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Firm-Level Prediction of Money Laundering Risk in Iranian Listed Companies; an Integrated Quantitative-Qualitative Approach

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Abstract

The primary objective of this study is to develop a predictive model for money laundering risk in Iranian listed firms. Initially, firm-level money laundering risk is measured using auditor assessments of anti-money laundering (AML) activities disclosed in annual audit reports. Subsequently, a quantitative modeling approach is employed, using financial and governance-related variables identified in prior research. To validate the quantitative findings, a qualitative approach based on grounded theory is also applied to identify additional explanatory factors. This research follows a mixed-methods design, incorporating both quantitative and qualitative phases. In the quantitative phase, a panel logit regression model is estimated using data from 1,680 firm-year observations covering the period 2012–2023. Independent variables include firm size, return on equity, leverage, investment opportunities, board independence, and board size. In the qualitative phase, semi-structured interviews were conducted with 10 experts to identify key risk factors, followed by the design and administration of an 18-item questionnaire distributed to 110 professionals. Exploratory factor analysis was then used to extract latent variables. The quantitative analysis reveals significant relationships between money laundering risk and several variables, such as firm size (positive), return on equity (negative), leverage (positive), and board independence (negative). The qualitative analysis identifies three core factors: (1) organizational culture and employee training, (2) corporate governance, and (3) a composite factor comprising compliance, organizational complexity, financial performance, firm size, and capital structure. Together, these factors explain over 50% of the variance in expert responses. The convergence of results from both methodological approaches confirms the robustness of the proposed model. Corporate governance indicators—particularly board size and independence—alongside financial attributes such as firm size, profitability, and capital structure, are found to be significant predictors of firm-level money laundering risk. The findings underscore the importance of strengthening internal control mechanisms and compliance structures in reducing money laundering risk.

Keywords: Money Laundering Risk (MLR), Corporate Governance, Financial Performance, Grounded Theory, Risk Prediction Model

JEL Classification: G21, G28, E52, G32, E44

Introduction

Money laundering (ML) is a global financial crime that enables criminals to legitimize illicit proceeds through complex financial transactions. According to the Financial Action Task Force (FATF, 2023), money laundering involves "the processing of criminal proceeds to disguise their illegal origin," a definition echoed by the United Nations Office on Drugs and Crime (UNODC), which describes it as "concealing or disguising the origins of illegally obtained money, typically by means of transfers involving foreign banks or legitimate businesses" (UNODC, 2024). These definitions underscore that money laundering is not only a standalone financial offense but also a facilitator of broader criminal activities, including corruption, terrorism financing, drug trafficking, and tax evasion.

The scale of money laundering is alarming. Based on recent estimates by the UNODC, the annual volume of global money laundering is equivalent to 2–5% of global GDP, amounting to approximately USD 2.2-5.5 trillion as of 2024 (UNODC, 2024). This substantial flow of illicit capital undermines legal economic activities, facilitates organized crime, and distorts resource allocation in financial markets. Moreover, it creates unfair competition, reduces tax revenues, and destabilizes both national and international financial systems (Masciandaro et al., 2020).

The adverse macroeconomic consequences of money laundering are well documented. It weakens financial institutions, distorts capital and investment flows, impairs government fiscal policies, and promotes corruption and political instability (Unger, 2009; Ferwerda, 2009). At the microeconomic level, firms exposed to money laundering face reputational damage, loss of investor trust, regulatory sanctions, and operational disruptions. The costs associated with regulatory non-compliance and remediation efforts further intensify the financial risks for businesses (Melnik, 2001; Habib et al., 2017). Therefore, effective risk identification and mitigation strategies are vital to maintaining both financial system integrity and corporate sustainability.

While considerable academic attention has been devoted to money laundering at the national or systemic level, research into firm-level money laundering risk (MLR) remains scarce. This gap is particularly significant in emerging economies such as Iran, where structural and regulatory peculiarities shape unique risk profiles. Iran has consistently ranked among the most vulnerable countries in terms of money laundering risk, according to the Basel Institute on Governance (2023). However, firm-level empirical models for predicting MLR remain largely underdeveloped, mainly due to the sensitivity of the topic and limited access to reliable data.

In this context, the present study addresses a critical research question: Can the risk of money laundering be predicted at the firm level using financial, corporate governance, and operational indicators? The aim is to develop a robust predictive model that integrates both quantitative and qualitative insights to assess the probability of firms—deliberately or inadvertently—being involved in money laundering activities.

