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Modelling the Risk Profiles of Clients in the Fight Against Money Laundering and Terrorism Financing

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Abstract

Global standards require financial intermediaries (FIs) to develop risk profiles to fight money laundering and terrorism financing. International typologies and multivariate analysis techniques are used to define profiles and develop models to classify clients; indicators are proposed to assess the vulnerability and exposure of intermediaries and the quality and stability of the models. Statistical evidence proves significant to validate profiles, avoiding the use of subjective criteria, generalizations, or stereotypes; a time-, resource-, and cost-efficient process is designed for FIs to monitor transactions and clients; the models are shown to be useful to assist intermediaries and regulators to deter these types of crimes.

Key words: emerging markets and developing economies; anti-money laundering and combat of terrorism finance; financial and capital markets; profiling risky clients

JEL classification: E44; G21; K42

1. Introduction

1.1 The Fight against Money Laundering and Terrorism Financing

As recipients of significant and continuously growing capital flows, Emerging Markets and Developing Economies (EMDEs) have been under the scope of international organizations and regulators, under the presumption that its financial intermediaries (FIs), mainly banks, money exchanges, and security houses, could be highly vulnerable and possible conduits of money laundering (ML) and terrorism financing (TF) funds. Concerns with ML and TF are not new, nor specific to these markets. Anti-money laundering (AML) controls have been in place for more than 4 decades following the 40 recommendations of the Financial Action Task Force on Money Laundering ("FATF 40 Recommendations, 2001"). An additional nine special recommendations to combat terrorism financing (CTF) were introduced following the terrorist attacks of September 11, 2001.

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On the international front, the International Monetary Fund (IMF) and the World Bank (WB) endorse the FAFT recommendations and have introduced World Standards to fight ML and TF. On the regulatory side, the Basle Committee on Banking Supervision (BCBS), the International Association of Insurance Supervisors (IAIS), and the International Organization of Security Commissions (IOSCO) have joint initiatives to combat these activities.

The recommendations require FIs to screen and monitor their clients and transactions and to report to special government authorities, known as financial intelligence units (FIUs), the cases believed to be tied to ML or TF crimes. FIUs have been responsible to further review those cases to determine which ones should be submitted to law enforcement agencies (LEAs) to be processed and possibly condemned.

FIs worldwide have joined the efforts in AML and CTF, in particular implementing the recommendations of the USA Patriot Act that (Section 352) reinforce the need to monitor client activities and to detect suspicious transactions and that (Section 326) place great emphasis on and outlines the requirements of know your customer (KYC) and customer identification programs (CIP). In addition, FIs have adhered to the Bank Secrecy Act on its Anti-Money Laundering Examination Manual, which emphasizes the need to implement a rigorous client due diligence (CDD) process developed by the US Federal Financial Institutions Examination Council, which includes representation of the Board of Governors of the Federal Reserve System, the Federal Deposit Insurance Corporation, the National Credit Union Administration, the Office of the Comptroller of the Currency, the Office of Thrift Supervision, and the State Liaison Committee.

1.2 Making Sense about the Origin, Legitimacy, and Impact of Capital Flows in EMDEs

Differentiating legal capital inflows from investments derived from money coming from ML or directed towards TF is not an easy task. Efforts to validate and quantify the origin of direct and portfolio investments throughout the world have been significant. As a result, detailed information about the origin, type of investment, and even the type of financial instruments preferred by investors from and in most markets as presented in the IMF "Coordinated Portfolio Investment Survey" and "Coordinated Direct Investment Survey", which is available to regulators, analysts, and researchers. This information allows analysis of capital flows and of dirty money from three different angles: (1) the economic perspective, focusing on the causes and impact on the short-term stability and long-term growth; (2) the legal and regulatory perspective, exploring the requirements to prevent the use of financial systems and capital markets as conduits for these types of funds; and, (3) the firm's perspective, evaluating the impact on the operations and costs of FIs.

From the economics perspective, Agénor (1998) highlights the push and pull factors of capital flows, while Camacho (2001) addresses the role macroeconomic distortions and its impact on economic stability. Masciandaro et al. (1995, 1999, 2001) explore the macroeconomic effects of dirty money going through the economy and the financial system, and microeconomic impact for the banking industry that results from asymmetric and incomplete information. Quirk (1996, 1997) analyses the various channels through which money laundering influences macroeconomic performance and growth rates. Tanzi (1996) works on the macroeconomic impact of large movements of dirty money and indicates effects on asset prices, interest rates, and exchange rates. And Bartlett (2002) signals the difficulties in the efforts to quantify the effects of money laundering but concludes that it they clearly damage the financial sector and increases crime and corruption.

From a legal and regulatory perspective, the analysis focuses on the standards and measures that financial institutions and law enforcement agencies should implement to fight ML and FT, an in particular, on their effectiveness. Arnone and Paduan (2007) analyze the impact of what they call the "regime for financial integrity" introduced by the AML and CTF program at the end of 2001 by the IMF and WB in conjunction with the FATF. Ferwerda (2009) models the process associated with ML and TF activities assuming rational behavior of its participants. In a recent study, Gordon (2011) indicates that, although global standards are widely observed, there is substantial evidence to suggest that they have not worked.

With respect to the impact on financial and security markets, and with the role of regulatory and supervisory authorities, Davanath (2003) analyzes the vulnerability to ML in the securities and futures markets and businesses and points to the responsibilities of capital market regulators. Boyer and Light (2008) also analyze the threat of ML at the level of brokerage houses.

