Effect of Corruption and Money Laundering on the Profitability of Licensed Finance Companies in Sri Lanka

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Abstract

This study investigates the association between country-level corruption, money-laundering risk, and the profitability of Licensed Finance Companies (LFCs) in Sri Lanka. The analysis employs panel data from 26 LFCs covering the period 2018–2024, encompassing the 2022 economic crisis and subsequent strengthening of anti-money laundering (AML) supervision. Profitability is measured using Return on Assets (ROA). Perceived public-sector corruption is proxied by Transparency International's Corruption Perceptions Index (CPI), while country-level money-laundering risk is measured using the Basel Anti-Money Laundering (AML) Index, scaled by firm size. Firm size and management efficiency are included as control variables. Corruption and money-laundering risk are examined in separate model specifications to account for the overlap between the two indicators. The Hausman specification test supports the use of a fixed-effects estimator. Diagnostic tests identify heteroskedasticity, serial correlation, and cross-sectional dependence; accordingly, both models are estimated using fixed effects with Driscoll–Kraay standard errors. The results indicate that the CPI score is positively associated with ROA, whereas the adjusted Basel AML Index is negatively associated with ROA, with both relationships statistically significant at the 10% level. Management efficiency exhibits a positive association with ROA across both model specifications. These findings establish management efficiency as a consistent correlate of LFC profitability, while the corruption and money-laundering coefficients are significant only at the 10% level. The findings are subject to limitations arising from the use of country-level composite indices as proxies for institutional risk and the seven-year observation period.

Keywords*:* corruption, money laundering, profitability, licensed finance companies, Sri Lanka

1. Introduction

Licensed Finance Companies (LFCs) constitute an important segment of Sri Lanka's non-bank financial sector. Operating under the regulatory framework administered by the Central Bank of Sri Lanka (CBSL), LFCs provide leasing, hire-purchase facilities, gold loans, and other credit services (Central Bank of Sri Lanka, 2023). Their customer base includes small businesses, farmers, and households with limited access to commercial bank financing.

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Proceedings of the 6th Annual International Conference on Emerging Financial Markets and Policy (EFMP 2026)
© 2026 Sri Lanka Finance Association
ISSN 2792-1220, eISSN 2806-514X

Accordingly, the financial performance of LFCs has broader implications for credit accessibility, financial inclusion, and the resilience of Sri Lanka's financial system.

Corruption and money-laundering risk constitute important institutional and regulatory concerns within Sri Lanka's financial environment. Transparency International (2023) reports that Sri Lanka's Corruption Perceptions Index (CPI) score remained below 50 out of 100 in recent years, reflecting persistent concerns regarding public-sector corruption. The Basel Institute on Governance (2023) also identifies money-laundering risk as a relevant institutional concern in Sri Lanka. These challenges acquired particular significance during the economic crisis of 2022, which was characterised by severe foreign-exchange shortages, elevated inflation, and sovereign debt default. The Central Bank of Sri Lanka (2023) and the Financial Intelligence Unit of Sri Lanka (2022) strengthened anti-money laundering (AML) supervision. The period from 2018 to 2024 therefore provides a relevant empirical setting for examining the relationship between CPI and Basel AML Index and the profitability of LFCs.

The institutional characteristics of LFCs provide a distinct rationale for examining them separately from commercial banks. LFCs rely on deposits and borrowings to finance lending activities and serve customer segments that frequently face constraints in accessing conventional bank credit. Their operating models, customer profiles, and institutional capacities distinguish them from large commercial banks. Nevertheless, LFCs remain subject to anti-money laundering obligations, including customer identification, customer due diligence, and the reporting of suspicious transactions (Financial Intelligence Unit of Sri Lanka, 2022). These characteristics establish a distinct institutional context in which the financial implications of corruption and money-laundering risk warrant independent empirical investigation. Findings derived from commercial banking institutions cannot automatically be generalised to LFCs without considering these institutional differences.

