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What explains money laundering risk? Empirical evidence from a risk-based approach in the Brazilian financial system

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ABSTRACT

This study investigates the determinants of money laundering (ML) risk in the Brazilian financial system, addressing the lack of empirical evidence supporting risk-based regulatory models. The results provide partial empirical validation of Brazil's AML framework, showing that cash transactions and major metropolitan areas are the only robust and persistent determinants of reported ML risk. Using a mixed-methods approach, the research combines a systematic literature review with panel data econometric analysis (2010-2022). The scarcity of empirical studies testing ML risk determinants limits the refinement and comparability of internal risk assessment (AIR) models. Given legal restrictions on access to customer-level data, the study relies on publicly available information to evaluate whether regulatory risk factors effectively explain suspicious transaction reporting. The findings indicate that gross domestic product, border location, mining activity, and informal settlements have limited or unstable explanatory power. The findings contribute by demonstrating that major metropolitan areas should be treated as structural risk-weighting factors in AIR models, supporting more efficient allocation of compliance resources and evidence-based regulatory improvements. The study combines a systematic literature review with panel data econometric analysis of Brazilian federative units from 2010 to 2022. Multiple regression models and Chow structural break tests were employed to assess the stability of risk determinants before and after major regulatory changes.

Keywords: internal risk assessment, anti-money laundering, suspicious transaction reports, financial regulation, risk-based approach.

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1. INTRODUCTION

Money laundering (ML) represents a structural challenge to the integrity and stability of the financial system. By allowing illicit proceeds to be integrated into the formal economy, ML distorts incentives, undermines market efficiency, and increases reputational and integrity risks for financial institutions. Understanding the factors that influence ML risk is, therefore, essential for improving regulatory mechanisms and for the development of internal risk assessment (AIR) models established under the current regulatory framework.

Measuring this risk, however, involves both conceptual and empirical challenges. The "real" ML risk is, by nature, hidden; the "detected" risk depends on the identification capacity of internal control systems; and the "reported" risk is empirically observed through Suspicious Transaction Reports (Comunicações de Operações Suspeitas [COS]), which constitute the only publicly available measure. This distinction, often overlooked in the literature, is central to correctly interpreting observed statistical determinants.

Against this backdrop, this study analyses the behavior of COS from 2010 to 2022, relating it to economic, geographic, and operational variables, with the aim of identifying robust determinants of reported ML risk. By combining a systematic literature review, scientometric analysis, and quantitative methods, the research seeks to contribute to the refinement of AIR models and to the alignment of domestic practices with international anti-ML (AML) standards.

1.1 Contextualization

ML consists of a set of procedures aimed at concealing, disguising, or obscuring the illicit origin of assets, allowing offenders to enjoy the economic proceeds of the predicate crime. Under the Brazilian legal system, ML constitutes an autonomous criminal offence, independent of proof of the underlying crime, as consolidated in judicial precedent. The dynamics of ML traditionally involve three stages – placement, layering, and integration – and mobilize multiple sectors of the economy, with particular relevance for the financial system, given its capacity to move, convert, and disperse financial resources.

Traditional financial institutions represent the most widely used channel for transferring funds, which makes them subject to enhanced scrutiny and supervision (Fernandes & Zani, 2021). Money launderers typically seek to recycle criminal proceeds rapidly, transferring them to bank accounts in jurisdictions where controls over financial transactions are weaker (Nikoloska & Simonovski, 2012).

In Brazil, the regulatory framework for AML evolved significantly from 2012 onwards, culminating in the issuance of Banco Central do Brasil (BCB), Circular nº 3.978/2020 (BCB, 2020c) and Carta Circular nº 4.001/2020 (BCB, 2020b), which assign financial institutions the obligation to maintain their own AIR models. These models, however, face limitations arising from information asymmetry, the presence of non-observable determinants, and the inherent difficulties involved in identifying suspicious patterns. In this context, it becomes relevant to empirically investigate which factors are, in fact, associated with higher levels of reported risk.

The evolution of the Brazilian and international AML framework is summarized in Figure 1, which presents the principal regulatory and institutional milestones that shaped the development of the risk-based approach adopted by financial institutions and supervisory authorities over time.

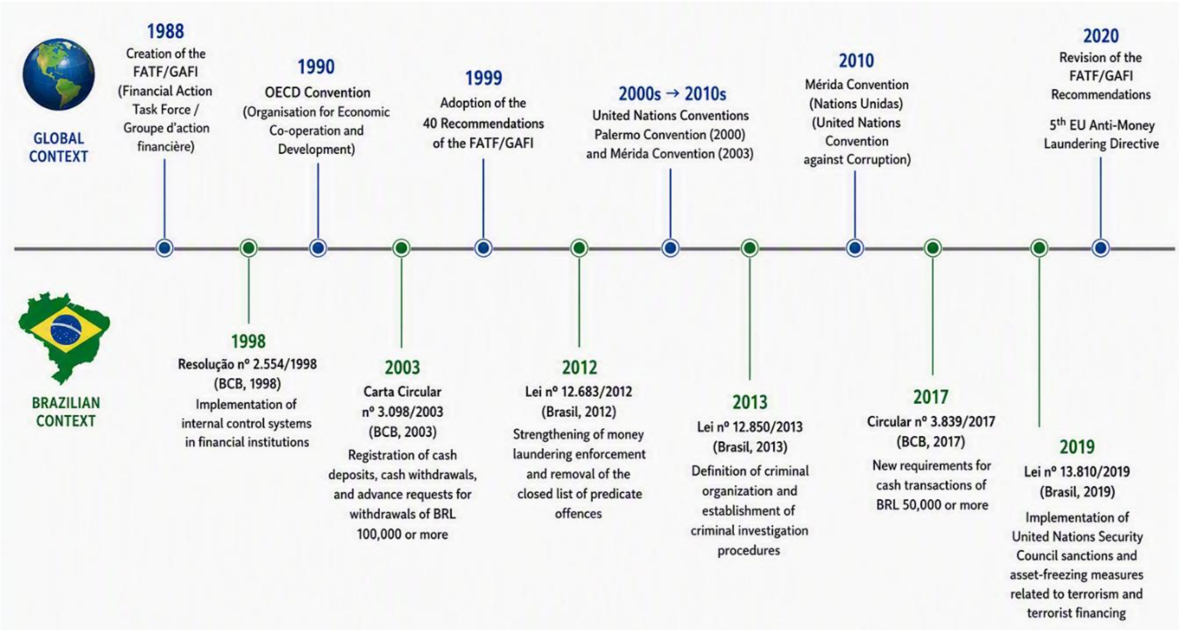

Figure 1 *Anti-money laundering regulatory framework, 1988-2020 (Brazil and global context)*
Note: *Timeline of major anti-money laundering milestones in Brazil and internationally, including the recommendations of the Financial Action Task Force (FATF)/Groupe d'action financière (GAFI) , international conventions, and Brazilian legislation. COAF = Conselho de Controle de Atividades Financeiras; COE = Comunicações de Operações em Espécie; ENCCLA = Estratégia Nacional de Combate à Corrupção e à Lavagem de Dinheiro; OECD = Organisation for Economic Co-operation and Development.*
Source: *Prepared by the authors.*

Two key concepts frequently used throughout this study, Cash Transaction Reports (Comunicações de Operações em Espécie [COE]) and COS, are explained here. Both are fundamental instruments for AML in Brazil and constitute mandatory reports submitted to the Conselho de Controle de Atividades Financeiras (COAF), the country's financial intelligence unit, by entities subject to AML obligations under Lei nº 9.613/1998 (Brasil, 1998). COS identify atypical transactions that may indicate potential financial crimes. COE refer to transactions involving physical cash that exceed thresholds established by the competent authority and must be compulsorily reported due to the higher risk of concealing the origin of funds.