1.3 Challenges for FIs in the AML and CTF Fight

Up until 2010, FIs have relied on procedures that "red flag" suspect cases by using the typologies, lists of activities, and factors that characterized ML and TF activities, as suggested by the FAFT and other agencies (1996–2009). When a suspect case is identified, an internal review is conducted, adding external information to either discard potential links to criminal activities or to report it to the corresponding FIU. New recommendations introduced to intensify and render more effective the fight against ML and TF now require FIs to broaden the scope of their work by establishing and periodically updating a risk profile for their clients. The institutions are asked now to take action one step closer to the source of crime, as they require developing ML and TF risk profiles for all their clients.

To meet this task, FIs face significant challenges, the first of which is to define profiles based on strong criteria and to classify clients based on solid models. Turvey (2002) defines criminal profiling as the process of inferring distinctive personality characteristics of the individuals responsible for criminal acts. He signals the weaknesses of inductive methods that develop types based on generalizations from known offenders and recommends the use of deductive methods, in which profiles are based not only on the unique aspects of the individual but also on the use and test of hypotheses. Godwin (2002) points to the need to turn profiling from an art to a science, recommending rigorous investigative processes and data management procedures. Schauer (2006) indicates that profiling has to avoid the use subjective criteria, generalizations, or stereotypes. He establishes that the models have to be based on a solid conceptual framework and that the classifications methods need to be substantiated by statistical evidence. He also indicates that models should not be under-inclusive or over-inclusive. In the first case, the model would be leaving out key factors or variables, thus limiting its predictive ability. In the second case, introducing too many variables makes it difficult to assess the significance of any of them.

The second challenge is related to the quality and reduced availability of information. The data includes personal and financial information about clients, their businesses and activities, as well as information from external sources that is frequently hard to access. When the information is obtained, FIs have to rely on link analysis to establish the possible connections of their clients with ML and TF activities. The information also needs to be frequently updated, a task that has to be performed in a time-, resource-, and cost-efficient manner. Therefore, the process has to be designed so that FIs can stratify clients to focus on and continuously monitor riskier clients, while periodically reviewing all the other clients.

The third challenge relates to the selection of the techniques and variables to develop the models and classify clients according to the predefined profiles. The variables are qualitative and in general categorical, while inferences have to be made based on a limited number of suspects (red-flagged cases). To adequately adjust for these restrictions, the following conditions have to be met: the links between the risk profiles and the variables have to be clearly established; the algorithms and techniques used have to combine both the quantitative results from the models with qualitative analysis of the internal review; the models have to be developed using a combination of time series and cross sectional data; and the models have to establish a clear distinction between cases to be dismissed, those that should continue to be monitored, and those that need to be reported.

1.4 Purpose of the Study

This paper presents the process and the model developed to assist FIs to meet the global standards and local regulations in the AML and the CTF fight. The study uses data from suspect cases of a financial group operating in a developing economy to define the profiles and estimate a classification model. It also generates a set of key indicators to measure the risk exposure of any institution to these types of crimes and to evaluate the quality of the model.

The study validates the following propositions.

Proposition 1: The typologies and variables suggested by international standards provide a solid basis to ensure the quality and effectiveness of the profiling process.

Proposition 2: Multivariate analysis techniques can be used to develop models based on link analysis to generate strong risk profiles.

Proposition 3: A time-, resource-, and cost-effective process can be implemented to effectively comply with the standards and requirements in the efforts to combat ML and TF crimes.

Proposition 4: Compliance with global standards reduces the vulnerability of its FIs and capital markets to ML and TF crimes.

2. Planning the Response to the New Challenges

2.1 Costa Rica and the Case of Mercado de Valores de Costa Rica S.A.

Costa Rica is a middle-to-high per capita income economy according to the WB criteria. The country is recognized for its long-standing democratic tradition and political stability, its highly educated population, and its good health and living standards. It has also been designated as the happiest place on earth, according to the "Happy Planet Index" of the New Economics Foundation, becoming a popular tourist and a second home and retirement destination. Costa Rica is also, in proportional terms, one of the largest recipients of foreign direct and portfolio investments in Latin America. While the foreign direct investment has favored growth and employment generation, the large portfolio inflows have increased domestic liquidity and demand, these factors have also generated negative macroeconomic effects, including a significant degree of appreciation of the currency, a widening of the trade deficit, and loss of competitiveness of the export sector, which has raised concerns by local firms in recent years.

Mercado de Valores de Costa Rica S.A. (MVAL) is the largest non-bank financial group in the country. The firm was established in 1976 and provides advisory and intermediary services to institutional and private clients. The group conducts transactions in the domestic capital market and operates an international and a wealth management division. It also has an investment management company and several mutual funds. In compliance with the KYC, CIP, and CDD requirements, the firm maintains an investor profile for each customer, with specific investment criteria and limits. In addition, the firm's compliance unit (CU) maintains and updates a database of key risk factors for all clients and monitors transactions and relies on triggers to identify suspect cases to meet the AML and CTF requirements.

To meet the new regulatory requirements, MVAL evaluated several software solutions available in the market but found that most of them still focused on the process of red-flagging suspects and on the generation and maintenance of data and reports. As a consequence, the group proceeded with the development of an internal solution to include company-specific criteria and parameters to develop the risk profiles and redesign the review process.

This study illustrates the response to the MVAL's need to design a process of classification and a model to measure risk exposure to ML and TF crimes. The process allows MVAL to define the risk profiles and to classify clients, while the model establishes both indicators to measure the company's exposure to ML and TF risks and indicators to evaluate the quality of the model. The implementation of the model allows the company to focus monthly on riskier cases, while reviewing all cases at least once a year.