Despite the relevance of institutional integrity and financial-crime prevention to non-bank financial intermediation, the relationship between corruption, money-laundering risk, and LFC profitability remains underexplored in the Sri Lankan context. This study addresses this research gap by examining the associations between country-level corruption and money-laundering risk indicators and the firm-level profitability of LFCs. The study contributes to the literature in two respects. Theoretically, it draws on agency theory and the economics of crime to examine the relevance of institutional governance and financial-crime-related risks to the profitability of non-bank financial institutions. Practically, it provides empirical evidence relevant to LFC managers, the Central Bank of Sri Lanka, and the Financial Intelligence Unit in assessing the relationship between country-level CPI and Basel AML Index and firm-level financial performance, while accounting for firm size and management efficiency.

The study addresses two research questions: (1) What is the impact of corruption on the profitability of licensed finance companies in Sri Lanka? and (2) What is the impact of money laundering on the profitability of licensed finance companies in Sri Lanka? To address these questions, the study employs panel data from 26 LFCs covering the period 2018–2024. Firm-level financial information is combined with country-level indicators of perceived corruption and money-laundering risk to estimate their respective relationships with profitability, measured by Return on Assets (ROA).

2. Literature Review

This study draws on three theoretical perspectives to explain the relationship between corruption, money-laundering risk, and the profitability of Licensed Finance Companies (LFCs): agency theory, the economics of crime, and the competing grease-the-wheels and sand-the-wheels perspectives on corruption.

Agency theory, established by Jensen and Meckling (1976), explains how conflicts of interest between principals and agents can undermine organisational performance. Managers exercise delegated authority on behalf of owners, yet differences in objectives and incentives can encourage decisions that prioritise private interests over organisational objectives. In financial institutions, such conflicts can manifest in compromised credit assessments, preferential lending decisions, inadequate risk controls, and inefficient resource allocation. These practices can increase operating costs, weaken loan recovery, and undermine profitability. Empirical evidence from the banking sector supports the relationship between corruption and financial-sector performance. Ben Ali et al. (2020) demonstrate that corruption undermines banking stability, while Bolarinwa and Soetan (2019) examine its implications for bank profitability. From this perspective, corruption is expected to be negatively associated with financial performance through its effects on governance, lending quality, and operational efficiency.

The economics of crime, developed by Becker (1968), provides a second theoretical foundation. This perspective explains engagement in illegal activities through the relationship between expected benefits and the anticipated costs of detection and punishment. Weak enforcement and inadequate deterrence reduce the expected costs of financial crime, creating conditions that facilitate illicit financial activities. For financial institutions, elevated money-laundering risk can increase expenditure on customer due diligence, transaction monitoring, compliance systems, and regulatory reporting. Exposure to financial crime can also generate regulatory penalties, reputational damage, and deterioration in credit quality. Takáts (2011) demonstrates that enforcement incentives can encourage defensive reporting of suspicious transactions, increasing compliance burdens without a corresponding improvement in the informational value of reports. Similarly, Hussain et al. (2021) identify an association between money laundering and weaker bank loan quality. These arguments indicate that greater exposure to money-laundering risk can be negatively associated with profitability through compliance costs, credit risk, and reputational consequences.

A third theoretical perspective concerns the competing grease-the-wheels and sand-the-wheels views of corruption. The grease-the-wheels perspective argues that corruption can facilitate transactions in environments characterised by inefficient bureaucracy, restrictive procedures, and institutional rigidities (Leff, 1964; Huntington, 1968). Under such conditions, informal payments can accelerate administrative processes and facilitate business transactions. In contrast, the sand-the-wheels perspective maintains that corruption undermines economic performance by increasing transaction costs, creating uncertainty, distorting resource allocation, and weakening institutional accountability (Shleifer & Vishny, 1993; Mauro, 1995). Méon and Sekkat (2005) provide evidence that corruption remains detrimental to economic performance, including in institutional environments characterised by weak governance. These

competing perspectives establish that the relationship between corruption and profitability is theoretically ambiguous. Accordingly, the present study does not impose a predetermined direction on the association between corruption and LFC profitability.