The methodological framework adopted in this study is twofold. First, a panel logit regression model is employed to assess the impact of key firm-level variables, including firm size, return on equity, leverage, board independence, and board size, on money laundering risk. These variables have been identified in prior literature as potential indicators of financial misconduct or weak internal controls (Beasley, 1996; Uzun et al., 2004). Second, grounded theory is applied through expert interviews and questionnaire-based factor analysis to extract latent variables and deepen our understanding of organizational, behavioral, and governance-related determinants of MLR.

A review of the most recent literature underscores the complexity of money laundering mechanisms and the limitations of conventional macro-level assessments. Ghulam and Zalai (2023) demonstrated that exchange rate volatility, trade volume, and financial transparency have a significant impact on national-level MLR. Meanwhile, Bolgorian and Mayeli (2020) proposed a firm-level index based on audit opinions to quantify AML compliance in the Iranian capital market. Similarly, Habib et al. (2017) linked higher audit fees with elevated MLR in U.S. firms, indicating that external scrutiny often correlates with underlying risk exposures.

The theoretical contribution of this study lies in bridging the gap between firm-level governance and financial attributes and the systemic risk of money laundering. By integrating financial data with qualitative insights from industry experts, this research proposes a multidimensional model that not only predicts MLR but also identifies its root causes within organizational structures. This approach responds to calls in the literature for more granular, data-driven models that can inform both regulatory policy and corporate strategy (Vaithilingam, 2007; Raza et al., 2017).

From a policy standpoint, the implications are profound. In line with Iran's

Anti-Money Laundering Act (2008) and the FATF recommendations, firms are increasingly required to implement robust internal controls, conduct ongoing customer due diligence, and report suspicious transactions. However, compliance remains uneven across sectors, and enforcement mechanisms are often reactive rather than preventive. A predictive model, such as the one developed in this study, can help regulators, auditors, and managers proactively identify firms at high risk of involvement in money laundering.

In summary, this research contributes to the academic and practical understanding of money laundering risk by providing an empirically validated framework for predicting it at the firm level. The findings are particularly relevant for emerging economies, where regulatory enforcement is evolving and transparency mechanisms are still in the development stage. By highlighting the financial and governance dimensions of MLR, the study advances the broader agenda of corporate accountability and financial integrity.

Literature Review

In recent years, money laundering has emerged as a significant challenge to the global economy, primarily due to its role as a conduit for illicit financial gains (Unger, 2009). The core mechanism of money laundering involves disguising the illicit origins of financial assets. Despite various national and international anti-money laundering (AML) initiatives, their effectiveness has been limited, with only partial success in curbing the overall scale of laundering activities (Ferwerda, 2009).

Money laundering exerts far-reaching negative effects on economies and governance structures. As Cotterill (2001) notes, it not only destabilizes economic systems but also undermines political institutions and governance mechanisms. At the macroeconomic level, money laundering impacts economic performance through multiple channels: (1) destabilizing the economic environment, thereby reducing investment; (2) causing inefficient allocation of resources due to distorted cost structures; (3) generating monetary shocks by altering money demand unpredictably; (4) increasing financial system vulnerability to capital flight; (5) decreasing tax revenues and weakening governments' capacity to counteract organized crime; and (6) promoting corruption, criminal activity, and broader socio-economic instability (Habib et al., 2017; Melnik, 2001; Drayton, 2002; Dowers & Palmreuther, 2003).

Ghulam and Zalai (2023) conducted a cross-country analysis of 84 nations, identifying trade volume, exchange rate volatility, audit quality, and financial transparency as key factors associated with money laundering risk. Similarly, Rana and Rawal (2020) employed questionnaire data and factor analysis to study the drivers of money laundering in Bangladesh. They concluded that bribery, accelerating money flows, and concealing the sources of money are primary contributors to money laundering. They also identified high investment returns and avoidance of high tariffs as contributing factors, all stemming from a lack of ethical standards. Income-expenditure imbalances also motivated individuals to engage in crime. They ultimately advocated for effective measures and strict punishments to control the phenomenon. Raza et al. (2017) proposed an AHP-based framework to assess money laundering risk in financial institutions by categorizing intrinsic and control-related risks. Begala et al. (2009) also developed a dynamic general equilibrium model using simulation techniques to estimate time series data on money laundering volumes in the U.S. and European Union between 2000 and 2007. The study concluded that money laundering accounted for 16% of the EU's GDP and 18% of the U.S.'s GDP. Vaithilingam (2007) found that technology had a limited effect on money laundering across 88 countries. In contrast, legal regulations and organizational ethics played a crucial role in addressing the problem. He recommended the formulation of effective laws with adequate deterrents to prevent money laundering.