2.2 The Data and the Risk Categorizations

The data consist of 50 cases that had been red-flagged by the CU of MVAL as suspect and potentially related to AML and CTF activities during the 2008–2010 period. The cases were separated into four categories looking for consistency with the process of first identifying potential risk clients and second conducting the internal review to determine which cases could be dismissed, which should continue to be monitored, and which ones should be reported to the FIU.

The predefined profiles algorithms were defined as follows. Low Risk Clients: no red flags are identified in the opening of the account or in the monitoring of transactions. Medium Risk Clients: triggers are activated but, after the internal review, the identity of the client and the legitimacy of the transaction are verified. High Risk Clients: after the initial review, further analysis is required to validate the origin of funds. Extreme Risk Clients: after further review the case is reported to the FIU because of the inability to legitimate the activity or origin of funds.

Table 1 presents a summary of the characteristics of the cases and the risk variables used to classify them. As can be observed, the reported economic activity and the inability to document the origin of the funds are the most frequent triggers of suspect cases. Those risk factors persist after conducting the internal review and when reporting extreme cases to the FIU. In addition to those factors, the frequent use of funds transfers and check requests is present in most of the reported cases to the FIU. The client's nationality and large transactions appear as a trigger in a significant number of cases but are not the main explanatory factors in the reported cases. This supports the idea that stereotypes and generalizations should not be used for profiling clients. Information from external sources, such as news reports, FIU requests, or automatic triggers do not seem to be factors characteristic of extreme risk cases.

2.3 Mapping the Process of Analysis

The algorithm used to define the model focuses on adequately handling the data, promoting efficiency in the allocation of time and resources, increasing the effectiveness of the process, and reducing the cost of compliance for the FI.

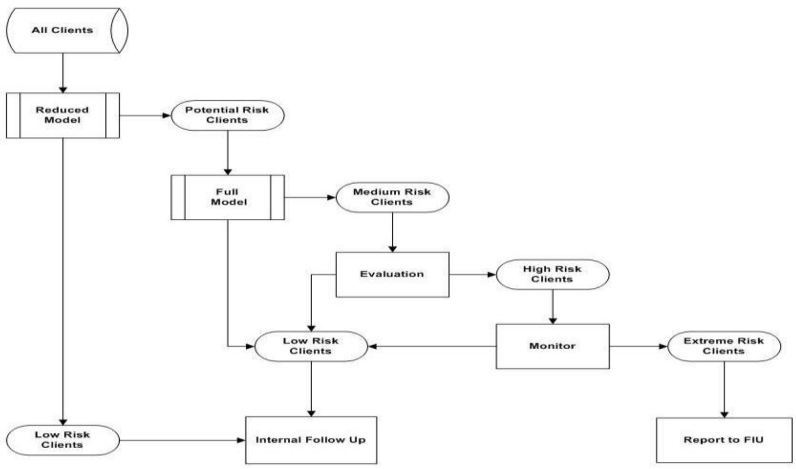
The process consists of four stages as follows. Stage 1: all clients are scanned through a reduced model based on a subset of risk factors to separate low risk to be reviewed periodically from those considered of potential risk requiring further information and analysis. Stage 2: potential risk cases are submitted to a full variable model to assess their risk profile in the three additional categories, establishing the priority assigned for the internal review. Stage 3: the results are consolidated and the risk profile of each client and a preliminary risk distribution of the company's clients are established. Stage 4: the classification results are used to define the periodicity of review, after which the final risk distribution is determined.

Table 1. Classification Categories and Explanatory Variables Total Number of Cases Red Flagged and Processed 2007-2009

			CATE: Classification Category		
Variable		**Red Flagged/ Potential Risk**	**1: Discarded/ Medium Risk**	**2: Monitored/ High Risk**	**3: Reported/ Extreme Risk**
	Total	**50**	**23**	**22**	**5**
Code	**Description**				
ECAT	Economic Activity	26	9	13	4
NEWS	News Reports	15	9	5	1
CREP	Credit Reports	7	7	0	0
AWARN	Automatic Warnings	11	2	8	1
BLIST	Black Lists	4	1	3	0
TRSF	International and Domestic Transfers	16	4	8	4
ADF	Fund Administration	5	3	2	0
POLEX	Political Exposure	5	5	0	0
CHK	Check Requests	8	3	2	3
DEP	Reported Origin of Funds	8	2	6	0
INTR	Transfer from and to Related Accounts	5	1	3	1
NAC	Nationality	6	1	5	0
JUD	Judicial Orders	4	1	3	0
ORIG	Verification of Origin of Funds	21	6	11	4
INTEL	Intelligence Unit Requests	12	5	6	1

Source: Mercado de Valores de Costa Rica S.A.

Figure 1. Mercado de Valores de Costa Rica S.A. Internal Risk Classification Process



2.4 Model Specification and Variable Selection

Multiple regression analysis and discriminant function estimation are the most used techniques to model the relationship between qualitative defined categories and nonmetric variables. Multiple regressions are used to determine the relationship between an endogenous variable with a collection of exogenous variables. The technique allows for the definition and test of hypothesis about the sign and significance of the relationship of the variables and to identify and correct econometric problems that may reduce the explanatory power of the model. Crouhy (2009) illustrates how most credit risk models and business solutions use multiple factor models and regressions, and Lischewski and Voronkova (2012) reference models for financial and capital markets that rely on the same techniques.

Discriminant analysis focuses on the ability to correctly classify an observation rather than on the significance of the coefficients. The technique has been used in a large number of applications to estimate probabilities or assign risk profiles. Altman (1968) develops Z-scores to predict bankruptcies. Taffler (1982) uses it for forecasting company failures in the UK. Camacho (1996) develops an early warning system to identify problem banks in Costa Rica. And Gumparthi and Manickavasagam (2010) generate a risk classification model for enterprises in India.