These reporting obligations are central to Brazil's accountability framework in combating ML, as they institutionalize transparency and reinforce the role of COE and COS within the broader system of financial oversight (Suxberger & Pasiani, 2018).

It is important to note that these reports do not constitute accusations or complaints. Rather, they reflect legal obligations based on the analysis of transaction history, customer financial capacity, and other criteria defined by specific regulations. Such information provides inputs for the financial intelligence unit to filter cases that may ultimately give rise to investigations by the Public Prosecutor's Office.

1.2 Research Problem, Gaps, and Objectives

Identifying the determinants of ML risk is essential for the efficient allocation of monitoring resources and for strengthening regulatory supervision. Despite the widespread adoption of a risk-based approach, the literature still lacks empirical studies that test the determinants of ML risk, limiting the refinement of AIR models used by financial institutions. This gap hinders comparability across institutional practices and may lead to inconsistencies in the implementation of preventive and control measures (Haffke, 2021; Turki et al., 2021).

Furthermore, restrictions arising from data protection laws, banking secrecy, and investigative confidentiality constrain access to detailed customer and enforcement information, even after advances introduced by access-to-information legislation. The absence of granular data and limited data sharing on fraud and predicate offences hinder the development of more robust modelling strategies and confine risk assessments largely to formal regulatory frameworks.

Financial institutions also face challenges in quantifying losses associated with predicate crimes, which may obscure the true magnitude of ML risk and weaken risk mitigation strategies.

Against this backdrop, this study addresses the following research question: what are the key determinants of ML risk in Brazilian financial institutions? The study aims to empirically identify these determinants by synthesizing the relevant literature, organizing public data related to COS, and applying econometric models to assess the explanatory power and temporal stability of the selected variables.

1.3 Justification and Relevance of the Study

The relevance of this study stems from the growing complexity of suspected ML activities in Brazil and from the sharp increase in the volume of reports submitted to the COAF. The *Relatório de Inteligência e Gestão* (COAF, 2024) documents a substantial rise in both COS and financial intelligence reports, indicating improvements in data processing capacity alongside persistent structural vulnerabilities within the system. This context underscores the need for more robust AIR models capable of addressing higher transaction volumes, increasingly sophisticated criminal techniques, and the transnational nature of ML.

The strengthening of national and international cooperation, through extensive information exchanges and partnerships among financial intelligence units, highlights that ML operates through cross-border networks and requires responses aligned with global best practices. The implementation of COAF System 4.0 and the expanding monitoring of vulnerable sectors, such as cryptoassets, real estate, and online gaming, further illustrate a regulatory environment in transition, in which ML risk shifts in response to technological and regulatory incentives.

Against this backdrop, this study contributes by providing an empirical analysis of the determinants of ML risk, with implications that extend beyond accounting to encompass regulatory law, corporate governance, and compliance. By offering empirical evidence to support the refinement of AIR models, the study informs regulatory decision-making, strengthens internal control mechanisms, and enhances the effectiveness of AML strategies adopted by financial institutions, in light of the significant and persistent economic impacts associated with ML.

1.4 Theoretical Framework

The literature defines ML as the process through which proceeds from illicit activities are concealed, disguised, and subsequently integrated into the formal economy, giving an appearance of legitimacy to criminal assets (Fernandes & Zani, 2021; Nikoloska & Simonovski, 2012). The risk of asset confiscation associated with crimes such as trafficking, corruption, and fraud incentivizes increasingly sophisticated concealment structures, requiring continuous regulatory, technological, and operational responses from states and financial institutions.

Financial institutions play a central role in this process, as they concentrate capital flows and function simultaneously as potential channels and critical barriers to ML (Fernandes & Zani, 2021). In the Brazilian banking sector, reporting practices are not random but stem from consolidated structures of risk management and internal controls, which shape institutional responses to suspicious transactions (Fernandes & Zani, 2021). Criminal organizations, particularly in transnational settings, operate through complex structures involving multiple jurisdictions, regulatory loopholes, and corrupt practices aimed at reducing detection risk (Nikoloska & Simonovski, 2012). This environment exposes financial institutions to growing operational, legal, and reputational risks, reinforcing the need for robust prevention and compliance systems (Turki et al., 2021).

In Brazil, the AML regulatory framework has evolved significantly since the 1990s, notably with Lei nº 9.613/1998 (Brasil, 1998) and its amendment by Lei nº 12.683/2012 (Brasil, 2012), which expanded the range of obligated entities and strengthened control mechanisms. Subsequent regulations issued by COAF, the Receita Federal, and the BCB modernized reporting obligations, incorporated new sectors, and introduced stricter monitoring requirements. Internationally, successive European directives and the recommendations of the Financial Action Task Force consolidated the risk-based approach, incorporating customer-, geographic-, and product-related risks, including cryptoassets (Satink et al., 2023).

Recent regulatory developments in Brazil, particularly from 2016 to 2020, expanded reporting mechanisms, reinforced monitoring of politically exposed persons (PEPs), regulated cryptoasset platforms, and strengthened compliance programs. These changes occurred alongside accelerated digital transformation, intensified by the COVID-19 pandemic, which increased exposure to fraud and the misuse of emerging technologies, as reflected in the growth of reports analyzed by COAF.

From a theoretical perspective, this study also draws on the theory of deliberate ignorance, or willful blindness, which addresses conscious omission in the presence of illicit indicators (Soares, 2019). In financial environments, such behavior may arise from structural failures, misaligned incentives, or operational negligence, increasing ML risk.

National literature also highlights that strengthening internal audit functions is essential to reduce institutional blindness to suspicious operations, directly connecting with the theory of deliberate ignorance and reinforcing the preventive role of audit in combating fraud and corruption (Fernandes e Zani, 2021).

Although the empirical literature on ML risk determinants is extensive, it remains fragmented and lacks methodological standardization. Few studies empirically test integrated models combining customer, geographic, and operational risk dimensions. This gap motivates the present research.

Within this context, Carta Circular nº 4.001/2020 (BCB, 2020b) constitutes the main Brazilian regulatory framework for AIR, structuring analysis across customer-, geographic-, and product-related risks. By operationalizing the risk-based approach established by Circular nº 3.978/2020 (BCB, 2020c), the framework guides proportional controls. This study engages directly with this framework by empirically testing its risk factors and assessing their explanatory power over the behavior of COS.