Additionally, some studies have employed grounded theory to investigate risk factors in financial systems. For instance, Zhao et al. (2022) used grounded theory to classify risks associated with business model innovations into managerial, technical, and environmental categories. Sun et al. (2020) employed grounded theory to assess risks in an international Chinese project, identifying 10 risk factors. Elhaei Sahara et al. (2020) employed a similar method to investigate momentum-based trading strategies in Iran's stock market, conducting interviews with 32 financial experts that led to the development of a conceptual model of behavioral, market, and firm-level risk factors.

Several studies have been conducted on the issue of money laundering in the Iranian context. For example, Bolgorian and Mayeli (2020) examined the relationship between money laundering risk and accounting conservatism. They used audit opinions from financial statements of Iranian publicly traded firms to construct a risk index, finding a negative association between accounting conservatism and money laundering risk. Peyvandi and Gol Arzi (2024) analyzed the ethical and behavioral contributors to laundering behavior.

Their findings indicated that elements such as ethics, behavior, education, beliefs, patriotism, income disparities, employment, bribery, cash flow, risk and return, future security, family support, and taxation significantly affect the likelihood of money laundering. Ghasemi and Pourmahdian (2017) employed the Strauss and Corbin grounded theory paradigm to investigate laundering-related behaviors among bank clients. In another study, Ghaemi (2013) applied the Solow growth model to estimate the negative impact of money laundering on Iran's economic growth. The results showed that money laundering had a negative impact on the country's economic growth between 1981 and 2010. Amiri (2012) conducted a study aimed at developing a comprehensive plan to reduce money laundering and prevent its harmful consequences, offering a comprehensive review of legal, economic, and religious perspectives on the issue.

An integrated theoretical framework

To develop our theoretical framework and subsequently formulate our hypothesis, we employ agency theory to examine the existence of money laundering risk at the firm level. According to this theory, the separation of management from ownership in companies leads to conflicts of interest between managers and shareholders. The theory states that managers (agents) are self-interested, which in many cases leads to corrupt actions on their part (Eisenhardt, 1989). Money laundering practices can be explained by agency theory because, although the adverse financial impacts of money laundering at the firm level, such as regulatory penalties, reputational damage, and financial distress, impose significant costs on the company, in many cases, it also yields significant benefits for managers (Naheem, 2020).

In addition to agency theory, other perspectives, including behavioral finance and criminology theories, also help explain the money laundering behavior of managers within companies. According to the routine activity theory (Cohen & Felson, 1979), opportunities for money laundering arise in companies when there is both sufficient motivation and insufficient supervision of their activities. Based on this, companies with weaker corporate finance and hence less oversight are expected to be more involved in money laundering (Huang & Zhang, 2012).

However, in order to explain how people behave in the face of such opportunities, it is necessary to use behavioral finance theories. For example, overconfidence, one of the most well-known biases in behavioral finance (Russo & Schoemaker, 1992), often leads to money laundering in companies by creating the impression that perpetrators will not be caught. For example, in large companies, characterised by a complex structure and higher lobbying power, money laundering is more likely (Bugeja et al., 2012).

Considering the above-mentioned theories, if we present an integrated theoretical framework, it can be argued that the agency problem creates conflicts of interest, which subsequently create opportunities for managers to engage in misconduct. On the other hand, the existence of behavioral biases mentioned in behavioral finance leads to a decrease in supervision and an amplification of the agency problem, which ultimately fulfils the conditions outlined in the routine activity theory. Based on our unified theoretical framework, our first prediction is:

P1. The risk of money laundering is negatively related to the quality of corporate governance, ceteris paribus.

The second prediction is as follows:

P2. The risk of money laundering is positively related to a firm's size, ceteris paribus.

Overconfidence leads to increased risk-taking behavior, such as utilizing high leverage in a firm's capital structure. Hence, we expect:

P3. The risk of money laundering is positively related to a firm's leverage, ceteris paribus.