This study uses a combination of both techniques to develop the profiling model of risky clients. A backward stepwise regression is applied to sequentially remove from a full regression model variables that are not statistically significant to specify the reduced model and to select the variables to be used for the reduced and the full models. Then, two sets of discriminant functions are estimated. The reduced version is used to generate a preliminary risk distribution of the clientele base. The full version is applied to the potentially riskier clients to establish a more specific profile. The results are combined to generate the risk distribution.

Table 2. The Full Model and Variable Selection Results for the Reduced Model

Full Model for CATE (n=50)				Reduced Model for CATE (n=50)			
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**
C	1.3675	0.2003	6.8278***	C	1.6087	0.1178	1.3656***
EACT	0.0748	0.2567	0.2915				
NEWS	0.0449	0.2197	0.2042				
CREP	−0.5061	0.2516	−2.0118*	CREP	−0.6195	0.2242	−2.7634***
AWARN	0.3370	0.3402	0.9907				
BLIST	0.1505	0.3850	0.3909				
TRSF	0.3579	0.2395	1.4944	TRSF	0.3186	0.1786	1.7838
ADF	−0.8495	0.3251	−2.6127**	ADF	−0.6771	0.2601	−2.6034**
POLEX	−0.4489	0.2902	−1.5466	POLEX	−0.6179	0.2519	−2.4532**
CHK	0.3337	0.3122	1.0689				
DEP	−0.4656	0.3186	−1.4616				
INTR	0.0742	0.3662	0.2026				
NAC	0.3073	0.2943	1.0440				
JUD	0.3948	0.3563	1.1081				
ORIG	0.3157	0.2621	1.2046	ORIG	0.3465	0.1669	2.0768
INTEL	0.1365	0.2610	0.5231				
R-Squared	0.5145			**R-Squared**	0.4334		
Adjusted R-Squared	0.3003			**Adjusted R-Squared**	0.3690		
F-Statistic	2.4020			**F-Statistic**	6.7314		
P-value (F-Statistic)	0.0170			**P-value (F-Statistic)**	0.0001		
Durbin-Watson Statistic	1.3097			**Durbin-Watson Statistic**	1.1474		

Notes: ***, **, and * denote significance at 1%, 5%, and 10% levels.

Table 2 presents the results of both the full and the reduced regression models. F-statistics reject non-significance of the regression models at the 99% confidence level ($F_{15,34}$ = 2.60 and $F_{5,44}$ = 3.60). The Durbin Watson (DW) test for autocorrelation was inconclusive for the full model but allows the rejection of the hypothesis of autocorrelation for the reduced model (DW dl and du limits 0.76 and 2.18 for the full regression model, and 1.16 and 1.59 for the reduced model). With respect to the possibility of multicollinearity, it is assumed not to be present given the low correlations among the variables the persistence in sign and magnitude of the coefficient estimates between the two models and the fact that the reduced model improved the significance of the model.

The analysis of the results indicates that information from credit reports, a frequent use of transfers, reporting administering funds for third parties, political exposure, and the inability to document the origin of funds appear to be the most significant explanatory variables leading to identifying potential risk clients or transactions. Since these variables are either part of the basic records kept by the institution or can be easily fed into the data management systems, the reduced model can be applied periodically and in a cost- and resource-efficient manner. The emphasis on updating and continuously monitoring clients and transactions can then be established as a function of the results of implementation of the full model on the preliminary classified as potential risk clients.

3. Implementing the Strategy to Establish Risk Profiles

3.1 Discriminant Functions for the Full and Reduced Models

The estimation of discriminant functions allows the estimation of the probability that a specific case is a member of the predefined risk profiles as a function of the distance to the average set of variables that characterize that group (i.e., its centroid). Figure 2 presents a graphical representation of the centroids generated by the discriminant functions of the full and reduced models and the dispersion of the cases around those centroids. As can be observed, the centroids and the dispersion of cases is less clear in the reduced model than when applying the full model. In particular, the full model clearly separates the 3 categories, in particular increasing the distance of extreme cases (category 3) from the other two categories.

Table 3 presents the coefficients of the discriminant functions obtained from the application of discriminant analysis.[1] The results of the ex-post classifications and probabilities obtained for the 50 cases used in the analysis appear in Table 4. As can be observed, the overall accuracy of the reduced model is 66%, while the full model correctly classifies 72% of the cases analyzed.

The comparative analysis of the resulting classifications can be summarized as follows. The percentage of the medium risk cases correctly classified by the reduced model is 56%, and the remaining 44% cases are classified as high risk. As expected, the results of the full model are more accurate, with 80% of the medium risk cases correctly classified, while the remaining 20% are identified as high risk. The reduced model correctly classifies 91% of the high risk cases, identifying the remaining 9% of those as medium risk. The full model classifies 73% of the high risk cases correctly and identifies 5% of these cases as extreme risk, leaving 22% of the cases for review. The reduced model fails to identify the extreme risk cases but classifies 100% of those as high risk and then subject to monitoring. The full model classified 60% of the extreme risk cases correctly and signals 20% for review and 20% for continuous monitoring.