Empirical research examining corruption and financial performance reports mixed findings. Several studies link corruption to weaker financial performance because it adversely affects lending decisions, operating costs, institutional governance, and financial stability. Ben Ali et al. (2020), for example, report that corruption undermines banking stability. However, other studies identify positive associations between corruption and bank profitability under particular institutional conditions. Aburime (2009), examining Nigerian banks over a ten-year period, reports a positive relationship between corruption and bank profitability. Aish et al. (2021), investigating Islamic and conventional banks in Pakistan and Malaysia, also find that corruption and money laundering can be positively associated with bank profitability in highly corrupt environments. Bolarinwa and Soetan (2019) further examine circumstances in which corruption can facilitate business transactions. These findings demonstrate that the profitability implications of corruption are not uniform across institutional and regulatory settings. Differences in governance quality, enforcement mechanisms, operating environments, and institutional characteristics provide important contextual considerations when interpreting the relationship.

The literature on money laundering and financial performance primarily emphasises the adverse implications of financial-crime exposure for asset quality, operational efficiency, and regulatory compliance. Hussain et al. (2021) associate money laundering with higher non-performing loans and weaker loan portfolios, particularly where anti-money laundering monitoring is inadequate. Shah et al. (2022) similarly examine how impaired loan quality affects banking efficiency in Pakistan. In addition, Nobanee and Ellili (2018) investigate anti-money laundering disclosure practices and highlight limitations in the transparency of such disclosures, including in regulated financial markets such as the United Arab Emirates. These findings raise concerns about the extent to which publicly disclosed information captures underlying money-laundering exposure. Ho et al. (2019) further report an association between stronger anti-corruption efforts and greater banking stability, reinforcing the relevance of institutional governance to financial-sector resilience. Overall, the empirical literature identifies several channels through which corruption and money-laundering risk can influence financial performance, although the direction and magnitude of these relationships vary across studies and institutional contexts.

In Sri Lanka, Hendeniya et al. (2023) offer particularly relevant evidence by examining licensed commercial banks from 2015–2021. Their findings indicate that corruption is negatively and significantly associated with bank profitability and stability, whereas money laundering is positively and significantly associated with both outcomes. Bank size and management efficiency are also positively associated with profitability. This study provides an important basis for the present investigation because it examines a comparable national context and uses related country-level indicators of corruption and money laundering. Nevertheless, its focus on licensed commercial banks limits the extent to which its findings can be generalised to non-bank financial institutions. Furthermore, its observation period ends in 2021 and

therefore excludes the 2022 economic crisis and subsequent developments within the study period examined here.

The preceding theoretical and empirical literature identifies three principal research gaps. First, a sectoral gap persists in the evidence concerning corruption, money-laundering risk, and financial performance. Existing research predominantly examines commercial banks, while the corresponding relationships within Sri Lankan LFCs remain comparatively underexplored. This omission is important because LFCs operate within a distinct institutional and lending environment and provide financing to customer segments that frequently face constraints in accessing conventional bank credit. The present study extends the analysis beyond commercial banking by examining the profitability of 26 Sri Lankan LFCs.

Second, a temporal gap exists in the available evidence. Much of the relevant research relies on observations ending before Sri Lanka's 2022 economic crisis. Consequently, these studies do not incorporate the full observation period covered by the present investigation, which extends through 2024. By examining 2018 to 2024, this study includes observations from the pre-crisis period, the 2022 economic crisis, and subsequent developments in the financial and regulatory environment. This extended period provides broader evidence on the relationship between the CPI, the Basel AML Index and LFC profitability, although the research design does not independently identify the causal effects of the crisis or regulatory changes.