Other behavioral biases, such as mispricing, can also serve as a signal of misconduct in firms. In this regard, we hypothesize:

P4. The risk of money laundering is positively related to a firm's mispricing, ceteris paribus.

Short-termism, as well as overconfidence, makes financially performing companies a target for motivated criminal offenders to commit money laundering. Therefore, our final hypothesis is as follows:

P5. The risk of money laundering is positively related to a firm's financial performance, ceteris paribus.

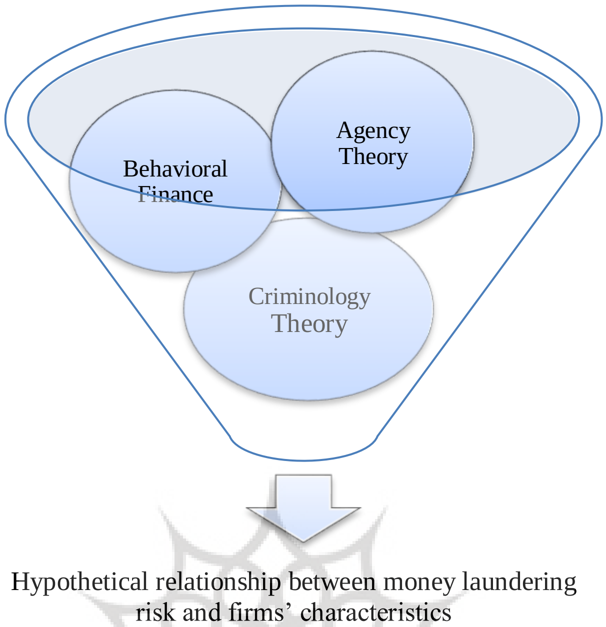

Figure1. Theoretical framework of the paper's model

Research Methodology

Measuring Money Laundering Risk

The process of managing money laundering risk involves two critical and interrelated phases: definition and measurement. The most common definition of money laundering describes it as an act of concealing the transformation of profits derived from illegal activities and corruption into legitimate assets. However, depending on the jurisdiction, it may encompass various types of offenses. For example, Title 18 of the United States Code considers any transaction involving monetary instruments or funds into or out of the U.S. with (1) the intent to promote unlawful activity or (2) knowledge that the funds represent proceeds from illegal activity, particularly when the transaction is designed to conceal the nature of the proceeds or to avoid federal or state reporting requirements (Habib et al., 2017).

In this study, the methodology proposed by Bolgorian and Mayeli (2020) is adopted to measure firm-level money laundering risk in Iran's financial market. A summary of the adopted methodology is as follows:

In early 2012, the Iranian Stock Exchange mandated all listed companies to initiate compliance activities related to anti-money laundering. The directive identified four specific activities to reduce money laundering risk and required auditors to report the status of these AML activities in the companies' audited financial statements. These four activities are:

1. Staff training;
2. Customer identification and verification;
3. Reporting suspicious activities;
4. Documentation and record-keeping.

Auditors were required to provide separate evaluations for each activity in the annual financial statements of listed companies. The following is a sample of such an audit opinion:

"In implementing Article 33 of the Anti-Money Laundering Executive Instructions by auditors, compliance with the provisions of the Anti-Money Laundering Law, related regulations and executive instructions, within the framework of checklists notified by the relevant authorities and auditing standards, has been assessed by this institution. In this regard, the failure to fully identify clients in transactions and include national ID and postal code in all forms, contracts and software, the development of reliable procedures for measures related to the discovery of suspicious operations and transactions, and the receipt and payment of funds solely through bank accounts have not been conducted."

To measure the level of money laundering risk at the firm level, Bolgorian and Mayeli (2020) proposed an index based on auditor opinions regarding company actions in each of the four activities. Let $\mathrm{AO}_{\mathrm{ikt}}$ denote the auditor's opinion for company i in year t regarding the k-th activity (k = 1, 2, 3, 4) If the auditor reports a positive opinion on the kth anti-money laundering activity of company i in year t, then $\mathrm{AO}_{\mathrm{ikt}} = 0$; otherwise $\mathrm{AO}_{\mathrm{ikt}} = 1$. The firm's overall money laundering risk index is then calculated as:

$MLR_{it} = \frac{1}{4}\sum_{k=1}^{4} AO_{ikt}$Where MLR_{it} denotes the money laundering risk of company i in year t. Clearly, a higher MLR_{it} indicates a higher money laundering risk.