Figure 2. Discriminant Functions Centroids

Reduced Model **Full Model**

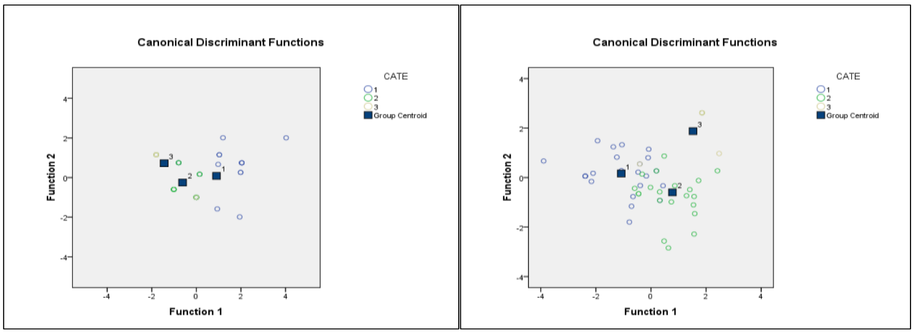


Table 3. Discriminant Function Coefficients

	Reduced Model			Full Model		
CATE	1	2	3	1	2	3
(Constant)	−2.03	−1.54	−5.07	−3.61	−4.17	−10.47
ECAT				1.98	2.27	2.70
NEWS				2.23	2.08	2.95
CREP	3.89	0.19	0.21	5.05	1.20	1.95
AWARN				0.56	2.98	2.75
BLIST				−1.47	0.73	−1.53
TRSF	0.79	1.40	3.76	1.45	2.24	5.43
ADF	2.12	−0.51	−3.08	−0.30	−4.30	−7.77
POLEX	3.50	0.04	−0.36	4.71	1.44	1.83
CHK				3.43	3.03	8.19
DEP				−1.23	−1.38	−7.22
INTR				0.84	0.43	2.20
NAC				3.22	5.15	5.49
JUD				2.65	5.54	5.18
ORIG	0.54	1.93	3.16	0.08	1.48	2.94
INTEL				2.80	2.39	4.97
(Constant)	−2.03	−1.54	−5.07	−3.61	−4.17	−10.47

Notes: Definitions of categories are as follows. 1: Red Flagged and Discarded. 2: Red Flagged and Monitored. 3: Monitored and Reported.

Table 4. Ex-Post Discriminant Functions Classification Results

Reduced Model Results						
			Classified as Category			**Total**
			1	2	3	
Member of Category	1	Frequency	13	10	0	23
	2		2	20	0	22
	3		0	5	0	5
	1	Probability	56.5%	43.5%	0.0%	100.0%
	2		9.1%	90.9%	0.0%	100.0%
	3		0.0%	100.0%	0.0%	100.0%
Full Model Results						
			Classified as Category			**Total**
			1	2	3	
Member of Category	1	Frequency	19	4	0	23
	2		5	16	1	22
	3		1	1	3	5
	1	Probability	82.6%	17.4%	0.0%	100.0%
	2		22.7%	72.7%	4.5%	100.0%
	3		20.0%	20.0%	60.0%	100.0%

Results	**Correct**	**Accuracy**
Reduced Model	33	66.0%
Full Model	38	76.0%

3.2 Risk Profiles, Relevant Probabilities, and Key Evaluation Indicators

The primary objective of the algorithm depicted in Figure 2 is to establish a risk-based distribution for all the clients of a FI. This objective is accomplished because the process allows establishing risk profiles for each case at three different stages. First, at the entry level, the reduced model will classify cases in two categories, low risk (LR) and potential risk (PR), and estimate the probability (P) of any observation of belonging to either category. The PR cases will be submitted to the full model and classified into one of three sub-categories, medium risk (MR), high risk (HR), and extreme risk (ER); the model also estimates probabilities of any observation belonging to any subcategory. Select cases will be submitted to the internal review process, focusing on riskier cases but ensuring all cases will be reviewed. At the exit level of the process, the ex-post classification will be obtained, by reclassifying cases in the ex-post final categories (LR and ER). With the final ex-post classification, ER cases have to be reported to the corresponding FIUs which are responsible for determining whether the case should be dismissed or processed by law enforcement authorities.

Based on the results of the implementation of the reduced and full models and after the internal review process, this study proposes four indicators to establish the risk exposure of the intermediary and the effectiveness of the model. The first indicator assesses the Vulnerability (V) of serving as a conduit for ML or TF. V is a measure of the ability of potential risky clients to go undetected during the initial screening conducted by the institution, which is mainly based on the KYC, CIP, and CDD measures implemented. V can be measured in terms of the probability of a client falling in the potential risk category and would be an indicator of how good screening process is and how prone the institution is to attract risky clients. V is defined as:

$$V = P\ (PR) = \text{Potential Risk Cases / Total Cases.} \tag{1}$$

The second indicator, Exposure (E), reflects the actual risk detected in the institution at the end of the complete process after the implementation of the internal review. The Exposure indicator can be obtained from the full model as follows:

$$E = P\ (ER) = \text{Extreme Risk Cases / Total Cases.} \tag{2}$$

A second and equally important objective of the algorithm is to make sure that the risk classifications are solid and substantiated by strong models. Since the probabilities have to be recalculated periodically, in order to meet this objective, the process can be analyzed using a Markov chain (MC) algorithm.[2] This algorithm allows the estimation of the transition probabilities, from one category to another, making it possible to describe dynamics of the process.

Transition probabilities are defined as the percentage of observations in a specific category that are reclassified or make the transition to the next higher risk category. A significant change in the simple probabilities P(PR) and P(ER) and in the transition probabilities can warn about possible changes in the risk profile of the clientele base, inform about the modus operandi of money launderers and terrorist financiers, and/or indicate the effectiveness of the models.