Third, a measurement and model-specification challenge arises from the country-level nature of the corruption and money-laundering risk indicators. These indicators capture aspects of the broader institutional environment rather than directly measuring corruption or money laundering within individual LFCs. Their conceptual relationship also creates a potential risk of multicollinearity when both variables are included simultaneously in a regression model. The present study therefore estimates separate model specifications for corruption and money-laundering risk to examine their respective associations with LFC profitability without including both indicators in the same specification. This approach addresses the potential overlap arising from their simultaneous inclusion, although it does not eliminate all possible sources of confounding or establish causal effects. The country-level measurement of these indicators also limits the interpretation of the estimated coefficients as firm-specific effects.

By addressing these sectoral, temporal, and methodological gaps, the study extends the empirical literature on institutional risk and financial performance to Sri Lanka's non-bank financial sector. It evaluates the relevance of established theoretical perspectives to LFC profitability and provides evidence on the relationships between country-level corruption and money-laundering risk indicators and firm-level financial performance, while accounting for firm size and management efficiency.

3. Methods

The study population comprises Licensed Finance Companies (LFCs) registered with the Central Bank of Sri Lanka (CBSL). From this population (33), 26 LFCs were selected based on the availability of complete annual report data for the period 2018-2024. The resulting balanced panel comprises 182 firm-year observations, representing 26 companies observed over seven consecutive years.

The observation period begins in 2018, the earliest year for which complete annual report data were available across all 26 sampled companies. The study period encompasses the pre-crisis environment, the economic crisis of 2022, and the subsequent period of strengthened anti-money laundering supervision. This temporal coverage provides evidence on the relationship between the country-level CPI, the Basel AML Index and LFC profitability during a period of substantial economic and regulatory change.

Table 1 presents the operational definitions, measurement procedures, and data sources for the variables included in the analysis. Profitability is the dependent variable, while corruption and money-laundering risk are the principal explanatory variables. Firm size and management efficiency are incorporated as control variables.

Table 1: Operationalisation of Variables

Variable	Symbol	Measurement	Source	Literature
Return on Assets	ROA	Net income ÷ average total assets. The values were then winsorised (extreme values limited) at the 3rd and 97th percentiles.	Annual reports of LFCs	Hendeniya et al., (2023)
Corruption	CORR	(100 − CPI score), then scaled by dividing by natural logarithm of firm size. A higher value means more corruption.	Transparency International (CPI)	Hendeniya et al., (2023)
Money Laundering	ML	Basel AML Index score ÷ firm size. A higher value means more money laundering risk relative to size.	Basel Institute on Governance (Basel AML Index); annual reports of LFCs	Hendeniya et al., (2023)
Firm Size	FCSIZE	Natural log of total assets	Annual reports of LFCs	Hendeniya et al., (2023)
Management Efficiency	MEF	Operating income ÷ operating expenses.	Annual reports of LFCs	Hendeniya et al., (2023)

Profitability is measured using Return on Assets (ROA), calculated as net income divided by average total assets. To limit the influence of extreme observations, ROA was winsorised at the 3rd and 97th percentiles. The Shapiro–Wilk test indicated a departure from normality in the unadjusted *ROA* distribution ($W = 0.827$, $p < 0.001$). After winsorisation at the 3rd and 97th percentiles, the test did not reject the null hypothesis of normality ($W = 0.994$, $p = 0.604$). The corresponding skewness and kurtosis values were 0.108 and 2.719, respectively.

Corruption is operationalised using the Corruption Perceptions Index (*CPI*) published by Transparency International. The *CPI* ranges from 0, indicating a highly corrupt public sector, to 100, indicating a very clean public sector. To reverse the scale so that higher values represent greater perceived corruption, the *CPI* score is subtracted from 100. The resulting score is then divided by the natural logarithm of the LFC's total assets to derive *CORR*:

Country-level money-laundering risk is measured using the Basel Anti-Money Laundering (AML) Index published by the Basel Institute on Governance. The index uses a 0–10 scale, with higher scores indicating greater country-level vulnerability to money laundering and

related financial crime. The score is divided by the natural logarithm of the LFC's total assets to construct ML.