Data, Model, and Variables

The research population includes all companies listed on Iran's capital market from 2012 to 2023. However, as is customary in such studies, the sampling method is judgmental, applying several standard filtering criteria:

1. Companies listed after 2012 with incomplete data (Bali et al., 2017);

2. Companies in the financial sector (banks, insurance firms, investment companies, etc.); since, unlike non-financial firms, where high leverage more likely indicates distress, the high leverage in financial firms does not have the same meaning (Fama & French, 1992; Kayhan & Titman,2007);

3. Companies with negative equity in any study year (Kayhan & Titman,2007; Titman & Wesseles, 1988; Bali et al., 2024);

4. Companies with trading halts longer than three consecutive months (Bali et al., 2024; Bali et al., 2017);

5. Companies listed on the base market of Iran OTC.

After applying these filters, the final dataset includes 1,680 firm-year observations.

As noted previously, the research employs a two-phase approach, comprising both quantitative and qualitative components. In the first phase, a panel logit regression model is used to predict money laundering risk:

$$MLR_{it} = \gamma_0 + \gamma_1 Size_{it-1} + \gamma_2 ROE_{it-1} + \gamma_3 TOB_{it-1} + \gamma_4 LEV_{it-1} + \gamma_5 BDIN_{it-1} + \gamma_6 BDSZ_{it-1} + YearFE_{it} + FirmFE_{it} \quad (1)$$

The model assumes that larger firms face a higher money laundering risk due to operational complexity (Bugeja et al., 2012); thus, SIZE is measured as the natural log of total sales. We did not use total assets as a measure of firm size because, due to very high inflation in Iran, some firms have revalued their assets, while others have not. Accordingly, differences in the amount of assets reported in the financial statements of firms do not necessarily indicate differences in the firms' sizes. However, the literature commonly uses a firm's market capitalization as a measure of its size. For this purpose, we also employ this measure to conduct a robustness test of our results.

ROE captures firm performance, assuming better-performing firms invest more in risk management. TOBINQ is used as a proxy for investment opportunities (Bugeja et al., 2012; Coles et al., 2011; Tosi et al., 2004). LEV captures leverage, with higher leverage expected to increase risk (Carter et al., 2017). Governance-related variables, such as board size and board independence, are also included, as better governance is typically associated with fewer law violations (Beasley, 1996; Uzun et al., 2004).

Variable definitions are summarized below:

Table 1. Variable Definitions

Variable	Definition
BDIN	Ratio of independent board members to total board members
BDSZ	Total number of board members
LEV	Total debt divided by lagged total assets
MLR	Money laundering risk index (as per equation 1)
ROE	Net income divided by equity
SIZE	Natural log of total sales
TOBQ	(Market value + debt) / book value

Table 2 below presents the descriptive statistics for the model's main variables. As can be seen, the average money laundering risk index for the companies studied during the review period is approximately 0.28. The highest and lowest values of this variable are 1 and 0, respectively.

Table 2. Descriptive Statistics

statistic	LEV	ROE	SIZE	TOBINQ	BDIN	BDSZ	MLR
Mean	0.٥٨	0.3٩	14.٩٤	1.7٩	0.6٩	5.03	0.2٤
Median	0.٥٥	0.3٣	13.٤١	1.٤٨	0.6٣	5.00	0.2٩
Max	0.٩٦	1.٥٢	٢٠.٤٣	4.٨٨	1	7	1.00
Min	0.01	-0.0٨	9.07	0.50	0	5	0.00
Std Dev	0.٢٥	0.2٦	1.٧٥	0.٦٩	0.15	0.21	0.٤1
Skewness	-0.٣١	0.٨4	0.٦٣	1.3١	0.11	0.29	0.٨٣
Kurtosis	٣.٧٧	٤.2٩	4.٩٩	5.٨٧	0.19	7.35	2.٧٣
Jarque-Bera	١٢.٩٥	٤٢.٠٩	٩٤.١٢	٢٤١.١١	19.45	١٤٢.51	11٧.٤١
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	١,٦٨٠	١,٦٨٠	١,٦٨٠	١,٦٨٠	١,٦٨٠	١,٦٨٠	١,٦٨٠

Additionally, to consider the structural variables of the selected sample, industry type, ownership concentration, and government ownership were entered into the model as control variables. The descriptive statistics of these variables are reported in Table 3. As one can see, the government is a controlling shareholder in the petrochemical and industrial metal industries, which are the two leading non-oil exporters of the Iranian economy.