Despite the growing need for a risk-based approach in AML, the existing literature continues to exhibit substantial gaps. In particular, there is a lack of studies that offer standardized and consistent measurement frameworks for determining ML risk. While many authors stress the importance of robust risk assessment, few develop empirical models that integrate multiple variables and indicators in a systematic and replicable manner. This limitation constrains comparability across institutions and jurisdictions and underscores the need for empirical research capable of testing and refining risk-based frameworks in practice, a gap that the present study seeks to address.

Contemporary Brazilian literature emphasizes that the fight against ML in Brazil transcends mere legal compliance, establishing itself as a core element of institutional accountability (Suxberger & Pasiani, 2018). Within this framework, the effectiveness of the prevention system relies on the robustness of internal controls and risk management in the banking sector, which serve as essential filters for detecting illicit financial flows (Fernandes e Zani, 2021). Furthermore, strengthening internal audit structures is vital to mitigating fraud and corruption risks, thereby addressing institutional omission and reducing the potential for willful blindness in the monitoring of suspicious transactions (Fernandes e Zani, 2021).

1.5 Carta Circular nº 4.001/2020 (BCB, 2020b) and the Risk Assessment Framework

As the main regulator of the Brazilian financial system, the BCB establishes mandatory parameters for AIR models adopted by supervised institutions. The key regulatory instrument governing this process is Carta Circular nº 4.001/2020 (BCB, 2020b), which operationalizes the provisions of Circular nº 3.978/2020 (BCB, 2020c) by specifying the risk factors to be considered in AML and counter terrorist financing assessments.

According to the BCB, AIR models should be structured around three core dimensions: (i) customer risk, encompassing the nature of economic activity, source of funds, ownership structure, and PEP status; (ii) geographic risk, related to jurisdictions with weak AML regimes and sensitive locations such as border areas; and (iii) product, service, transaction, and delivery channel risk, including factors such as anonymity, cash transactions, and non-face-to-face channels.

By presenting this regulatory framework, this section anchors the study in a concrete supervisory model, clarifies the risk assessment framework that is empirically tested, and ensures that the analysis is directly aligned with the regulator's underlying logic. This approach avoids detachment from prevailing institutional practices and promotes coherence between the theoretical framework, the methodology, and the empirical results.

The regulator explicitly adopts a risk-based approach, under which the intensity of controls should be proportional to the level of risk identified. This study engages directly with this framework by empirically testing the association between selected regulatory risk factors and the behavior of the financial intelligence system, proxied by the volume of COS.

Accordingly, the study does not seek to challenge the BCB's framework, but to provide empirical validation that may support its ongoing refinement by identifying which factors exhibit greater explanatory power within the Brazilian financial system.

2. METHODOLOGICAL PROCEDURES

This study adopts a mixed qualitative and quantitative approach, structured around four main components: literature-based variable selection, data sources and variable construction, econometric modelling, and assessment of research limitations.

2.1 Research Design and Literature-Based Variable Selection

The research begins with a systematic literature review of studies published over the last 20 years focusing on ML risk assessment. The scope of the review was defined around the theme of "determinants of ML risk," which guided both the scientometric analysis and the subsequent selection of explanatory variables.

Data were collected from the Web of Science and Google Scholar databases using the search terms "money laundering prevention" and "prevenção à lavagem de dinheiro." The combined search yielded 4,220 scientific publications, of which 1,178 met the initial relevance and thematic criteria. Following the application of a specific filter related to ML risk assessment, 138 studies were identified as directly connected to the core theme of the research, as illustrated in Figure 2.

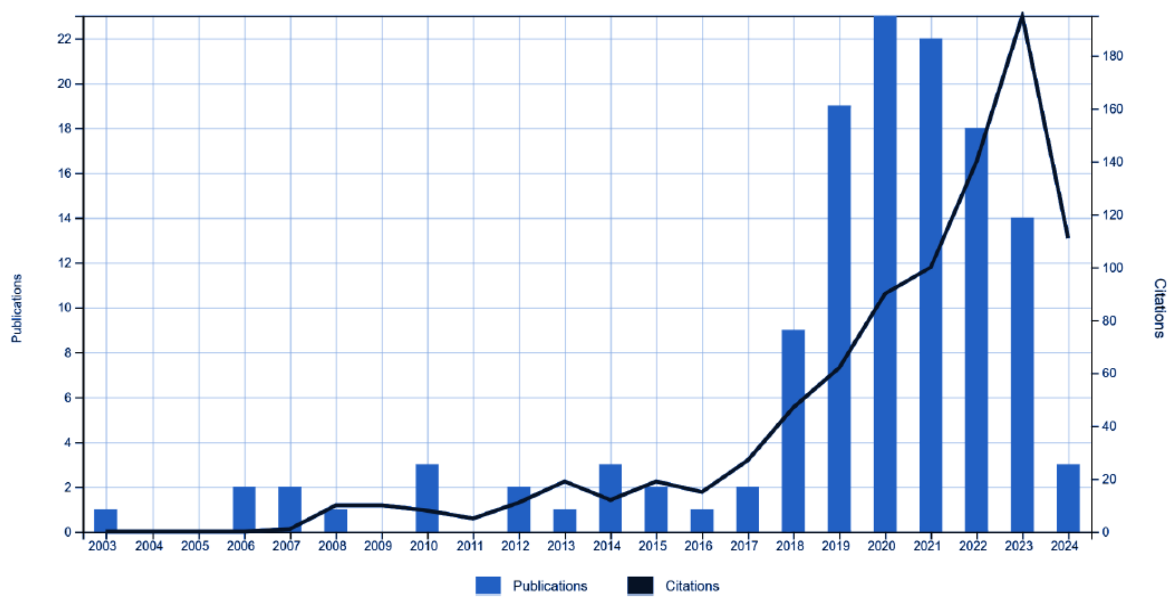

Figure 2 *Frequency of publications on money laundering risk, 2003-2024. Annual numbers of publications and citations on money laundering risk assessment, based on a Web of Science search conducted on September 1, 2024 (138 articles)*
Source: *Prepared by the authors.*

A further screening stage based on exploratory reading and explicit focus on risk determinants reduced the sample to 38 studies. Of these, six were excluded due to a lack of open access and one due to limited relevance to the research objectives. After the inclusion of one relevant online journal article, a final set of 32 studies was retained for detailed analysis.

Scientometric techniques were then applied to this corpus to quantify publication patterns, citation impact, and keyword co-occurrence networks. This process enabled the identification of dominant thematic clusters and their interrelationships, providing empirical support for the theoretical framework and informing the selection of variables subsequently tested in the econometric models.

2.2 Econometric Strategy and Structural Break Analysis

The dependent variable is the volume of COS, by federative unit (*unidade federativa* [UF]), used as a proxy for reported ML risk. Independent variables include two continuous indicators and a set of dummy variables capturing structural, geographic, and operational risk factors.

