Money laundering control in Mexico

A risk management approach through regression trees (data mining)

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Abstract

Purpose – This paper is aimed at developing a regression tree model useful to quantify the Money Laundering (ML) risk associated to a customer profile and his contracted products (customer's inherent risk). ML is a risk to which different entities are exposed, but mainly the financial ones because of the nature of their activity, so that they are legally obliged to have an appropriate methodology to analyze and assess such a risk.

Design/methodology/approach – This paper uses the technique of regression trees to identify, measure and quantify the ML customer's inherent risk.

Findings – After classifying customers as high- or low-risk based on a probability threshold of 0.5, this study finds that customers with 56 months or more of seniority are more risky than those with less seniority; the variables "contracted product" and "customer seniority" are statistically significant; the variables origin, legal entity and economic activity are not statistically significant for classifying customers; institution collection, business products and individual product are the most risky; and the percentage of effectiveness, suggested by the decision tree technique, is around 89.5 per cent.

Practical implications – In the daily practice of ML risk management, the two main issues to be considered are: 1) the knowledge of the customer, and 2) the detection of his inherent risk elements.

Originality/value – Information from the customer portfolio and his transaction profile is analyzed through BigData and data mining.

Keywords Data mining, Money laundering, Regression trees, Risk control methodology

Paper type Research paper

1. Introduction

The Mexican National Banking and Securities Commission (CNBV for its acronym in Spanish) defines money laundering (ML) as the process whereby the origin of the funds generated by the exercise of any illegal activities is concealed (drug trafficking, weapons smuggling, corruption, fraud, tax evasion, human trafficking, kidnapping, prostitution, extortion, piracy, tax evasion, etc.), making these proceeds appear to have originated from legitimate activities.

The process of ML mainly consists of three stages:

(1) Placement, this is the physical disposal of cash proceeds derived from illegal activity. The funds are placed in the legitimate financial system, for example, by making bank deposits in cash or by investing in financial instruments.

Journal of Money Laundering Control
Vol. 23 No. 2, 2020
pp. 427-439
© Emerald Publishing Limited
1368-5201
DOI 10.1108/JMLC-10-2019-0083

JEL classification – C02, C14, G21, D81

(2) Layering, this stage involves the separation of funds from their illegal source through transaction layers meant to cover up the audit trail and achieve anonymity, it involves moving money through various financial transactions (bank transfers, real estate or luxury goods purchase) to change its form, making it difficult to track.

(3) Integration, this stage consists of giving legitimate appearance to the illicit wealth by integrating laundered money back into the economy from what appears to be a reputable source.

Mexico faces a wide variety of social, political and economic problems derived from illicit money, which is incorporated into the financial system through ML. The effects and consequences on the country of activities related to ML are adverse, but above all harmful, since according to Cuervo (2017):

- It diminishes tax revenue, indirectly impacting, honest taxpayers that have to shoulder an additional tax burden. Besides, the decline in tax revenue dwarfs government budgets, which may lead to loss of control of economic policy.
- It affects competition by weakening the legitimate private sector. That is, the funds both companies legally established and shell companies have access allow subsidizing products and services below market. As a result, these companies have a competitive advantage over legitimate companies that have no access to these resources, which means that legitimate businesses cannot compete.
- Some sectors of the economy can be controlled through ML, which enhances the potential for an economic instability due to an inadequate allocation of resources resulting from artificial distortion prices on assets.
- Besides the legal and operational impact, financial institutions associated with ML have an impact on their reputation, which limits the ability of entities to negotiate with their counterparts.
- It can distort prices of exported or imported consumption goods, but mainly on real estate.
- It can lead to inexplicable alterations on interest rates and on money demand since the investment decisions of the illicit funds follow the need of hiding the origin of the resources and not to financial criteria.
- Because of unforeseen transfers of assets, it can also cause volatility in international capital flows and in the exchange rate.
- It feeds the cycle of crime and corruption, aggravating the direct costs associated with the specific type of crime, thus worsening the population security conditions and damaging the social structure and the rule of law.
- Changes in official statistics are generated, hindering appropriate decision-making.

Due to the nature of the main activities of financial institutions, they are the most exposed to ML. According to the general provisions referred to article 115 of the *Ley de Instituciones de Crédito* (Law on Credit Institutions) published in *Diario Oficial de la Federación* (Official Diary of the Federation) on April 20, 2009, and its last reform on February 24, 2017, financial institutions are obliged to have a method to analyze and assess risks.