According to the MC algorithm, the final probability of the process can be decomposed as the product of the initial probability and the transition probabilities. The dynamics involved in the process would indicate that the probability of any client ending up as extreme risk would require that, once accepted, a client would have to:

- Be red-flagged to be considered of potential risk (PR).
- Deteriorate into the medium risk category, with a probability P(MR/LR), after the initial review.
- Continue to deteriorate and transition into the high risk (HR), with a probability P(HR/MR), when additional information is considered.
- End up being classified as extreme risk, with a transition probability of P(ER/HR).

The decomposition of the being probability of being reported P(ER) and the estimation of the other relevant probabilities are summarized as follows:

$$P(ER) = P(PR) \times P(MR/LR) \times P(HR/MR) \times P(ER/HR). \tag{3}$$

$$P(MR/PR) = \text{Medium Risk Cases} / \text{Potential Risk Cases}. \tag{4}$$

$$P(HR/MR) = \text{Medium Risk Cases} / \text{Low Risk Cases}. \tag{5}$$

$$P(ER/HR) = \text{Medium Risk Cases} / \text{Low Risk Cases}. \tag{6}$$

Once the relevant probabilities have been calculated, the model can be evaluated in terms of its quality and stability. The Quality (Q) of the model can be established as a function of the number cases forwarded by FIUs to law enforcement authorities that end up being processed. The better the Quality, the higher the number of cases processed. The Q is defined as the proportion of cases processed and indicates the effectiveness of the model. The higher this proportion, the better the quality of the model. The Q indicator is estimated as follows:

$$Q = \text{Processed Cases} / \text{Reported Cases}. \tag{7}$$

Using the transition probabilities, the Stability (S) of the model can be evaluated to explain the total exposure of the FI. A stable model would be one where all probabilities remain about the same through time. The S indicator proposed is a combined index of the magnitude of the changes of each one of these probabilities. The magnitude of S is calculated as the relative change (RC) with respect to the maximum change possible for each probability as follows:

$$RC = (100\% - PR_t) / (100\% - PR_o). \tag{8}$$

The interpretation of the RC indicator is quite simple. Any probability has a maximum level of 100%. The differences between the probability at time t (P_t) and this maximum and between the probability in the previous period (P_o) and this maximum are measures of distance. In a stable model, all relevant probabilities would experience little changes, and all RC indicators would be close to one. When a specific probability increases, contributing to higher exposure, the distance would decrease with respect to the one observed the previous period. As a consequence, the RC indicator would be less than one. If the probability decreases, potentially reducing the exposure, the distance would increase, leading to an RC greater than one.

The proposed S indicator is the simple average of the four probabilities or factors explaining the FI's exposure as follows:

$$S = \Sigma(RC(PR) + RC(PM) + RC(MH) + RC(HE)) / 4. \quad (9)$$

An S indicator greater than one reflects lower risk exposure as a result of the combined ratios of change. An S indicator less than one reflects an increase in risk exposure as a result of the combined probabilities. Significant changes in the S indicator would reflect an unstable model which could be the result of changing risk profiles of the clients, a change in the modus operandi of money launderers and financiers, or a change in the effectiveness of the internal review process. As a consequence, high variability in the S indicator would call for a revision of the classification criteria and a recalibration of the model.

The implementation of the "Vulnerability, Exposure, Quality, and Stability Model" (VEQS) can lead to a wide range of results. On one extreme, the best combination of indicators and most efficient AML/CBT profiling solution would be to have low V and E indicators for the FI obtained from a high Q and S model. On the other extreme, the worst combination and least efficient solution would be to have high V and E indicators at the FI level derived from a low Q and S model. For the intermediate cases, the results have to be interpreted taking into account the following considerations:

- A high V indicator may be indicative of an over-inclusive reduced model, identifying too many potential risk cases, thus generating an overload and increasing the costs of compliance to FIs.
- A high E indicator may be the result of a limited ability of the full model to discriminate between medium, high, and extreme risk cases, thus reducing the effectiveness of the model.
- A low Q indicator could suggest an over-inclusive full model, identifying too many extreme cases, increasing the cost and reducing the effectiveness of the process.
- A low S indicator may suggest a change in the modus operandi of money launderers and terrorist financiers, thus requiring a revision of the typologies and key variables to use as proxies of risk factors and recalibration of the model.

4. Evaluating the Results of the VEQS Model

4.1 Ex-Ante Probabilities Based on the Sample of Suspect Cases

Based on the set of the 50 red-flagged and processed cases, the ex-ante AML and CBT probability distribution can be estimated for the full set of accounts of MVAL. In addition, the transition probabilities can be estimated under the assumption of stable probabilities. The results of the ex-ante analysis, presented in Table 5, indicate that 97.9% of MVAL's clients are considered low risk, while 1.3%, 0.7%, and 0.1% would be classified as medium risk, high risk, and extreme risk respectively. And, according to the transition matrix, the V of the institution, measured as the sum of probabilities of all suspect cases, is 3.1%. Once at this level, there would be a 54.0% probability of transitioning to the HR category, with a 18.5% probability of the case transitioning to the ER category. The product of these probabilities would lead to a level of E of 0.1%.

Table 5. Frequency Distribution and Ex-Ante Transition and Cumulative Probabilities

		Frequency Distributions			
	Total	**Not Red-Flagged/ Low Risk**	**Red-Flagged/ Medium Risk**	**Monitored/ High Risk**	**Reported/ Extreme Risk**
Number of Cases: 3715	**3715**	**3665**	**50**	**27**	**5**
Ex-Ante Probability of Arriving at Level	**100.0%**	98.7%	1.4%	0.7%	0.1%
		Explicit Transition Probabilities			
			To		
From		Low Risk	Medium Risk	High Risk	Extreme Risk
Low Risk			1.4%		
Medium Risk				54.0%	
High Risk					18.5%
Cumulative Probabilities		98.6%	1.36%	0.74%	0.14%
Expected Distribution	**100.0%**	**99.9%**			**0.1%**

4.2 Implementation of the VEQS Model to the Full Database of MVAL

Table 6 presents the results of the application of the full model applied to all clients of MVAL (3,715 accounts). The results are presented also as a function of the stages of the process that generates the preliminary (ex-ante) and final (ex-post) risk profiles. Every case was submitted to both the reduced and the full model.