COE represents the volume of cash-based operations by UFs and serves as a key operational indicator. State-level gross domestic product (GDP) controls for differences in economic scale across Brazilian states. Dummy variables were constructed based on objective and replicable criteria: major metropolitan area equals 1 for UFs with officially defined metropolitan regions (Instituto Brasileiro de Geografia e Estatística [IBGE]) that include metropolitan areas with populations above 750,000 inhabitants, according to IBGE criteria applied to the period; border equals 1 for states with international land borders; mining equals 1 for states with relevant extractive activity; and informal settlement equals 1 for UFs with a high concentration of informal settlements, recognized as areas of socioeconomic vulnerability and higher exposure to illicit financial flows. These variables capture structural geographic and economic factors relevant to ML risk.

Due to data availability constraints from official statistical sources, the analysis covers the period from 2010 to 2022.

2.3 Econometric Model

Multiple regression models were estimated using annual data for the period from 2010 to 2022. Both log-log and log-linear specifications were employed, allowing coefficients to be interpreted as elasticities or semi-elasticities, respectively.

Ordinary least squares (OLS) estimation was adopted for its interpretability and suitability for analyzing linear relationships. Diagnostic corrections were applied to address heteroskedasticity, autocorrelation, and multicollinearity. Particular attention was given to the potential correlation between COE and COS, as discussed in the theoretical framework.

The relationship between COE and COS was explicitly considered in the model specification, given their interaction within the operational dynamics of the AML system. Cash transactions frequently form part of the set of operations subject to suspicious reporting; however, the two reporting categories follow distinct regulatory logics. COE are driven by compulsory reporting thresholds based on objective criteria, reflecting the intensity of cash usage. In contrast, COS result from qualitative assessments related to the consistency of transactions with the client’s financial profile, focusing on operations that exceed declared capacity. At the UF level, COE and COS capture distinct yet complementary dimensions of the system – transactional intensity and institutional reporting response – whose association reflects the structure of the monitoring framework. Multicollinearity diagnostics (variance inflation factor [VIF]) indicate acceptable levels, and clustered robust standard errors were employed. The results are interpreted as structural associations at the aggregate level. Table 1 presents the Pearson correlation matrix between log(COS) and log(COE), while Table 2 reports the VIF diagnostics, jointly supporting the inclusion of both variables in the model.

Table 1

Pearson correlation matrix between log(COS) and log(COE)

Variables	log(COS)	log(COE)	log(GDP)	IndiBorder	IndiMjMetropArea	IndiMining	IndiInfSettlem
log(COS)	1.0000	0.8006	0.5388	-0.1106	0.4961	0.3061	0.5038
log(COE)	0.8006	1.0000	0.4314	-0.1238	0.4197	0.1889	0.4787
log(GDP)	0.5388	0.4314	1.0000	-0.3673	0.2938	0.3304	0.2413
IndiBorder	-0.1106	-0.1238	-0.3673	1.0000	-0.3371	0.0574	-0.3673
IndiMjMetropArea	0.4961	0.4197	0.2938	-0.3371	1.0000	0.1083	0.7545
IndiMining	0.3061	0.1889	0.3304	0.0574	0.1083	1.0000	0.3171
IndiInfSettlem	0.5038	0.4787	0.2413	-0.3673	0.7545	0.3171	1.0000

Note: *Correlation coefficients demonstrating the association between Suspicious Transaction Reports (Comunicações de Operações Suspeitas [COS]) and Cash Transaction Reports (Comunicações de Operações em Espécie [COE]), supporting their joint inclusion in the econometric model.*

GDP = gross domestic product.

Source: *Prepared by the authors based on data from the Conselho de Controle de Atividades Financeiras.*

Table 2
VIF diagnostics

Explanatory variables	VIF
log(COE)	1.583
log(GDP)	1.707
IndiMjMetropArea	2.591
IndiBorder	1.436
IndiMining	1.435
IndiInfSettlem	3.174
Média VIF	1.987

Note: *Multicollinearity diagnostics for the explanatory variables, confirming acceptable levels and supporting the robustness of the regression specification.*
COE = Comunicações de Operações em Espécie; GDP = gross domestic product; VIF = variance inflation factor.
Source: *Prepared by the authors.*

Alternative panel data specifications, including fixed effects (FE) and random effects (RE), were estimated as robustness checks. The final specification adopts pooled OLS with clustered robust standard errors due to its adequacy in capturing structural relationships across UFs. The empirical strategy prioritizes the identification of aggregate patterns while preserving time-invariant variables relevant to the analysis. The consistency of results across specifications reinforces the robustness of the findings.

The analysis was conducted at the UF level rather than at the individual city level. This choice reflects the standard practice in the banking sector, which commonly estimates ML risk by UF. Such an approach allows capturing geographic heterogeneity more effectively, including states with extensive border areas adjacent to other countries, where cross-border risks are structurally relevant.

To assess the stability of relationships over time, the Chow test was applied to identify structural breaks associated with major regulatory changes. Breakpoints corresponding to 2016 and 2020 were examined, reflecting regulatory reconfiguration by the BCB and the effects of the COVID-19 pandemic.

2.4 Variable Selection and Model Specification

Based on the determinants identified in the literature and subject to data availability, the following model was estimated:

$$\log(COS) = \beta_1 + \beta_2\ \text{IndiInfSettlem} + \beta_3\ \text{IndiMjMetropArea} + \beta_4 \log(GDP) + \beta_5\ \text{IndiMining} + \beta_6\ \text{IndiBorder} + \beta_7 \log(COE) + \varepsilon$$

where dummy variables capture major metropolitan areas, international border regions, mining activity, and areas with a high concentration of informal settlements. The model was estimated annually for each Brazilian UF from 2010 to 2022.

2.5 Research Limitations

This study is subject to limitations arising from both the Brazilian legal framework and methodological constraints inherent to the analysis of ML risk. Legal confidentiality established under Lei nº 9.613/1998 (Brasil, 1998) and reinforced by the amendments introduced by Lei nº 12.683/2012 (Brasil, 2012) prevents access to disaggregated information on reported transactions submitted to the COAF, including age, PEP status, and individual vulnerability indicators. As a result, some tests initially planned, particularly those aimed at assessing individual-level characteristics, could not be conducted, even though such factors are recognized as relevant in Financial Action Task Force (FATF) recommendations and in the international literature. The data gaps associated with legally protected variables are summarized in Table 3, presented in the following section.