The guide for the development of a risk control methodology in the prevention of operations with resources of illicit origin and delinquency financing of the Mexican National Banking and Securities Commission (CNBV, 2017, 2018) defines the risk assessment methodology as the set of processes for the identification, measurement and mitigation of ML risk to which the obligated subjects are exposed. These obligated subjects include general warehouse companies, investment advisors, brokerage firms, foreign exchange firms, foreign exchange centers, credit institutions, Savings and Loans Cooperative Societies (SOCAPS, Spanish Acronym for *Sociedades Cooperativas de Ahorro y Préstamo*), regulated and non-regulated Multiple Purpose Financial Companies (SOFOMES, Spanish Acronym for *Sociedades Financieras de Objeto Múltiple*), Popular Financial Companies (SOFIPOS, Spanish Acronym for *Sociedades Financieras Populares*), Community Financial Companies (SOFINCOS, Spanish Acronym for *Sociedades Financieras Comunitarias*), financial rural integration agencies (OIFR, Spanish Acronym for *Organismos de Integración Financiera Rural*), stock distributing investment funds societies, investment funds operators, money remitters and credit unions. The guide establishes, in general, the elements of the methodology for conducting a risk assessment of potential ML. However, specific actions are required for an adequate measurement of risk. In this regard, the present research proposes a statistical technique to analyze and quantify the ML risk to which financial institutions are exposed.

2. Elements and indicators of risk

To develop a methodology to assess the ML risk to which a financial institution is exposed, we established key risk elements and their respective indicators. Table I provides a list of these indicators and a brief description thereof.

Risk elements are classified as transaction risk, institutional risk and inherent risk. Here we will understand transaction risk as the risk related to the transaction profile of the customers. Inherent risk has to do with the economic activity or business of the company or institution, and with the geographic location of the customer. In general, it refers to the identification of the potential customer before being a formal customer of the financial institution. Institutional risk is the risk of financial institutions being used for ML purposes due mainly to failures in internal controls, administrative failures, automation level and untrained employees. The interrelation between the three types of elements of risk, and the type of information, either qualitative or quantitative, that is generated in the identification process are shown in Table II.

3. Risk control methodology for money laundering prevention: regression tree for inherent risk measurement

In this work, the inherent risk is a customer or user-related risk determined mainly by the independent variables:

- legal entity (natural person or legal person);
- origin (state of the republic);
- economic activity;
- seniority; and
- contracted product.

The information used in this work to calculate the associated risks comes from a financial institution focused on the real estate sector, which for reasons of confidentiality, we will call the "obligated subject".

The approach is "Know Your Customer". The procedure consists in identifying and knowing the customer through the information provided and transaction profiling. The *a priori* level of risk is assigned (low or high) based on the experience of the experts of the institution and by considering the criteria stated in the ML risk assessment survey

Table I.
Elements and indicators of risk

Risk elements	Indicators	Description
Transaction profile	Amount of money Frequency Legal basis Cash restrictions Shipping channels	Information provided by the client and institution's own information
Unusual operations	Legal basis	There is no verifiable justification for unusual patterns of customer activity
Relevant Operations	Frequency Limit Shipping channels	Number of operations. Limit amount (activity-dependent) more than 10,000 USD through ATMs, electronic banking, among others
Internal worrying operations	Employee collusion Shareholder behavior	Activities not allowed for internal personnel
Cash operations	Money deposits	Receive less than 583,000 pesos in cash (in Mexico 2016)
Customer identification	Natural person/Legal person Age/Creation date National/Foreign Economic activity/ Commercial activity Occupation Country History	General data. The minimum necessary information that the institution must own for any authorization. Complete files must be generated
Customer knowledge	Social networks Transaction profile	A way to know the customer better after a consistent identification
Automation level	Automation of business lines and/or processes	Automated processes decrease the risk
Internal structure	Internal controls and corporate governance	The Institution must comply with the organization manuals and procedures, as well as technical documents, disaster recovery plans, and detection programs
Training	Updating Improvement of the functions	Employees must be well trained to properly perform their functions
Products and services	Corporate finance Negotiation and sales Retail banking Commercial banking Payments and settlements Consultancy services Asset management Retail middlemen	Generate a file and keep it for 10 years if it is a financial record, and for 5 years otherwise. Based on the laws and parameters established for compliance the CNBV, SHCP, SAT, CNSF, UIF, and Federal Law for the prevention and identification of operations with illicit proceeds, reports or as it may correspond It depends on the institution or market to which the financial companies and the business lines are directed
Countries and geographic areas	Tax havens Higher risk countries National high-risk areas List of restricted people	Based on GAFI or UIF Avoid the "Off-Shore" (tax havens). The OECD provides a list of "Off-Shore" financial centers
Politically exposed person	Public officials Second-degree relatives	The term expires after the following 2 years of holding office

