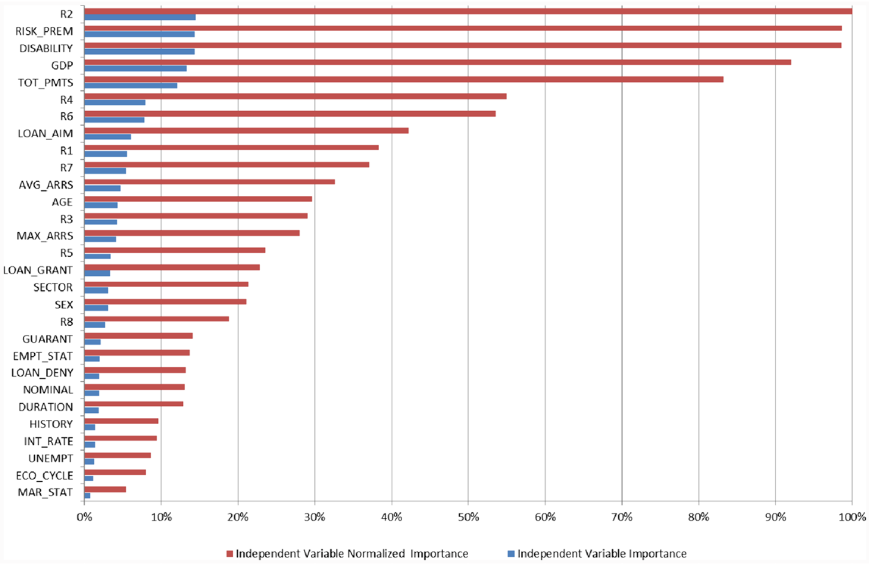

Fig. 2 Normalised importance of the variables in MLP (model 1) Source: own elaboration

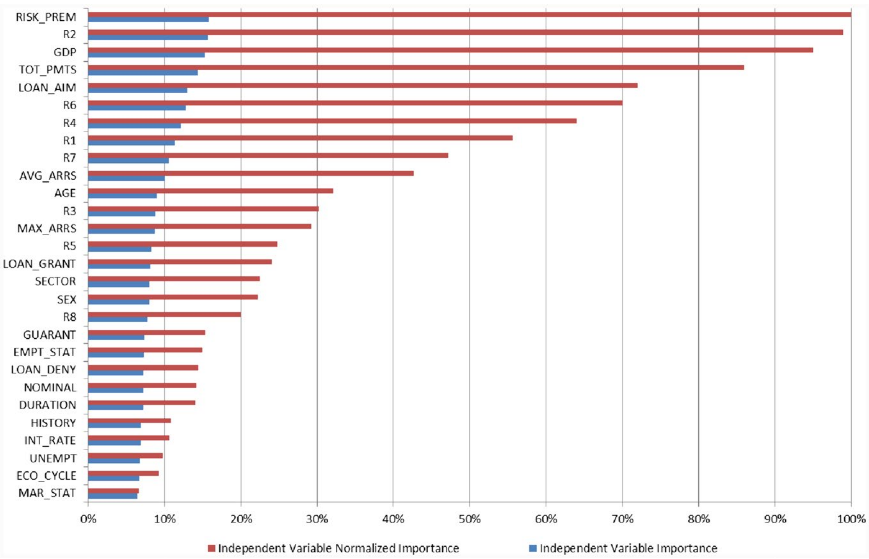

Fig. 3 Normalised importance of the variables in MLP (model 2) Source: own elaboration

The remaining results show that the signs of all the variables that were found to be statistically significant in the different credit scoring models considered are in line with our expectations and with the results of previous research, thus corroborating the rigour and consistency of our analysis. Moreover, the empirical evidence we present provides novel information on credit risk in PWDs.