Table 3

List of risk variables identified in the study

Category/risk variable	Data availability	Regulatory reference (Brazilian framework)	Literature reference
Customer			
Customer identification (KYC)	Information confidentiality	Lei nº 9.613/1998, art. 10, inciso I (Brasil, 1998)	Fernandes and Zani (2021), Nikoloska and Simonovski (2012)
PEP	Information confidentiality	Carta Circular nº 4.001, item 4.2.1.5 (BCB, 2020b)	Central Bank of Oman (2022), OECD (2022)
Complex ownership structure	Information confidentiality	Carta Circular nº 4.001, item 4.2.1.3 (BCB, 2020b)	Menyhei (2022), OECD (2022)
Beneficial owner	Information confidentiality	Carta Circular nº 4.001, item 4.2.1.4 (BCB, 2020b)	Menyhei (2022), OECD (2022)
Age/marital status/over-indebtedness	Information confidentiality	-	Esoimeme (2020)
Customer onboarding channel (non-face-to-face)	Information confidentiality	Carta Circular nº 4.001, item 4.2.3.4 (BCB, 2020b)	Central Bank of Oman (2022), Turki et al. (2021)
Geolocation			
Geographic location (state/region)	BCB, IBGE	Carta Circular nº 4.001, item 4.2.2 (BCB, 2020b)	Gaspareniene et al. (2022), Korystin et al. (2020)
Major metropolitan center	IBGE	-	Gaspareniene et al. (2022), Korystin et al. (2020)
Border regions	IBGE	Carta Circular nº 4.001, item 4.2.2.2 (BCB, 2020b)	Esoimeme (2020)
Mining activity	IBGE, COAF	-	Teichmann and Falker (2023)
Economic-financial			
Economic sector	COAF	Carta Circular nº 4.001, item 4.2.1.1 (BCB, 2020b)	Korystin et al. (2020), de Oliveira et al. (2017)

COE	COAF	Carta Circular nº 4.001, item 4.2.3.2 (BCB, 2020b)	Gaspareniene et al. (2022), Korystin et al. (2020)
High-risk products/services	Information confidentiality	Carta Circular nº 4.001, item 4.2.3.1 (BCB, 2020b)	Central Bank of Oman (2022), OECD (2022)
Cryptoassets/virtual assets	Information confidentiality	Resolução nº 30 (COAF, 2018)	Beebeejaun and Mahadew (2024), U.S. Department of the Treasury (2024)

Note: *List of customer, geographic, and economic-financial risk variables considered in the analysis, with information on data availability, regulatory references, and literature sources.*
BCB = Banco Central do Brasil; COAF = Conselho de Controle de Atividades Financeiras; COE = Comunicações de Operações em Espécie; IBGE = Instituto Brasileiro de Geografia e Estatística; KYC = Know Your Customer; OECD = Organisation for Economic Co-operation and Development; PEP = politically exposed person.
Source: *Prepared by the authors.*

A further limitation concerns the inability to link reported transactions to cases that were subsequently investigated, prosecuted, or resulted in convictions, since judicial and law enforcement information remains largely protected by secrecy rules. Consequently, it is not possible to assess, using public data, how many COS led to administrative or criminal accountability. As noted by Suxberger and Pasiani (2018), an information deficit between investigative authorities constrains the measurement of system effectiveness and limits empirical validation. This gap also helps explain why COS are widely used as a proxy for ML risk by financial institutions and supervisory authorities, as acknowledged by COAF (2024), despite the methodological limitations of such a proxy.

Brazilian data protection legislation, while essential to safeguard privacy, imposes additional barriers to the collection, storage, and sharing of information that could strengthen ML risk modelling, including behavioral variables and client relationship history. These constraints are compounded by data fragmentation, as relevant information is dispersed across central banks, investigative bodies, financial institutions, and international entities, each operating with distinct recording standards. The lack of standardization reduces comparability across jurisdictions and limits the development of more granular models.

The analysis is conducted at the UF level. While this aggregation supports macrostructural comparisons and ensures statistical robustness for a nationwide study, it may conceal substantial intra-state heterogeneity. This choice reflects both legal restrictions that limit access to COS and COE data at the municipal level and the methodological need to maintain model feasibility.

Finally, the econometric models capture statistical associations rather than causal relationships. COS reflect reported risk and are therefore influenced by institutional incentives, regulatory asymmetries, and heterogeneous reporting practices across sectors and institutions. Potential underreporting, particularly during regulatory transitions, may affect coefficient stability and temporal comparability. These limitations are explicitly considered in the integrated discussion of the empirical findings.

3. RESULTS ANALYSIS

To assess whether a variable explains the volume of COS, three criteria are considered: statistical significance, explanatory power, and impact. Statistical significance is evaluated using p-values, with $p < 0.01$ indicating strong evidence, $0.01 \leq p \leq 0.05$ indicating moderate evidence, and $p > 0.05$ indicating a lack of explanatory relevance. Explanatory power is measured by the coefficient of determination (R^2), while impact is assessed through the magnitude of the estimated β coefficients.

3.1 Model Specification and Diagnostic Tests

To ensure the statistical validity of the estimated regression models, diagnostic tests were conducted using the full sample period from 2010 to 2022. Tests for autocorrelation, normality, and homoskedasticity were applied to verify the classical assumptions of linear regression.

The variables GDP, COS, and COE were transformed into natural logarithms to improve economic interpretability, mitigate heteroskedasticity, and approximate the normality of residuals. For instance, the coefficient of log(COE) (0.806) indicates that a 1% increase in cash transactions is associated with an approximate 0.81% increase in COS.

Although the logarithmic transformation did not fully eliminate heteroskedasticity, it contributed to variance stabilization and residual normality, as confirmed by the Shapiro-Wilk test ($\chi^2 = 1.533$, $p = 0.465$).

Diagnostic tests revealed violations of the autocorrelation and heteroskedasticity. The Wooldridge test rejected the null hypothesis of no first-order autocorrelation ($t(26) = 30.0544$, $p < 0.001$), while the White test rejected homoskedasticity ($TR^2 = 69.75$, $p < 0.001$). To address these issues, the models were estimated using pooled OLS with robust standard errors clustered at the UF level. This specification, reported in Table 4, yields consistent coefficients and reliable inference. VIF tests indicated no relevant multicollinearity, with VIF values ranging from 1.436 to 3.174.

Table 4

Summary of statistical models, 2010-2022

Variables	Coefficient (β)	p-value	R^2	Key observations
2010-2016				
log(COE)	0.808	< 0.0001	0.709	Most relevant determinant
IndiMjMetropArea	0.771	0.0106		Statistically significant and positive
IndiMining	0.423	0.1482		Not statistically significant
IndiBorder	0.343	0.3211		Not statistically significant
IndiInfSettlem	-0.207	0.6410		Negative and not statistically significant
log(GDP)	0.363	0.1166		Not statistically significant
2017-2022				
log(COE)	1.079	< 0.0001	0.838	Remains the main determinant
IndiMjMetropArea	0.608	0.0008		Consistent and statistically significant
IndiBorder	0.213	0.1862		Not statistically significant
IndiMining	0.217	0.2160		Not statistically significant
IndiInfSettlem	-0.248	0.2136		Not statistically significant
log(GDP)	0.118	0.4169		Loses statistical significance entirely
2020-2022				
log(COE)	1.120	< 0.0001	0.867	Highest coefficient across periods
IndiMjMetropArea	0.455	0.0160		Reduction in the coefficient but remains significant
IndiMining	0.260	0.0896*		Marginally significant (p < 0.10)
IndiInfSettlem	-0.346	0.1257		Not statistically significant
IndiBorder	0.036	0.7725		Not statistically significant
log(GDP)	0.047	0.7222		No statistical relevance

Note: *Estimated coefficients, p-values, and explanatory power (R^2) for the regression models across different periods, highlighting the statistical relevance of each variable. COE = Comunicações de Operações em Espécie; GDP = gross domestic product. * $p < 0.10$.*

Source: *Prepared by the authors.*

3.2 Regulatory Change and Structural Break Analysis

As discussed in the introduction, the period analyzed (2010-2022) encompasses substantial regulatory changes in Brazil's AML framework. Two moments are particularly relevant: 2016, marked by Lei nº 13.260 (Brasil, 2016) and Resolução nº 29 (COAF, 2017), which expanded predicate offences and reporting obligations; and 2020, when Resolução nº 30 (COAF, 2018), Circular nº 3.978/2020 (BCB, 2020c), and Carta Circular nº 4.001/2020 (BCB, 2020b) introduced stricter reporting criteria, updated PEP definitions, and reinforced automated monitoring requirements.