Source: Authors' own elaboration

Table II. Types of risk, interrelation and information about the risk elements

Type of risk	Risk elements	Correlation with others elements	Justification	Type of information
Transaction risk	Transaction profile. Operations: Unusual Relevant Internal Worrying In cash	Customer knowledge. Customer identification	For the knowledge and identification of the customer, the possible transactions that he/ she has made or intends to make must be observed	Quantitative information
Institutional risk	Automation level	Internal structure	The level of automation is better by having a good structure and well-trained employees, in addition to having an efficient system with a good database	Quantitative information
	Internal structure	Internal worrying operations	Operations lacking a good internal structure or employee collusion make the Institution more vulnerable	Qualitative information
	Training	Internal structure. Automation	A good training of the users may generate better internal and external results	Qualitative information
Inherent Risk	Customer identification	Transactional profile. Products and services. Countries and geographic areas. Politically exposed people	The minimum requirements that the institution requires must be requested to identify the customer. This element of risk is where most information is needed, the customer can grant it in a uniform manner	Qualitative information
	Customer knowledge	Customer identification	Whenever after customer identification, the information requested is not enough, other sources (social networks and search engines) must be resorted to getting a better customer knowledge	Qualitative information
	Products and Services	Transaction profile	Every product or service has a different risk level	Qualitative and quantitative information
	Countries and geographic areas (additional)	Customer identification	Depends on the area of location, some areas may be more, or less, prone to risk	Qualitative information
	Politically exposed people	Transaction profile	Investigate if a position in the government was held a maximum of 2 years ago, or if there is any second-degree relative in the Government	Qualitative information

Source: Authors' own elaboration

coordinated and implemented by the Ministry of Finance and Public Credit of Mexico (SHCP, Spanish acronym for *Secretaría de Hacienda y CréditoPüblico*) in 2016[1].

The decision tree technique will be used to calculate the *a posteriori* level of risk of the customer or user, considering the aforementioned five independent variables. The decision tree constitutes a classification algorithm widely used in data mining. In classification techniques, the objective is to predict an event (a specific value of a categorical variable) or estimate values of a continuous variable. We work with historical data in which there is a known result, the rows arranged therein correspond to the individuals to be classified and columns are the attributes and the label (predictor variables and target variable). The models are built on training data and validated on test data.

The decision tree algorithms generate decision rules that are presented by a tree-like graph, where the total population (root node) is further split (intermediate branch nodes) until obtaining segments of similar behavior (leaf nodes) in relation to the target variable. The leaf nodes predict the value of the output variable. In each split, the predictor that best separates the population from the target variable is selected. When the target variable is categorical in nature, the decision tree is referred to as a classification tree, and for a continuous target variable, the tree is called a regression tree. Reasons such as the nature of the data to be classified, the number of branches in which the tree splits, splitting criteria, the method for handling missing values and pruning methods (tree simplification procedures) generate distinct algorithms (Safavian and Landgrebe 1991).

The classification and regression tree algorithm from Breiman *et al.* (1984) is perhaps the most well-known decision tree method in statistics. However, one of the first referenced is the Chi-squared Automatic Interaction Detection (CHAID) method proposed by Kass (1980). Other algorithms of decision trees are QUEST by Loh and Shih (1997), the Iterative Dichotomizer 3rd (ID3) algorithm developed by Quinlan (1986) and his later versions C4.5 (Quinlan, 1993) and C5.0 (Quinlan, 1990). In the present work, the analysis is based on the CHAID method and is performed using the statistical software SPSS version 23.

4. Data description

We use information from a list of 181 customers of the obligated subject. For illustrative purposes, Table III shows a sample of the database from the obligated subject by State in the Mexican Republic.

5. Risk factors for money laundering

To determine the initial risk level of customers or users, the risk factors determined by the five independent variables previously mentioned are analyzed in an integral manner, and a standardization process is carried out considering the results of the proposed ML risk assessment survey.