Table 3. Structural variables of selected samples

Industry	Proportion of Firm-year in sample %	Average Institutional ownership %	Average Government Ownership %
Cement	18	20	53
Automobile	15	24	40
Drug	14	10	53
Petrochemicals	14	9	61
Food and Beverage	12	50	10
Industrial Metals	10	9	63
Equipment	5	44	14
Tire	3	17	60
Non-ferrous Metals	3	7	14
Ceramic	2	18	36
Metal Products	2	20	54
Paper	2	10	30

The results of the estimation model are reported in the table below.

Table 4. Regression Results

	Model (1) (Size measured as total sales)		Model (2) (Size measured as Market Capitalization)	
Variable	t-stat	Coefficient	t-stat	Coefficient
C	5.14	0.772	5.01	0.714
SIZE	۲.32	0.154	۲.01	0.130
ROE	1.93	-0.047	-1.85	-0.061
TOBINQ	0.87	0.134	0.55	0.109
LEV	3.32	0.074	3.14	0.062
BDIN	-4.12	-0.194	-3.06	-0.212
BDSZ	-1.43	-0.037	-1.03	-0.012
Industry	-0.08	-0.073	-0.07	-0.013
Ownership Concentration	2.46	0.015	1.93	0.081
Government's Ownership	0.83	0.043	0.44	0.012
Time effect		✓		✓
Firm effect		✓		✓
Adjusted R-squared		38.74%		39.05%

Findings

The results of the main model estimation are reported in Table 4 for two models. In model (1), the firm size is measured by total sales, while in model (2), we used the firms' market capitalization to measure size. As observed, the variables of firm size, return on equity (ROE), leverage, and the number of independent board members all have statistically significant coefficients in explaining the risk of money laundering.

In model (1), where size is measured as total sales, the coefficient for firm size is 0.154 and statistically significant at the 1% level. This suggests that as firm size increases, the likelihood of money laundering risk also increases. The same is true in model (2). These results align with our second theoretical prediction.

In both models, firm performance, measured by ROE, has a negative coefficient and is significant at the 5% level. This indicates a negative and significant relationship between company performance and the likelihood of involvement in money laundering activities. While we expected a positive relationship between financial performance and money laundering risk, the negative relationship might be due to the positive correlation between misconduct in companies and a reduction in profitability and efficiency.

Conforming with our third theoretical prediction, leverage exhibits is also significant at the 1% level. Therefore, higher leverage is associated with an increased level of money laundering risk in firms.

The coefficient for the number of independent board members is negative and significant at the 1% level. This implies that an increase in the number of independent board members — and consequently, improvements in corporate governance — leads to a reduction in firm-level money laundering risk. Furthermore, although the coefficient of board size in both models is not significant at the 95% significance level, the coefficients are negative. These results support our first prediction, as described above.

Finally, as reported in the table, Tobin's Q has an insignificant coefficient in both models, which is contrary to our prediction. The reason for this is likely the lack of information transmission related to illegal activities through trading signals in the Iranian capital market, primarily due to its low efficiency.

Regarding the structural variables in the model, as can be seen, the institutional concentration coefficient is positive and significant at the 95% level. This result is consistent with the findings reported by Burns et al. (2010). This positive relationship can be justified given the passive role of many financial institutions in Iran and the complex and bureaucratic nature of their management structures. However, the industry factor and the level of government ownership are not significant. The lack of significance of the industry means that there is no significant difference in money laundering activities among the industries active in the Iranian capital market. The high level of government ownership in most companies listed on the Iranian stock exchange may be one of the main reasons for the variable's lack of significance in the model. Chen et al. (2006) find similar results by studying Chinese companies.

Due to the presence of heteroskedasticity in standard errors, standard regression models are not suitable for determining the significance of parameter estimates. To estimate standard errors that are robust to heteroskedasticity, we re-estimated our main model using a bootstrapping technique and reported the results in Table 5. As one can see, we obtain the same results using bootstrapped standard errors, which emphasises the credibility of our findings.