The classification was assigned using the following criteria. The cases that, according to the reduced model, did not have high probability of being classified as medium, high, or extreme risk categories were defined as low risk. The other cases, considered as of potential risk, were submitted to the full model to generate the ex-ante profile and to schedule them for weekly, monthly, and quarterly review and data updates. The ex-ante probabilities were reassessed, assigning to each case the category for which it had the highest probability of belonging according to the results of the full model (i.e., shortest distance to the group centroid). Given the classification obtained from the full model, the cases were distributed for the internal review process, focusing on riskier cases, but ensuring all cases are reviewed.

Once the ex-ante risk profiles were assigned, the work plan of the CU was designed to continuously update information and monitor all clients and transactions. The main results of the process can be summarized as follows.

- The reduced model (Stage 1) identified 3,188 cases as low risk, representing 85.8% of the population. These cases exhibited few or no positive risk factors.
- The full model (Stage 2) distributed the remaining 527 potential risk cases, representing 14.2% of the population, into low, medium, high, and extreme risk categories.
- The consolidation of results (Stage 3) dismissed 189 cases as low risk, increasing the total percentage of this category to 90.2%, and classified 6.3% as medium risk, 2.2% as high risk, and 0.7% as extreme risk.
- Following the review process (Stage 4), the cases were distributed in the work plan as follows:
    - 25 extreme risk cases were assigned for weekly monitoring.
    - 80 high risk cases were assigned for monthly monitoring to evaluate the possibility of dismissal or reporting as extreme risk.
    - 233 medium risk cases were assigned for quarterly monitoring to determine if they should be dismissed or reclassified as high risk.
    - 3,377 low risk cases were assigned for annual review.

4.3 Results of the Application of the Methodology and Adequacy of the Model

The distributions and transition probabilities for the subset of suspect cases used for the development of the model and for the full dataset of MVAL's clients are presented in Table 7. As can be observed, relying only on red flags would identify fewer clients as of potential risk, but a higher proportion of them would have transitioned to riskier categories. In contrast, the full model results indicate that a larger number of clients would have merited further review, but a lower proportion of them would have transitioned to the riskier categories. Therefore, the results suggest that inferences made using only the suspect cases could underestimate the firm's vulnerability to ML and TF. Furthermore, relying only on suspect cases would keep the CU playing a passive role, waiting for a red flag, and distributing inefficiently the task of updating the clients' data throughout the year. While the application of the model signals more potential risk cases, it allows MVAL to work more efficiently, distributing the work load according to its available resources, and to act in a more targeted way focusing on riskier cases. In terms of the firm's exposure, the ex-ante probabilities derived from suspect cases indicate that only 0.1% of MVAL's accounts could end up as extreme cases and need to be reported. By using the VEQS model, up to 0.7% of its clients could end up as extreme risk cases and need reporting.

Table 6. Mercado de Valores de Costa Rica Classification Process and Results

Stage 1		**Reduced Model Preliminary Results**				
Risk Profile		**Low Risk**	**Potential Risk**			**Total**
Classification Result	**Accounts**	3188	527			3715
	Category	**Normal**	**Warning**			
	% Obs	85.8%	14.2%			
Process		**Normal Follow Up**	**Further Evaluation**			

Stage 2		**Full Model Classification Process Results**				
Risk Profile		**Low Risk**	**Medium Risk**	**High Risk**	**Extreme Risk**	**Total**
	Accounts	189	233	80	25	527
Predicted as Member of	**% Obs**	35.9%	44.2%	15.2%	4.7%	

Stage 3		Consolidated Results				
		Low Risk	Medium Risk	High Risk	Extreme Risk	Total
Carry Over Stage 1		**85.8%**				
Distribution State 2	**14.2%**	5.1%	6.3%	2.2%	0.7%	
Final Classification		**90.9%**	**6.3%**	**2.2%**	**0.7%**	**100.0%**

Stage 4	Review Process				
	Low Risk	Medium Risk	High Risk	Extreme Risk	Total
Cases	3377	233	80	25	**3715**
Periodicity	**Annually**	**Quarterly**	**Monthly**	**Weekly**	

Also according to the results, the full model would allow the company to be more selective in the process of acceptance of clients based on typologies and indicators substantiated by the statistical evidence. Additional benefits could derive from the higher efficiency generated in the review process. The final task to be performed by MVAL is to assess the quality (Q) and stability (S) of the model. Prompt feedback from FIUs about the number of reported cases forwarded for processing by LAEs is necessary to assess the Q of the model and the potential need for its revision. In that respect, since the model was developed based on the collection of positive cases for a 3-year period, it is recommended that MVAL wait for 3 years before it proceeds to recalibrate the parameters of the discriminant functions. This would allow the company to develop the Q and S records of the model and to conduct back testing and stress testing in a similar fashion as it is done for operational risk.