These changes visibly affected the volume of COS, as illustrated in Figure 3, and are expected to have altered the relationship between explanatory variables and reported risk. To test for structural breaks, the Chow test was applied. The results, presented in Table 5, confirm statistically significant breaks in 2016 and 2020, justifying separate model estimations for the pre-regulatory, post-regulatory, and pandemic periods.

Figure 3 *Suspicious Transaction Reports (Comunicações de Operações Suspeitas [COS]) in Brazil, 2010-2022. Annual volume of COS (thousands of reports), showing a cumulative increase of 261.57% over the period*
Source: *Prepared by the authors based on data from the Conselho de Controle de Atividades Financeiras.*

Table 5
Chow test results for structural break analysis

Variables	Coefficient	SE	t-statistic	p-value	Significance
const	1.71335	0.648494	2.642	0.0086	***
IndiInfSettlem	0.525004	0.325771	1.612	0.1080	
IndiBorder	−0.629728	0.203720	−3.091	0.0022	***
IndiMjMetropArea	0.167509	0.282467	0.5930	0.5536	

IndiMining	0.582082	0.237175	2.454	0.0146	**
log(GDP)	−0.217941	0.0915272	−2.381	0.0178	**
log(COE)	0.738592	0.0510057	14.48	2.62e-037	***
splitdum	−10.0215	3.89384	−2.574	0.0105	**
sd_IndiInfSettlem	0.779513	0.267850	2.910	0.0039	***
sd_IndiBorder	1.02981	0.268819	3.831	0.0002	***
sd_IndiMjMetrop Area	0.512341	0.241876	2.118	0.0348	**
sd_IndiMining	−0.849622	0.307257	−2.765	0.0060	***
sd_log(GDP)	2.43273	0.754964	3.222	0.0014	***
sd_log(COE)	−0.249143	0.0732425	−3.402	0.0008	***

Model statistics	**Value**	**Chow test – Main results**		
Number of observations	351	**Test statistic**	**Value**	**p-value**
Dependent variable	log(COS)	Chi-square (6)	79.3458	0.0000
Mean of the dependent variable	8.774734	F(6.338)	13.2243	0.0000
SD of log(COS)	1.638973	Structural break point: 2016 (observation 14:02)		
R^2	0.782109	Interpretation: null hypothesis of parameter stability rejected, indicating strong evidence of a structural break.		
Adjusted R^2	0.774373	Splitdum: structural dummy capturing the intercept shift following the regulatory break identified by the Chow test, assuming value 0 before and 1 after the breakpoint.		
SE of the regression	0.778516			

Note: *Results of the Chow test applied to identify structural breaks in 2016 and 2020, including coefficients, standard errors (SE), t-statistics, and significance levels.COE = Comunicações de Operações em Espécie; COS =* Comunicações de Operações Suspeitas; *GDP = gross domestic product; SD = standard deviation.*
*Significance levels: *** = 1%; ** = 5%; * = 10%.*
Source: *Prepared by the authors.*

Figure 4 summarizes the main regulatory developments introduced from 2020 to 2025, including reforms issued by the BCB, COAF, and other supervisory authorities. These measures illustrate the continued evolution of the Brazilian AML framework and provide institutional context for the changes observed in reporting behavior and risk assessment practices.

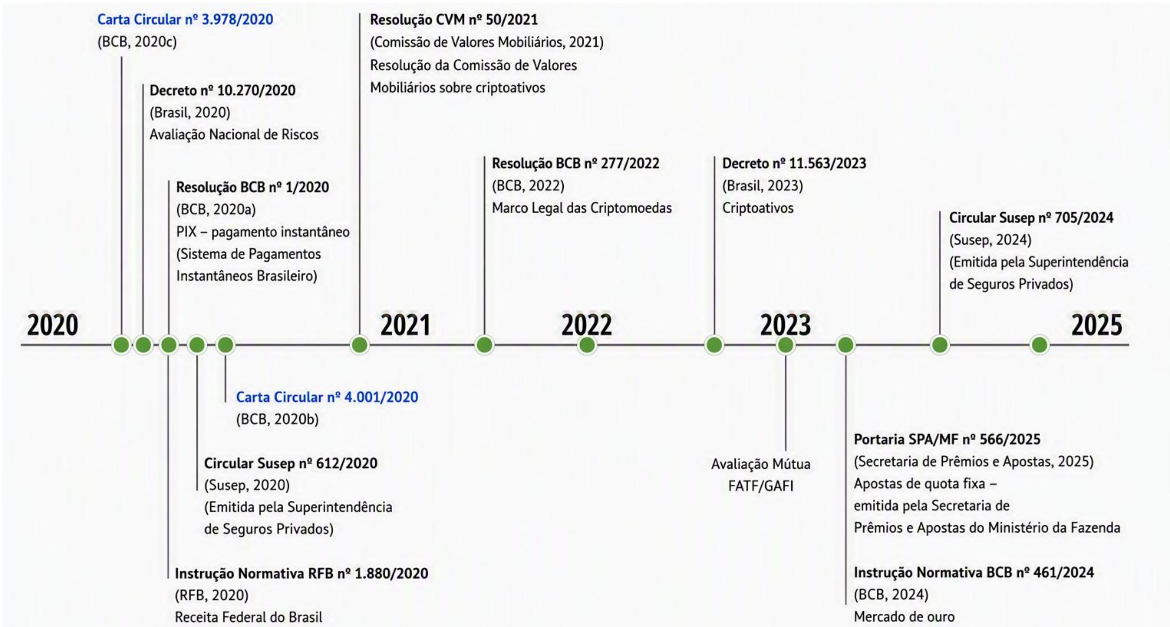

Figure 4 *Key anti-money laundering milestones (AML) in Brazil, 2020-2025*
Note: *Timeline of regulatory developments in Brazil's AML framework from 2020 to 2025, including Banco Central do Brasil (BCB) resolutions, Superintendência de Seguros Privados (SUSEP) circulars, and decrees related to cryptoassets and sports betting. CVM = Comissão de Valores Mobiliários; FATF/GAFI = Financial Action Task Force/Groupe d'action financière; SPA/MF = Secretaria de Prêmios e Apostas/Ministério da Fazenda.*
Source: *Prepared by the authors.*

3.3 Pre-Regulatory Period (2010-2016)

During the period preceding the major regulatory reforms, COE emerged as the most relevant determinant of COS, presenting a positive and highly significant coefficient ($\beta = 0.808$, $p < 0.0001$). Major metropolitan areas also exhibited a positive and statistically significant association with COS ($\beta = 0.771$, $p = 0.0106$), indicating a greater concentration of suspicious financial activity reporting in large urban centers.