Table 5. Regression Results with the Bootstrap Technique

	Model (1) (Size measured as total sales)		Model (2) (Size measured as Market Capitalization)	
Variable	Observed	95% Confidence Interval	Observed	95% Confidence Interval
C	0.612	(0.431 0.920)	0.594	(0.482 0.889)
SIZE	0.173	(0.143 0.202)	0.122	(0.094 0.287)
ROE	-0.182	(-0.312 -0.14)	-0.077	(-0.255 -0.114)
TOBINQ	0.109	(-0.071 0.099)	0.188	(-0.071 0.199)
LEV	0.062	(0.011 0.120)	0.044	(0.005 0.120)
BDIN	-0.155	(-0.717 -0.020)	-0.180	(-0.660 -0.033)
BDSZ	-0.072	(-0.233 0.125)	-0.051	(-0.148 0.125)
Industry	-0.015	(-0.312 0.147)	-0.033	(-0.254 0.111)
Ownership Concentration	0.022	(0.003 0.354)	0.045	(0.008 0.242)
Government's Ownership	0.012	(-0.45 0.179)	0.078	(-0.220 0.114)

Qualitative Analysis

In grounded theory, data analysis begins with the coding process. According to this approach, coding involves three stages: open coding, axial coding, and selective coding (Corbin & Strauss, 1998). Strauss and Corbin emphasize the fluid nature of the open and axial coding processes.

At the outset of coding, initial concepts are identified through an open coding process. In the axial coding phase, related concepts are grouped into broader categories. Subsequently, through selective coding, the findings are integrated to develop a theoretical model based on the relationships identified between the initial concepts.

To achieve the research objectives, with the guidance of three experts in the field of money laundering risk, eight semi-structured interview questions were developed. For instance, one of the questions was: “What conditions in economic entities increase the risk of money laundering and related activities?”

In the next step, semi-structured interviews were conducted with ten experts in the field of research. Theoretical saturation was achieved after the eighth interview. The interviews were conducted from February 2025 to April 2025. The demographic characteristics of the interviewees are presented below.

Table 6. Demographic Characteristics of Interviewees

Education	Faculty Member	Financial Manager	CEO	Total
Ph.D.	3	2	2	7
M.A./M.Sc.	0	3	0	3
Total	3	5	2	10
Percentage	30%	50%	20%	100%

As shown above, the expert panel included 30% university faculty members, 50% financial managers, and 20% CEOs of economic entities. This composition was chosen to incorporate both theoretical and practical considerations, particularly with respect to money laundering risk.

After conducting the interviews, test-retest reliability was employed to assess their reliability. Reliability refers to the consistency of data categorization over time. In this method, a single coder re-coded the exact text at two different time points. Similar codes between the two time intervals were labeled as "agreement," while dissimilar codes were labeled as "disagreement."

Based on the test-retest reliability formula, the reliability scores for the first and second interviews were 83% and 81%, respectively. Given that both scores exceeded the 60% threshold, the interviews were deemed reliable.

Following data collection through semi-structured interviews, the three-stage coding process—open, axial, and selective coding—was employed for data analysis. After identifying the initial codes and grouping similar ones, 18 conceptual codes were extracted. These were then categorized into seven main themes, as presented below.

Table 7. Open and Axial Coding in the Qualitative Phase

No.	Open Coding Concepts	Axial Coding Categories
1	Organizational awareness raising	Training
2	Employee training	
3	Financial transparency	Transparency
4	Operational transparency	
5	Proper financial reporting	
6	Board effectiveness	Corporate Governance
7	Board independence	
8	Role of the Audit Committee	
9	Management performance evaluation	
10	Shareholder structure of the company	
11	Enterprise-level risk management	
12	Lack of incentives	
13	Compliance with laws and regulations	Legal Compliance
14	Oversight by regulatory authorities	
15	Organizational complexity and size	Firm Size
16	Financial performance of the firm	Firm Performance
17	Unjustified investments	
18	Capital structure of firms	Capital Structure

Based on the concepts derived from open and axial coding, a questionnaire consisting of 18 items was developed. A 5-point Likert scale was used, ranging from 1 (strongly disagree) to 5 (strongly agree). To assess the reliability of the questionnaire, it was emailed to 30 knowledgeable individuals in the field of money laundering, and 20 responses were returned. Cronbach's alpha was calculated to be 0.84, confirming the instrument's reliability.

Subsequently, an online version of the questionnaire was distributed to 110 professionals and individuals involved in anti-money laundering practices in business enterprises. A total of 63 completed responses were received. To address the primary research question, exploratory factor analysis (EFA) was employed. Using a minimum loading threshold of 0.50, the factor loadings, eigenvalues, and cumulative explained variance are reported below.