Table 7. Mercado de Valores de Costa Rica Transition Probabilities and Final Classification

	Risk Profile Distribution			
Category	**Low**	**Medium**	**High**	**Extreme**
Sample Distribution	98.7%	1.3%	0.7%	0.1%
Full Model Distribution	90.9%	6.3%	2.2%	0.7%
	Ex-ante Transition Probabilities			
		To		
From		Medium Risk	High risk	Extreme Risk
Low Risk		1.3%		
Medium Risk			54.0%	
High Risk				18.5%
Initial Classification Distribution	98.7%	1.3%	0.7%	0.1%
Final Expected Distribution	**98.7%**			**0.1%**
	Fill Model ExPost Transition Probabilities			
		To		
From		Medium Risk	High Risk	Extreme Risk
Low Risk		9.1%		
Medium Risk			31.1%	
High Risk				23.8%
Initial Classification Distribution	90.9%	9.1%	2.8%	0.7%
Final Expected Distribution	**99.3%**			**0.7%**

4.4 Further Research and Recommendations

The proposed method offers opportunities for regulators and supervisors to improve their contribution to the AML and CTF fight. If indeed requiring FIs to define ex-ante risk profiles for their clients may reduce the probability of funds being channeled through these institutions, the categories and the techniques used by intermediaries are different among them. As a consequence, the profiles may not be comparable and might not reflect the actual vulnerability and exposure of FIs to these types of risks. As has been done with other risks, supervisors could develop their own internal model to assess and monitor the risk exposure of FIs.

A methodology similar to the one presented in this study could be implemented to generate consistent and comparable vulnerability and exposure indicators for all institutions. To do so, supervisors should standardize as much as possible the typologies used to classify clients and require a minimum uniform set of key risk factors to be reported for all suspect cases. Then, based on the reported cases and the key risk factors, they could generate discriminant functions for each institution and determine their corresponding distribution of risk profiles. Once the model is calibrated, the model could serve both as a device to identify riskier institutions and as an early warning system to require preventive and more effective monitoring actions from those institutions.

International organizations and law enforcement agencies also have to continue and even further their efforts in AML and CTF. International organizations need to continuously revise the typologies and variables used to characterize the profiles of ML and TF criminals, since they always seem to be one step ahead in finding "innovative" ways to conceal their activities. And tougher actions have to be taken by LEAs in order to process and condemn guilty individuals to render the efforts of FIs more effective.

5. Conclusions

Capital flows into EMDEs have grown significantly in the last two decades, driven by the growth potential and expected high returns offered by the investment opportunities in those markets. The improvement of the macroeconomic fundamentals, the amelioration of the investment climate, and the reduction in the level of country risk have favored direct and portfolio investments. At the same time the efforts in the fight against ML and TF have intensified. EMDEs have received attention from both regulators and law enforcement authorities, as analysts and researchers have warned about the potential vulnerability of their financial markets and institutions serving as conduits for these types of funds.

As part of the adoption of global recommendations, FIs have taken over the responsibilities in the implementation of the KYC, CIP, and CDD guidelines and toughening the evaluation criteria used to screen clients and their business activities. They have also strengthened the internal review processes in the analysis of suspect cases. While these actions may have reduced the vulnerability of FIs to the ML and TF risks, there are still have concerns about the capability of FIUs and LEAs to process and condemn criminals. As a result, new regulations have broadened the responsibilities and scope of work of FIs, asking them to develop models and to establish ex-ante risk profiles for all their clients, thus taking action one step closer to the source of crime. To meet this task, FIs have to avoid relying on subjective criteria, generalizations, or stereotypes and instead have to be able to link nonmetric or qualitative variables with those criminal activities. They also have to face restrictions about the quality and availability of information and work carefully on the design of models to ensure time-, resource-, and cost-efficient processes.

This study proposed the use of the typologies and variables recommended by global standards and international organizations and the implementation of discriminant analysis functions to define and validate four risk profiles (low, medium, high, and extreme risk). A four-stage process is designed to first separate low risk and potential risk cases though the use of a reduced model based on a subset of risk factors. Second, a full model that incorporates the complete set of risk factors is then used to discriminate between medium, high, and extreme risk cases. Third, an internal review process is applied to validate the results of the full model. And fourth, a work plan should be developed to update information and monitor cases so that the compliance unit can focus on riskier cases while ensuring that all cases are reviewed at least once a year.

The model developed includes four indicators: vulnerability, exposure, quality, and stability (VEQS). The first two indicators allow assessing the risk faced by the intermediary both at the client screening level and the one carried in their current client portfolio. The second two indicators are used for evaluating the accuracy of the model and to determine the need to recalibrate the model as a result of changes in the client portfolio or in the modus operandi of ML and TF criminals. The results of the implementation of the VEQS model suggest that the ex-ante or historical distributions generated by the suspect cases may have underestimated the current level of risk associated with ML and TF activities in FIs. The use of the VEQS model allows FIs to focus on improving the screening criteria and on strengthening the internal review process. In addition, by efficiently distributing the work load, they not only reduce their vulnerability and exposure to ML and TF crimes but also the cost of compliance with local regulations and global standards.

Finally, this study reinforces the need to continuously revise the typologies, risk factors, and models used to define the profiles of ML and TF criminals. Unfortunately, as is the case with other legal and regulatory issues, criminals constantly change their modus operandi to conceal and continue with their activities. So, even when FIs can contribute in this fight, regulators and supervisors also have to take further action. It would be desirable for them to develop their own standard methods to, first, ensure that the profiles developed by institutions are comparable and, second, use these methods as a monitoring device and as an early warning system to identify the more vulnerable FIs and request or take corrective actions. At the other end of the process, FIUs and LEAs also have to work on making sure that they can effectively process and condemn those involved in these types of crimes.

Notes

1. SPSS Statistics Software 17.0 was used to perform discriminant analysis.
2. A Markov chain can be applied to a system that undergoes transitions from one state to another, between a finite or countable number of possible states or categories.

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