5.1 Data standardization

The actions carried out within the framework of the ML risk assessment survey resulted in the risk perception questionnaire applied by the SHCP in 2016 and forwarded by the obligated subjects which consist of 46 universal banking institutions. These institutions are divided into 4 segments: G5 (the 5 banks that dominate the market), investment and financial services banking (14 institutions), household credit (8 institutions) and commercial banking (19 institutions). For the study, we consider the results of the commercial banking segment, as the obligated subject analyzed here belongs to that segment. Table IV shows the economic activities that the ML risk assessment survey considers most risky. The level of risk was assigned as high (H) or low (L) according to the number of obliged subjects.

Legal entity	Origin (State of The Republic)	Economic activity	Seniority[a]	Contracted Product
Natural person	México	Service sector employee	115	Individual credit[b]
Natural person	Ciudad de México	Service sector employee	137	Individual credit
Natural person	México	Service sector employee	130	Individual credit
Natural person	México	Service sector employee	21	Individual credit
Natural person	Chihuahua	Service sector employee	99	Individual credit
Natural person	Baja California	Service sector employee	116	Individual credit
Natural person	Jalisco	Service sector employee	120	Individual credit
Natural person	Jalisco	Service sector employee	117	Individual credit
Natural person	Baja California	Service sector employee	30	Individual credit
Natural person	México	Service sector employee	61	Individual credit
Natural person	Jalisco	Service sector employee	122	Individual credit
Natural person	Quintana Roo	Service sector employee	120	Individual credit
Natural person	San Luis Potosí	Service sector employee	31	Individual credit
Natural person	Jalisco	Service sector employee	116	Individual credit
Natural person	México	Service sector employee	30	Individual credit
Natural person	Ciudad de México	Service sector employee	111	Individual credit
Natural person	Baja California	Service sector employee	162	Individual credit
Natural person	Baja California	Service sector employee	135	Individual credit
Natural person	Quintana Roo	Service sector employee	28	Individual credit
Natural person	Quintana Roo	Service sector employee	115	Individual credit
Natural person	San Luis Potosí	Service sector employee	50	Individual credit
Natural person	Quintana Roo	Service sector employee	126	Individual credit
Natural person	Baja California	Service sector employee	122	Individual credit
Natural person	México	Service sector employee	31	Individual credit
Natural person	Guanajuato	Service sector employee	104	Individual credit
Natural person	Baja California	Service sector employee	104	Individual credit
Natural person	Quintana Roo	Service sector employee	51	Individual credit
Natural person	Baja California	Service sector employee	107	Individual credit

Notes: [a]Number of months as a customer; [b]Refers to non-group credits
Source: Authors' own elaboration

Table III. Sample of the database with information of the dependent variables

Table V presents the States of the Mexican Republic that the ML risk assessment survey considers most risky, for which their level of risk was assigned as high (H) or low (L) according to the number of obliged subjects. The States that do not appear in Table V are considered low-risk.

Table VI shows the products that according to the ML risk assessment survey are considered risky. Based, in addition, on the number of obliged subjects, the risk level was assigned as high (H) or low (L).

For the obligated subjects stated in the ML risk assessment survey, we use different criteria to classify high-risk customers (natural or legal persons). Emphasizing that for natural persons there are more risk criteria (factors), so they are assigned a higher level of risk than the legal persons.

Customer information base is built by taking into account risk classifications in Tables IV-VI, together with the fact that natural persons have higher risk than the moral ones and that the greater the seniority, the greater risk. The base information includes the customer's status as dependent variable, which represents the priori risk classification. Table VII shows a sample of customer database that includes the initial classification assigned to the client by the obligated subject, where low risk and high risk are indicated by 0 and 1, respectively.

Table IV.
Level of risk by activity

Activities	No. of obligated subjects	Assigned risk
Vulnerable activities typified in the LFPIORPI	17	H
Some of the financial entities	8	H
Manufacturing and distribution of weapons	6	H
Purchase and sale of gasoline	5	H
Bars, canteens and nightclubs	4	H
Trade unions	4	L
Sales companies	3	L
Religious Organizations	3	L
Political parties	3	L
Construction	2	L
Livestock raising	2	L
NPO	2	L
Public sector employee	2	L
Housework	2	L
Civil associations	2	L