In contrast, mining activity ($\beta = 0.423$, $p = 0.1482$), border regions ($\beta = 0.343$, $p = 0.3211$), and informal settlements ($\beta = -0.207$, $p = 0.6410$) did not demonstrate statistically significant effects. Likewise, the proxy for regional economic size, represented by the logarithm of GDP (log(GDP)), showed a positive but statistically non-significant relationship with COS ($\beta = 0.363$, $p = 0.1166$). These findings suggest that, before the implementation of the principal regulatory changes, the intensity of suspicious activity reporting was driven primarily by cash-based financial movements and the concentration of economic and financial infrastructure in major metropolitan areas rather than by regional economic scale itself.

Overall, the model explains approximately 70.9% of the variation in COS ($R^2 = 0.709$). Consolidated results for this period are presented in Table 4 and provide an important baseline for comparisons with subsequent regulatory periods.

3.4 Post-Regulatory Period (2017-2022)

Following the regulatory reforms initiated in 2016, the risk profile changed substantially. Panel data analysis indicates a more precise and parsimonious model, with cash transactions and major metropolitan areas remaining the only robust and consistently significant determinants.

The explanatory power of the model increased markedly, with adjusted R^2 rising from 71% to 84%. In contrast, state-level GDP, previously significant, lost statistical relevance in the multivariate specification. These findings suggest that regulatory changes refined the system’s ability to discriminate between robust and spurious risk factors, improving analytical efficiency.

The Chow test confirms a significant structural break in 2016 ($\chi^2 = 79.3458$, $p < 0.001$), validating that regulatory changes fundamentally altered the relationship between explanatory variables and ML risk.

3.5 Pandemic Period (2020-2022)

The period from 2020 to 2022 represents an atypical context shaped by the COVID-19 pandemic and additional regulatory tightening. The issuance of Circular nº 3.978/2020 (BCB, 2020c) and Carta Circular nº 4.001/2020 (BCB, 2020b) reinforced real-time monitoring and annual policy reviews amid rapid digitalization and expanded emergency transfers.

As shown in the 2020-2022 section of Table 4, the pandemic period consolidated previous trends, with the multivariate model reaching its highest explanatory power (R^2 = 86.7%). Only cash transactions and location in major metropolitan areas remained unequivocally significant. Mining activity showed a marginal resurgence, while the reduced coefficient for major metropolitan areas suggests some geographic redistribution of suspicious activity during mobility restrictions.

The comparative analysis across the three periods (2010-2016, 2017-2022, and 2020-2022) reveals a clear evolution in ML risk determinants. Regulatory reforms enhanced detection efficiency and progressively refined the identification of the most robust risk drivers. Table 4 summarizes the estimated models for all periods analyzed.

4. DISCUSSION

The econometric analysis identified consistent statistical relationships between specific variables and the volume of COS from 2010 to 2022. In general, it was found that:

(i) COE showed high statistical significance in log-log models, constituting the most robust determinant of reported risk in all estimated scenarios. The coefficients indicate positive elasticity, suggesting that proportional increases in the volume of COE are associated with proportional increases in the volume of COS.

(ii) Major metropolitan areas maintained constant significance, both before and after 2016, corroborating the literature that associates dense urban environments with a higher probability of complex financial transactions (Barone & Masciandaro, 2011; Unger et al., 2014). This result indicates that urban structural variables capture ML risk better than traditional geographic proxies.

(iii) State GDP was significant only in the pre-2016 period. After the new regulatory framework, the association disappeared, signaling a change in reporting patterns or a shift in institutional behavior in the face of new regulatory obligations – as also observed in international contexts after relevant regulatory reviews (Ferwerda & Reuter, 2019).
(iv) International borders and mining activity showed statistical significance only at the beginning of the series, without support after 2016. This suggests that these variables may represent relevant contextual factors only in specific windows or that the change in the regulatory pattern reduced their explanatory power.
(v) The Chow test confirmed a structural break in 2016, a year of relevant regulatory reconfiguration. Therefore, the interpretation of the coefficients must consider that the phenomenon exhibits distinct behaviors before and after this milestone.

These results indicate that reported risk (COS) is influenced by specific operational and structural determinants more so than by broad macroeconomic variables.

The models presented here, therefore, reflect the relationships between available macroeconomic and institutional variables, aligning with the gaps identified in the international literature regarding the need to improve risk metrics without violating the confidentiality of investigations.

Given the results obtained, it is concluded that the objectives proposed in this research have been fully achieved. The identification of the main determinants of ML risk in the Brazilian financial sector, through theoretical review and statistical tests, has allowed for an understanding of the factors influencing the volume of COS.

4.1 Integration with Theoretical Findings

The persistent significance of COE and major metropolitan areas directly engages with international research indicating greater vulnerability of dense environments, with intense cash circulation and greater potential for operational anonymity (Levi & Reuter, 2006; Barone & Masciandaro, 2011). The consistency of these determinants throughout the entire period reinforces their suitability as structural variables in AIR models.

The weakening of the significance of GDP and borders after 2016 can be interpreted as a reflection of the reallocation of reporting mechanisms in the face of new regulatory requirements, aligning with patterns observed in other countries after changes in AML frameworks.

The integration of the theory of deliberate ignorance allows for a more sophisticated reading of the results. Heterogeneity in the significance of variables over time may indicate not only changes in real risk but also differences in the institutional willingness to report certain alerts.

Thus, COS patterns can simultaneously reflect real risks, detection biases, institutional incentives, and supervisory expectations.

Engaging with this theory, the results suggest that the absence of significance in historically vulnerable sectors (such as mining) may not signify a risk reduction but rather a change in reporting incentives.

4.2 Real Risk, Detected Risk, and Reported Risk

The results suggest that the behavior of COS does not necessarily reflect the “real risk” of ML, but rather the final stage of the detection chain. The decline in the significance of some variables after 2016 does not necessarily imply a reduction in real risk. It may indicate a change in reporting behavior, institutional adaptation to the new framework, prioritization of other types of alerts, under-detection or under-reporting, or even reallocation of internal capacities after an increase in regulatory demands.

This distinction, seldom explored in the literature, is essential to avoid misinterpretations of causality.

5. CONCLUSIONS

The research identified the most consistent determinants of reported ML risk in Brazil from 2010 to 2022, demonstrating that (i) COE and major metropolitan areas are variables that showed a robust and persistent association with reported risk, suggesting they should be considered priorities in risk models; while (ii) GDP, borders, and mining exhibit unstable behavior, indicating sensitivity to the regulatory environment. The 2016 milestone represents a significant change in the reporting pattern, as confirmed by the Chow test, suggesting a structural break associated with regulatory changes.