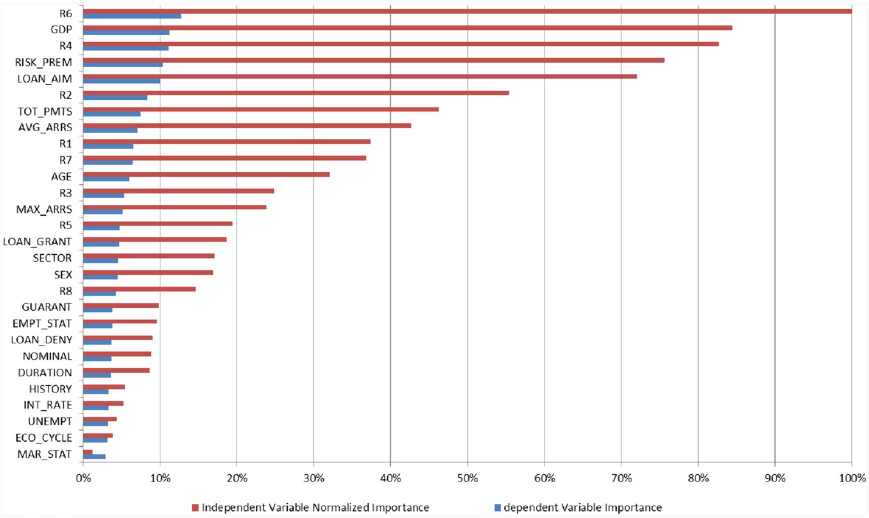

Fig. 4 Normalised importance of the variables in MLP (model 3) Source: own elaboration

The negative sign obtained in the TOT_PMTS variable confirms that clients with a higher number of loans and repayments are clients with more experience as borrowers and, therefore, with a lower associated default risk. This is an advance on previous literature by corroborating the results of authors such as (Kiruthika & Dilsha, 2015; Abdou et al. 2008) but now in the group of people with disabilities.

Continuing our discussion of the relevance of financial ratios of the borrowers, the results obtained corroborate previous research in that, regardless of the presence or otherwise of disability, a higher level of liquidity rotation (R4) and leverage (R6) is associated with a greater probability of default. However, an increase in the productivity ratio (R2) of PWD reduces the probability of default. Our findings are consistent with results obtained in previous research literature on credit rating models for commercial banking and microfinance.

Finally, in all three models the systematic variables *GDP* and *RISK_PREMIUM* influence PD, while PWD are more sensitive to variations in the systematic factors found to be statistically significant, a result that extends previous research finding (Lara-Rubio et al. 2017; Mackey 2014).

Conclusions

Based on the Basel III regulations and a logit model and an artificial neural network, through idiosyncratic and systematic variables for a population of 785 PWD our study identifies specific factors that impact on the default risk of PWD. Awareness of this influence may be to help efforts to overcome the barriers currently limiting access to credit and the full financial inclusion of these persons.

Our study results provide empirical evidence that granting more loans to PWD can help reduce the overall default risk of those receiving loans from financial institutions. The results of our first statistical model, which includes loans to persons with and without

Table 3 Classification matrix

Model 1							
Logistic regression				Neural network			
Observation	Prediction			Observation	Prediction		
	0	1	PCC (%)		0	1	PCC (%)
0	1.439	504	74.06	0	1.567	376	80.65
1	92	304	76.77	1	71	325	82.07
PCC			74.52	PCC			80.89
Model 2							
Logistic regression				Neural network			
Observation	Prediction			Observation	Prediction		
	0	1	PCC (%)		0	1	PCC (%)
0	561	162	77.59	0	600	123	82.99
1	12	50	80.65	1	8	54	87.10
PCC			77.83	PCC			83.31
Model 3							
Logistic regression				Neural network			
Observation	Prediction			Observation	Prediction		
	0	1	PCC (%)		0	1	PCC (%)
0	842	378	69.02	0	879	341	72.05
1	105	238	69.39	1	79	238	75.08
PCC			69.10	PCC			72.67

Source: Authors' analysis using the dataset

disabilities, indicate that a rise in the number of PWD among bank loan recipients can reduce the probability of default, overall, within a given financial institution. In fact, these results clearly show that the specific weight of clients with default is much higher among borrowers without disabilities (22%) than among PWD (7.89%). In consequence, the latter should be advantageously viewed in any application for a bank loan.