Firm size (*FCSIZE*) is measured as the natural logarithm of total assets expressed in Sri Lankan rupees millions. Management efficiency (*MEF*) is measured as operating income divided by operating expenses. These variables are included to account for differences in institutional scale and operating efficiency that are relevant to LFC profitability. Based on the literature, the following hypotheses were tested.

H_1: Corruption significantly affects LFC profitability in Sri Lanka.

H_2: Money laundering significantly affects the profitability of LFCs in Sri Lanka.

Two separate panel regression models were specified to examine the relationships between corruption, money-laundering risk, and LFC profitability. The models are expressed as follows:

$$ROA_{i,t} = \alpha_0 + \beta_1 CORR_{i,t} + \beta_2 FCSIZE_{i,t} + \beta_3 MEF_{i,t} + u_i + \varepsilon_{i,t} \quad \text{---------- (1)}$$

$$ROA_{i,t} = \alpha_0 + \beta_1 ML_{i,t} + \beta_2 FCSIZE_{i,t} + \beta_3 MEF_{i,t} + u_i + \varepsilon_{i,t} \quad \text{----------(2)}$$

Corruption and money-laundering risk are entered into separate specifications because the underlying country-level indices capture related dimensions of the institutional environment. Estimating separate models avoids including both indicators simultaneously and therefore removes direct multicollinearity between these two regressors within the estimated specifications

The Hausman specification test (Hausman, 1978) was used to assess the suitability of fixed-effects and random-effects estimators. The test results supported the fixed-effects specification. Four diagnostic procedures were then applied to examine the properties of the regression models.

First, the Variance Inflation Factor (VIF) was used to assess multicollinearity among the explanatory variables included in each specification. Second, the modified Wald test (Baum, 2001) was applied to assess groupwise heteroskedasticity in the fixed-effects models. Third, the Wooldridge test (Wooldridge, 2010) was used to examine first-order serial correlation within companies over time. Fourth, the Pesaran cross-sectional dependence test (Pesaran, 2004) was applied to examine whether the error terms were correlated across companies, potentially reflecting common macroeconomic shocks or other shared developments.

The diagnostic results identified heteroskedasticity, serial correlation, and cross-sectional dependence. Accordingly, the final specifications were estimated using the fixed-effects estimator with Driscoll-Kraay standard errors (Driscoll & Kraay, 1998; Hoechle, 2007). These standard errors account for heteroskedasticity, serial correlation, and cross-sectional dependence under the relevant asymptotic conditions. A maximum lag length of two was specified for the variance estimator. The same estimation procedure was applied to both models to maintain consistency in the estimation approach.

Robustness checks were conducted using pooled ordinary least squares, random-effects estimation, and fixed-effects estimation with conventional standard errors. Comparing these specifications provides a basis for assessing the sensitivity of the estimated coefficients and their statistical significance to alternative estimators and variance assumptions.

4. Findings and Discussion

Table 2 presents the descriptive statistics for the 182 firm-year observations. Table 3 reports the pairwise correlations among the variables included in the two regression specifications. Separate correlation panels are presented for the corruption and money-laundering risk models, consistent with the separate estimation strategy.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
ROA (winsorised)	0.146	0.052	0.043	0.265
CORR	2.68	0.151	2.377	3.003
ML	0.262	0.033	0.198	0.337
FCSIZE	4.90	0.120	4.601	5.163
MEF	2.001	0.733	-0.306	4.686

n = 182

Table 3: Correlation Matrix

Panel A: Model 1	ROA	MEF	FCSIZE	CORR
ROA	1.000			
MEF	0.463 (0.000)	1.000		
FCSIZE	0.268 (0.000)	0.172 (0.020)	1.000	
CORR	−0.129 (0.083)	−0.099 (0.183)	−0.011 (0.886)	1.000

Panel B: Model 2	ROA	MEF	FCSIZE	ML
ROA	1.000			
MEF	0.463 (0.000)	1.000		
FCSIZE	0.268 (0.000)	0.172 (0.020)	1.000	
ML	−0.076 (0.306)	0.135 (0.069)	−0.503 (0.000)	1.000

Note: p-values are in brackets. n = 182.