In this context, reported risk (COS) should not be confused with real risk, as it is influenced by regulatory and institutional incentives, as well as by detection and reporting dynamics.

The results partially validate the BCB’s framework (Carta Circular nº 4.001/2020 [BCB, 2020b]) and suggest conceptual adjustments, particularly regarding the relative importance and stability of different risk factors.

The study expands the understanding of measurable determinants of ML risk and proposes relevant theoretical and empirical refinements for regulators and financial institutions.

The results enable a more direct dialogue with the existing literature on determinants of ML risk. Consistent with prior studies, operational variables related to transaction patterns, particularly cash intensity, emerge as the most robust predictors of reported risk. This finding reinforces evidence that liquidity- and anonymity-related characteristics play a central role in the dynamics of illicit financial flows.

In contrast, the results diverge from studies that attribute greater explanatory power to macroeconomic variables, such as GDP, or to geographic factors, such as border regions. The loss of significance of these variables over time, particularly following regulatory changes, suggests that the evolution of the regulatory framework may reshape the relevance of traditionally associated risk factors.

In this context, the findings indicate that ML risk should be understood as a dynamic, institutionally mediated phenomenon, in which operational variables tend to exhibit greater explanatory stability than broader structural proxies. This evidence contributes to the literature by providing an empirical analysis in an emerging regulatory context and highlights the need for continuous reassessment of risk-based models.

In addition to these implications, it is important to note that the determinants analyzed in this study had not been previously tested as explanatory variables of ML risk in the Brazilian financial system. While prior literature has offered critical reflections on client profiles and other vulnerabilities, empirical testing of structural and operational determinants such as cash transactions, metropolitan areas, borders, and mining activity was absent. Our results, therefore, do not confirm or reject earlier national evidence but rather provide the first systematic assessment of these factors, establishing a baseline for future comparative research.

The data reflect reported risk, not real risk: non-observable determinants cannot be empirically included, and potential detection and reporting biases affect the results.

The quality of COS depends on the effectiveness of institutions' internal controls.

It is important to reaffirm that the econometric models applied here capture statistical associations and correlations, not permitting strict causal inferences. The identified relationship indicates that changes in the independent variables are systematically associated with changes in COS volume. Still, it does not prove that one directly causes the other, given the potential for omitted variables and the complexity of the phenomenon.

The interpretation of the empirical results allows for advancing the application of the theory of deliberate ignorance within the analyzed context. The observed association between COE and COS suggests that transactions subject to compulsory reporting are systematically incorporated into monitoring and analytical mechanisms.

This finding indicates that cash usage, while traditionally associated with opacity risk, also triggers institutional control routines that reduce the likelihood of omission when relevant indicators are present. In this sense, mandatory reporting of cash transactions contributes to transforming operational signals into formal inputs for detection, constraining behaviors consistent with deliberate ignorance.

Accordingly, the findings suggest that regulatory mechanisms based on objective reporting criteria play a significant role in mitigating behavioral failures and strengthening the system's ability to identify and report potentially suspicious activities.

5.1 Practical Implications for AIR Models

The analysis offers direct contributions to improving AIR models:

Mandatory incorporation of "major metropolitan area" into the structural risk weighting.

Revision of the weights assigned to COE, given its persistent significance.

Replacement of prescriptive lists with probabilistic models, aligned with the risk-based approach principle (FATF).

Integration of external and multidimensional data, reducing asymmetries and complementing non-observable variables.

These implications allow for greater adherence to international recommendations and strengthen AML governance.

5.2 Final Considerations

The application of the Chow test provided strong statistical evidence of a structural break in 2016, demonstrating that the regulatory changes of that year significantly altered the dynamics of the determinants of ML risk in Brazil. This finding confirms the temporal division adopted in the models and indicates that AIRs models should incorporate this dynamic dimension to maintain accuracy amid regulatory and economic transformations.

The results empirically validated parts of the framework established by Carta Circular nº 4.001/2020 (BCB, 2020b), while simultaneously revealing nuances not foreseen by the regulation, offering subsidies for improving AIR models. COE remained the main factor associated with COS volume across all periods, aligning with the regulatory emphasis on risks arising from transactions with potential anonymity.

The geographic component also showed relevance, as predicted in item 4.2.2 of of Carta Circular nº 4.001/2020 (BCB, 2020b), although its dynamics are more complex than models based solely on checklists suggest.

One of the most significant findings concerns the changing explanatory role of border regions over time. Although the IndiBorder variable displayed a positive coefficient during the pre-regulatory period, it was not statistically significant and subsequently lost even its limited explanatory relevance in the post-2016 and pandemic-period models. This pattern suggests that border location, while traditionally considered a relevant geographic risk factor in AML frameworks, does not consistently explain variations in reported suspicious transaction activity once other structural and operational determinants are considered. The results therefore indicate that the relevance of border-related risk may be highly sensitive to regulatory, institutional, and operational changes, reinforcing the importance of periodically reassessing geographic risk indicators within risk-based supervisory models.

Another highlight is the role of the major metropolitan area indicator (IndiMjMetropArea), which emerged as a consistent predictor of COS volume in the post-2016 period. This factor does not constitute an operational signaling tool for specific transactions but rather a basal risk multiplier that indicates a greater concentration of illicit flows in regions with higher financial density.

For this reason, it is recommended that financial institutions formally incorporate location in major metropolitan areas as a relevant geographic variable in their internal AIR models, through differentiated risk scoring rather than operational red flags, which would lose effectiveness in portfolios widely concentrated in these regions.

The findings also point to limitations of the regulatory framework itself. Although Carta Circular nº 4.001/2020 (BCB, 2020b) highlights border regions as a relevant risk factor, the results of this research indicate that their statistical significance has diminished in recent years, reinforcing the need for the regulator to periodically review the hierarchy of risk factors in light of empirical evidence.

Methodologically, the study faced limitations arising from legal secrecy surrounding ML investigations, which prevented access to critical variables such as demographic profiles, PEP status, and marital status. This limitation is reinforced by the fact that neither the national risk assessment nor the sectoral risk assessment provides public quantitative models, maintaining only qualitative guidelines. Consequently, the conclusions depend on models estimated with publicly available macroeconomic and sectoral variables. All results come from regressions with robust standard errors clustered by UF, a model that proved adequate for correcting heteroskedasticity and autocorrelation.

It is recommended that financial institutions test the geographic and macroeconomic patterns identified here in their internal databases, which include sensitive data such as PEP status, age, family structure, and financial vulnerability indicators, variables recognized as relevant but inaccessible to academic research due to legal restrictions. Thus, this study positions itself as a publicly validated external benchmark capable of supporting the calibration of internal models and contributing to more effective risk assessments aligned with the evolution of ML mechanisms in the country.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The entire dataset supporting the results of this study has been published within the article itself.

GENERATIVE AI DISCLOSURE

The authors declare that no generative artificial intelligence was used at any stage of the production of this manuscript (including research, writing, data analysis, formula generation, or the creation of graphic elements).