Source: Authors' own elaboration

Table V.
Risk level by state of the Mexican Republic

State	No. of obligated subjects	Assigned risk
Michoacán	10	H
Sinaloa	10	H
Jalisco	8	H
Ciudad de México	7	H
Nuevo León	7	H
Baja California	7	H
México	6	H
Veracruz	5	H
Tamaulipas	4	L
Chihuahua	3	L
Guerrero	3	L

Source: Authors' own elaboration

Table VI.
Level of risk by product

Product	No. of obligated subjects	Assigned risk
International transfers	7	H
Investment	5	H
Training	4	H
Trusts	4	H
Checking accounts	4	H
Cash transactions	4	H
Electronic transfers	2	L
Corporate credit	2	L
Foreign exchange operations	2	L
Consumer credit	2	L
Demand deposits	2	L

Source: Authors' own elaboration

Table VII.
A priori risk level

Legal entity	Origin (State of the Republic)	Economic activity	Seniority	Contracted product	Customer's status
Natural person	México	Service sector employee	115	Individual credit	0
Natural person	Ciudad de México	Service sector employee	137	Individual credit	0
Natural person	México	Service sector employee	130	Individual credit	0
Natural person	Chihuahua	Service sector employee	99	Individual credit	0
Natural person	Baja California	Service sector employee	116	Individual credit	0
Natural person	Jalisco	Service sector employee	120	Individual credit	0
Natural person	Jalisco	Service sector employee	117	Individual credit	0
Natural person	Baja California	Service sector employee	30	Individual credit	0
Natural person	México	Service sector employee	61	Individual credit	0
Natural person	Jalisco	Service sector employee	122	Individual credit	0
Natural person	Quintana Roo	Service sector employee	120	Individual credit	0
Natural person	San Luis Potosí	Service sector employee	31	Individual credit	0
Natural person	Jalisco	Service sector employee	116	Individual credit	0
Natural person	México	Service sector employee	30	Individual credit	0
Natural person	Ciudad de México	Service sector employee	111	Individual credit	0
Natural person	México	Service sector employee	74	Individual product	1
Natural person	Baja California	Service sector employee	58	Individual product	1
Natural person	Nayarit	Service sector employee	58	Individual product	1
Natural person	Jalisco	Service sector employee	58	Individual product	1
Natural person	Jalisco	Service sector employee	58	Individual product	1
Natural person	México	Service sector employee	58	Individual product	1
Natural person	Baja California	Service sector employee	58	Individual product	1
Natural person	Baja California	Service sector employee	53	Individual product	1
Legal person	Ciudad de México	Real estate management	32	Investment	1
Natural person	Ciudad de México	Service sector employee	51	Individual product	1
Legal person	Ciudad de México	Lender	37	Investment	1
Natural person	Baja California	Service sector employee	58	Individual product	1
Natural person	Baja California	Service sector employee	58	Individual product	1

Source: Authors' own elaboration

6. Results

The regression tree method was implemented in the software SPSS version 23, choosing the variable customer's status as the dependent variable, and the variables legal entity, origin, economic activity, seniority and contracted product, as predictor variables.

The distinct statistical tests conducted yield that the variables contracted product and seniority of the customer in the institution are the only statistically significant ones. Therefore, the other independent variables were not included in the construction of the regression tree. The effectiveness of the model is represented in Table VIII.

In the regression tree model, customers were classified as high-risk or low-risk based on a probability threshold of 0.5, and considering the two statistically significant variables, contracted product and customer seniority. If the probability is higher than this threshold, the customer is classified as high-risk; otherwise, he/she is classified as low-risk.

From the total number of clients with an *a priori* low level of risk, the model reclassified 19 as at high risk and kept 70 as at low risk, representing 78.7 per cent effectiveness. With regard to customers who were classified *a priori* as high-risk, the model kept them at this level, representing 100 per cent effectiveness. These results give an overall effectiveness of 89.5 per cent. From the results shown in the decision tree in Figure 1, the following is inferred:

- Products such as investment, business products and individual products are the most risky.
- Customers with 56 months or more of seniority are more risky than those with less seniority.
- The two variables contracted product and customer seniority are the only ones that are statistically significant.
- The variables origin, legal entity and economic activity are not statistically significant for classifying customers.