Table 4: Hausman and Diagnostic Tests

Test	Model 1 (CORR)	Model 2 (ML)	Result
Hausman test	$\chi^2(3) = 9.21$ ($p = 0.027$)	$\chi^2(3) = 8.15$ ($p = .043$)	Fixed effects
F-test	$F(25,153) = 5.05$ ($p = .000$)	$F(25,153) = 4.83$ ($p = .000$)	Fixed effects needed
Modified Wald test	$\chi^2(26) = 786.01$ ($p = .000$)	$\chi^2(26) = 905.26$ ($p = .000$)	Problem present
Wooldridge test	$F(1,25) = 5.219$ ($p = .031$)	$F(1,25) = 4.992$ ($p = .035$)	Problem present
Pesaran CD test	9.019 ($p = .000$)	9.724 (p = .000)	Problem present
VIF (mean / largest)	1.03 / 1.04	1.33 / 1.45	No problem

Table 3 reports the pairwise correlation coefficients and their associated p-values. As shown in Panel A, management efficiency exhibits a moderate positive correlation with *ROA* ($r = 0.463$, $p < 0.001$). Firm size also exhibits a positive correlation with *ROA* ($r = 0.268$, $p < 0.001$), although the association is comparatively weaker. The correlation between CORR and *ROA* is negative ($r = -0.129$, $p = 0.083$). This relationship is not statistically significant at the

5% level. In Panel B, *ML* exhibits a weak negative correlation with *ROA* (r = -0.076, p = 0.306), indicating no statistically significant bivariate association.

Table 4 presents the results of the Hausman specification test and the diagnostic procedures conducted for both regression models. The Hausman test results favour the fixed-effects specification in both models, with p-values of 0.027 and 0.043 for Models 1 and 2, respectively. The F-tests for company effects were statistically significant in both models ($p < 0.001$), indicating that the company-specific effects are jointly relevant relative to pooled ordinary least squares.

The diagnostic tests also identify violations of several conventional error-structure assumptions. The modified Wald tests reject the null hypothesis of homoskedasticity in both specifications. The Wooldridge tests indicate first-order serial correlation, while the Pesaran tests identify cross-sectional dependence. These results are consistent with an institutional setting in which LFCs are exposed to common macroeconomic conditions, including the 2022 economic crisis and subsequent changes in the regulatory environment. The VIF values are comparatively low, with maximum values of 1.04 and 1.45 for Models 1 and 2, respectively. These statistics do not indicate substantial multicollinearity among the regressors included in either individual specification.

Table 5: Regression Results (Fixed Effects with Driscoll-Kraay Standard Errors)

Variable	Coefficient	Std. Err.	*t*-value	*p*-value
Model 1: Dependent variable = ROA (winsorised)				
CORR	0.0951*	0.0459	2.07	0.083
FCSIZE	−0.0869	0.1020	−0.85	0.427
MEF	0.0295***	0.0067	4.38	0.005
Constant	0.2590	0.4581	0.57	0.592
Within R^2 = 0.1786; $F(3,6)$ = 31.68, p = 0.0004; n = 182; Groups = 26				
Model 2: Dependent variable = ROA (winsorised)				
ML	−0.1438*	0.0632	−2.28	0.063
FCSIZE	−0.0785	0.0856	−0.92	0.395
MEF	0.0277***	0.0057	4.87	0.003
Constant	0.5135	0.4057	1.27	0.253
Within R^2 = 0.1564; $F(3,6)$ = 17.31, p = 0.0023; n = 182; Groups = 26				

*Note: *Significant at 10%; ** significant at 5%,***significant at 1%.*

In response to the diagnostic results, the final models were estimated using the fixed-effects estimator with Driscoll–Kraay standard errors and a maximum lag length of two. This approach accommodates heteroskedasticity, serial correlation, and cross-sectional dependence under the estimator's relevant assumptions. Nevertheless, the panel contains only seven annual observations per company. The resulting statistical inference therefore requires caution because Driscoll–Kraay standard errors can perform poorly in very short panels (Hoechle, 2007).