The first factor alone explains approximately 19% of the total variance and includes organizational culture and employee training. The second factor accounts for approximately 16.5% of the variance and encompasses corporate governance variables, including board effectiveness, board independence, and the audit committee's role in mitigating money laundering risks.

The third factor, contributing roughly 15% of the total variance, combines legal compliance, firm complexity and size, financial performance, and capital structure. This factor captures the balance between regulatory compliance and financial structure in relation to organizational size and complexity.

Table 8. Factor Loadings Based on Principal Component Analysis

No.	Concept	Factor 1	Factor 2 / 3
1	Organizational awareness raising	0.742	
2	Employee training	0.874	
3	Financial transparency		
4	Operational transparency		
5	Proper financial reporting		
6	Board effectiveness		0.664
7	Board independence		0.867
8	Role of the Audit Committee		0.536
9	Management performance evaluation		
10	Shareholder structure		
11	Enterprise-level risk management		
12	Lack of incentives		
13	Legal compliance		0.741
14	Regulatory oversight		
15	Organizational size and complexity		-0.687
16	Firm financial performance		0.568
17	Unjustified investments		
18	Capital structure		0.560
	Eigenvalue	3.415	2.982 / 2.634
	Variance Explained (%)	18.9	16.5 / 14.6

Conclusion

The primary objective of this study was to develop a model for predicting firm-level money laundering risk in companies listed on Iran’s capital market. To achieve this goal, a mixed-methods approach was employed, combining both quantitative and qualitative methodologies.

In the quantitative phase, a money laundering risk index was constructed using auditors’ assessments of anti-money laundering (AML) compliance activities reported in companies’ audited annual financial statements. Based on relevant literature, several firm-level characteristics were identified as potential determinants of money laundering risk, and their relationships were examined using a panel logit regression model.

The results indicated that firm size (SIZE) and leverage (LEV) were significantly and positively associated with money laundering risk, while return on equity (ROE), board size (BDSZ) and board independence (BDIN) had a negative and significant effect. Specifically, larger firms were found to be more exposed to money laundering risk, likely due to greater operational complexity. In contrast, higher profitability and stronger corporate governance mechanisms were associated with reduced risk.

To evaluate the robustness of the quantitative findings, a qualitative phase was conducted using grounded theory methodology. Data were collected using a specially designed questionnaire and analyzed through exploratory factor analysis (EFA). The EFA results identified three latent constructs that together explained over 52% of the total variance. These core factors were:

(1) Culture and training,

(2) Corporate governance,

(3) A combined factor comprising regulatory compliance, organizational complexity, firm size, financial performance, and financial structure.

The consistency between the two phases confirms the robustness of the findings. In particular, both approaches emphasize the critical role of corporate governance (e.g., board size and independence), firm size, and financial performance in predicting the risk of money laundering. These findings suggest that enhancing governance practices and internal controls, particularly in large and complex organizations, can substantially reduce the likelihood of involvement in money laundering activities.

The findings of this study carry significant policy implications for combating money laundering. In order to show concretely how the model proposed in this paper can be used for identifying high money laundering risk companies, assume that, for example, historical information of 100 companies, including financial ratios and financial statements, ownership structure, and corporate governance indicators, is available. In the next step, by entering the required data into the model presented in this study, the amount of money laundering risk associated with each company is calculated using the estimated coefficients. Finally, the risk score for each company is determined on a scale, for example, 0 to 10. Finally, in the last step, companies can be classified based on which category they fall into as follows:

Low risk (risk score: 0 to 3)

Medium risk (risk score: 4 to 7)

High risk (risk score: 8 to 10)

According to the recent guidelines issued by the Financial Action Task Force (FATF), a critical aspect of anti-money laundering efforts involves identifying economic sectors with a high risk of money laundering activities. In this context, the results of the present research make a substantial contribution to identifying companies and industries characterised by elevated money laundering risk, in alignment with the FATF's recommendations. Furthermore, other supervisory bodies, such as securities and exchange commissions, audit organizations, and similar institutions, may benefit from these findings to enhance their monitoring and oversight of money laundering-related risks. Finally, corporate governance committees, which are also emphasized by international organizations such as the OECD, can utilize this research to supervise better and manage money laundering risks within economic enterprises.

In conclusion, the model presented in this research can help regulators improve decision-making, monitor compliance, and reduce monitoring costs by sending early warning signals.

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