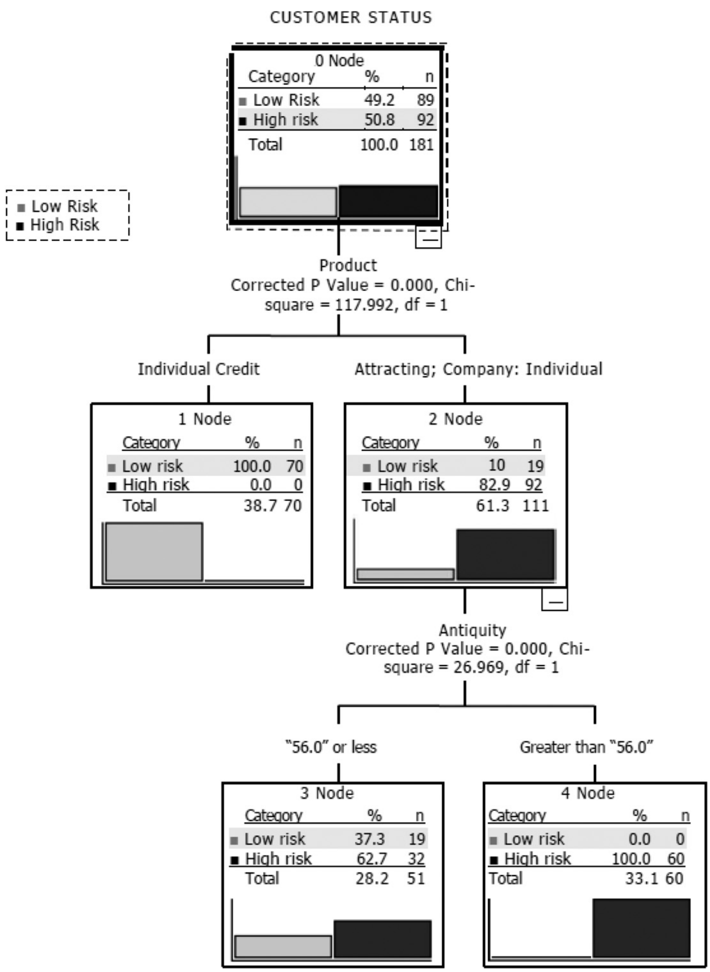
The percentage of effectiveness of 89.5 per cent suggests that the decision tree technique is robust to identify information patterns that allow classification, in our case for customers with different risk profiles.

Table VIII.
Model effectiveness

Classification			
		Predicted risk	
A priori risk	Low	High	Correct %
Low	70	19	78.7
High	0	92	100.0
Global percentage (%)	38.7	61.3	89.5

Growing method: CHAID
Dependent variable: Customer's status

Source: Authors' own elaboration by using SPSS



Source: Authors' own elaboration by using SPSS

Figure 1.
Regression tree

7. Conclusions

The financial sector, and specifically the banking sector, is highly susceptible of being used for ML. Despite all the efforts to control this risk, the organized crime is still capable of violating security mechanisms of the financial system. In Mexico, a number of ML cases have been detected, both in the formal banking sector and in alternative institutions such as SOFIPOS, SOFOMES, SOCAPS, among others. The financial sector in coordination with regulatory authorities designed regulatory instruments to address this threat. However, the results show that a high incidence and an impact on the economy are maintained because of ML activities. Intended to support and strengthen the ML risk management, this paper proposes the regression tree technique to quantify the inherent risk. The fundamental issue is the customer knowledge and the different types of risk factors which are classified into inherent, transaction and institutional.

As a result of the increasing use of electronic media for information sharing (BigData), the analysis necessary to identify the inherent risk factors represents great challenges. The information generated is largely unstructured and comes from different sources of information. Therefore, new tools such as data mining are required.

Information for transaction risk is generated from the customer portfolio and monitoring of customers' transaction profile, so for analysis and interpretation updated and accessible historical records are required. Regarding institutional risk, company information obtained from audit processes, internal controls, personnel training and fulfilling quality standards are essential elements to identify and measure this risk. To achieve a comprehensive measure of ML, transaction risk and institutional risk will be the object of future research to the extent that we have access to all the necessary information.

The main empirical findings, after classifying customers as high-risk or low-risk, are:

- Customers with more than 56 months are more risky.
- Only the variables "contracted product" and "customer seniority" are statistically significant.
- Institution collection, business products and individual products are the most risky.
- The percentage of effectiveness, suggested by the decision tree technique, is around 89.5 per cent.

Note

1. For more detail about *priori information*, see Martínez-Sánchez and Venegas-Martínez (2016).

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