Table 5 presents the fixed-effects regression estimates with Driscoll–Kraay standard errors. Model 1 examines the relationship between *CORR* and profitability, whereas Model 2 examines the relationship between *ML* and profitability. Both models include firm size and management efficiency as control variables. In Model 1, the coefficient on *CORR* is positive

(β = 0.0951) and statistically significant at the 10% level (p = 0.083). Firm size is not statistically significant (β = -0.0869, p = 0.427). Management efficiency exhibits a positive and statistically significant association with ROA (β = 0.0295, p = 0.005). The model reports a within (R^2) of 0.1786. The model-level F-statistic is statistically significant (p = 0.0004).

In Model 2, the coefficient on *ML* is negative (β = -0.1438) and statistically significant at the 10% level (p = 0.063). Firm size is again statistically insignificant (β = -0.0785, p = 0.395). Management efficiency remains positively associated with *ROA* and statistically significant at the 1% level (β = 0.0277, p = 0.003). The within (R^2) is 0.1564, and the overall model F-statistic is statistically significant (p = 0.0023).

4.1 Management Efficiency and LFC Profitability

Management efficiency exhibits a positive and statistically significant coefficient in both regression specifications. The estimated coefficients are 0.0295 in Model 1 (P=0.005) and 0.0277 in Model 2 (p = 0.003). The consistency of these results indicates a robust positive association between the operational efficiency measure and LFC profitability across the two model specifications.

This finding is consistent with Hendeniya et al. (2023), who identify a positive relationship between management efficiency and the profitability of Sri Lankan licensed commercial banks. It is also compatible with the agency-theoretic perspective developed by Jensen and Meckling (1976), under which managerial decisions concerning resource allocation, operating costs, and organisational performance influence the financial outcomes of firms. Efficient resource utilisation and effective cost management provide plausible channels through which managerial practices relate to profitability.

The operational characteristics of LFCs provide a relevant context for this relationship. These institutions finance their lending activities through deposits and borrowings and serve customer segments that frequently face constraints in accessing conventional bank financing. Effective management of operating expenditure and income generation is therefore relevant to their financial performance. However, the present models do not directly estimate the individual contributions of cost control, loan pricing, collection efficiency, or credit-risk management. These mechanisms should consequently be interpreted as possible explanations rather than independently established empirical findings. Accordingly, the positive MEF coefficient provides strong evidence of an association between the operating-income-to-expense ratio and profitability within the sampled LFCs.

4.2 Corruption and LFC Profitability

Model 1 produces a positive coefficient for *CORR* (β = 0.0951, p = 0.083). The estimate reaches the 10% significance threshold but does not satisfy the conventional 5% criterion. The positive coefficient differs from the adverse relationships between corruption and financial performance reported by Ben Ali et al. (2020), Ho et al. (2019), and Hendeniya et al. (2023). It is directionally consistent with studies reporting positive relationships between corruption and bank profitability, including Aburime (2009) and the findings discussed by Aish et al. (2021). It is also compatible with the grease-the-wheels perspective, which proposes that

corruption can facilitate certain transactions under inefficient administrative and institutional conditions (Leff, 1964; Huntington, 1968).

However, the coefficient should not be interpreted as evidence that corruption improves LFC profitability. *CORR* is constructed by reversing the national *CPI* score and dividing it by firm size. Its coefficient therefore represents an association involving a firm-size-scaled indicator derived from perceived public-sector corruption, rather than a direct estimate of the effect of corruption occurring within an individual LFC. This distinction restricts the substantive interpretation of the positive sign.