We also identify factors that specifically influence the default risk of PWD, thus building upon the conclusions drawn in previous studies. Our results show that the default risk of PWD is reduced when one or more of the following situations applies: a) the stated purpose of the loan is to obtain finance for investment in fixed capital; b) the borrower has limited financial liquidity; c) the borrower has limited financial leverage; d) in the national economy, the GDP is rising; e) in the national economy, the risk premium is falling.

Moreover, the comparative analysis of statistical models 2 and 3 shows that only two variables (productivity and total repayments made) influence the default risk of PWD but not that of persons without disabilities. The remaining factors found to be significant affect both population groups to the same degree and have identical signs.

Since the factors influencing the default risk of PWD are very similar to those for persons without disabilities, financial institutions have no objective reason to discriminate against PWD when deciding upon a loan application. In addition, factors that are systematic, and therefore not controllable by banks or borrowers (i.e. GDP and the risk premium), also have an identical impact on the default risk of PWD and on that of clients without disabilities.

The findings presented in this paper represent considerable progress over the conclusions drawn in previous work in this field, in which researchers have studied the causes of default by people without resources, but without specifically analysing the case of PWD. Our findings can usefully be applied by PWD in negotiating bank loans, enabling them to justify their solvency by means of arguments regarding the purpose of the loan required, their own financial liquidity and the relationship between the payment obligations assumed and their personal equity.

These results are also of great practical use to financial institutions, showing that default rates may be reduced by extending credit to PWD, whilst requiring compliance with conditions concerning the purpose of the loan, the borrower's liquidity and/or the financial leverage involved. In addition, our findings should be taken into consideration by policymakers wishing to foster the access of PWD to bank credits. In this respect, the results presented highlight the utility of measures such as tax benefits for loans for fixed capital investment. In addition, information campaigns might target PWD to inform them of the factors that would underpin their solvency and thus make their loan application more likely to succeed.

In summary, our empirical study has generated interesting new knowledge that may promote the full financial inclusion of PWD, by reducing their default risk, providing useful information on which the banks may base their decisions and helping prevent cognitive, sensory or mobility disabilities from being perceived as an impediment to creditworthiness. This information is also beneficial to associations of PWD, analysts and policymakers within financial entities, politicians and government managers interested in measures to facilitate financial insertion, banking authorities and international organisations working to achieve the greatest possible degree of financial inclusion.

These findings are very interesting to increase the financial inclusion of PWD in developing countries. First, according to the World Bank Group (2023), globally 15% of PWD are located in developing countries. Thus, in developing countries the variables identified in our empirical results can be useful to promote PWD's access to bank financing with minimal risks, which is very relevant for banking entities and entrepreneurs in these countries. Secondly, following the World Bank Group (2023), PWD are more vulnerable to suffering the results of adverse socioeconomic factors, such as the effects of two significant variables in our results: GDP and risk premium. Generally, developing countries have lower GDP levels and higher risk premiums. In short, our findings are relevant to developing countries and may have a greater impact even than in developed countries.

In parallel, our findings are interesting for the design of public policies aimed at promoting the financial inclusion of PWD. These conclusions suggest the usefulness of adopting some policy measures, such as the following: a) tax advantages for financial entities that grant loans to PWD; b) legal regulation on establishment of specific criteria for estimating the default risk of PWD, individually considered; and c) creation of databases on the default risks of PWD and making them available to financial entities for publish that their risks are not different from those of people without disabilities.

Finally, the results of this study are subject to the limitation that the analysis considers a database that does not contain some variables with evidence in the previous literature of a relationship with the probability of default. For example, the educational level and ethnicity of the borrower are variables that could be highly positively correlated with access to credit. Also, the variable related to the borrower's employment status could also incorporate a third category that captures the likelihood of unemployment of the credit applicant. However, these limitations also constitute an opportunity for future research.

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Declarations

Conflict of interest We have no conflicts of interest to disclose.

Ethical approval The authors declare to comply with Ethical Standards.

Consent for publication We confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere.

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