The result also differs across the reported estimation specifications. The simple correlation between *CORR* and *ROA* is negative ($r = -0.129$, $p = 0.083$), and the reported pooled regression coefficient is negative and statistically insignificant ($\beta = -0.029$, $p = 0.193$). By contrast, the fixed-effects estimate is positive. With conventional fixed-effects standard errors, the coefficient is reported as statistically significant at the 5% level ($p = 0.017$); after applying Driscoll–Kraay standard errors, its p-value increases to 0.083. The random-effects estimate is also smaller and statistically insignificant ($\beta = 0.021$, $p = 0.479$).

These differences indicate that the estimated relationship is sensitive to the estimator and the treatment of the error structure. The evidence is therefore insufficient to establish a stable positive relationship between perceived corruption and LFC profitability.

Three contextual considerations help explain why the present finding differs from the earlier Sri Lankan banking evidence. First, differences in institutional business models provide a potential explanation. LFCs conduct substantial leasing, hire-purchase, and gold-loan activities, many of which are supported by identifiable assets. Such lending arrangements may create different channels through which governance weaknesses influence credit allocation and recovery compared with some commercial banking activities.

Second, the observation periods and institutional samples differ. Hendeniya et al. (2023) examine licensed commercial banks over 2015–2021, whereas the present study covers LFCs from 2018 to 2024. The latter period includes Sri Lanka's 2022 economic crisis and subsequent developments in the financial and regulatory environment. Differences in institutional structure and macroeconomic conditions can contribute to differences in estimated coefficients, particularly when the present estimate is statistically weak.

Third, *CORR's* country-level construction creates an identification limitation. The underlying *CPI* score varies annually and is common to all sampled companies within a particular year. Dividing the reversed score by firm size introduces additional cross-sectional variation, but this variation arises partly from the denominator rather than differences in measured corruption across companies.

4.3 Money-Laundering Risk and LFC Profitability

Model 2 reports a negative coefficient for *ML* ($\beta = -0.1438$, $p = 0.063$), which is statistically significant at the 10% level. The estimated relationship is consistent with the proposition that

greater exposure to money-laundering risk can be associated with lower financial performance, although the statistical evidence is limited.

The direction of the coefficient is compatible with the economics-of-crime perspective developed by Becker (1968), which emphasises the role of expected benefits, detection probabilities, and enforcement costs in shaping incentives for illegal activity. In the context of financial institutions, exposure to money-laundering risk can create additional compliance requirements, monitoring expenditures, regulatory exposure, and reputational risks. These channels provide plausible explanations for a negative association with profitability.

The result is also directionally consistent with the concerns raised by Takáts (2011) regarding the costs associated with defensive suspicious-transaction reporting and with studies linking money-laundering-related risks to weaker loan quality, including Hussain et al. (2021) and Shah et al. (2022). Nevertheless, these studies address related risk and operational mechanisms, and their results should not be treated as direct replications of the present profitability model.

A central limitation concerns the operationalisation of ML. The variable is calculated by dividing the Basel AML Index score by the natural logarithm of firm size. The underlying Basel index captures country-level vulnerability to money laundering and related financial crime rather than the actual amount of money laundered through a particular LFC. The resulting measure therefore combines national institutional risk with a firm-size adjustment. It does not directly quantify an individual company's money-laundering exposure, compliance expenditure, or regulatory burden.

The result differs from Hendeniya et al. (2023), who report a positive and statistically significant relationship between their money-laundering measure and the profitability of Sri Lankan commercial banks. Several factors could contribute to this difference, including differences in the institutional samples, observation periods, business models, and measurement procedures. Prior studies also discuss circumstances in which financial institutions may obtain short-term revenue from deposit or transaction activity. However, the present study does not measure such activities and cannot establish whether they explain the positive relationship reported in earlier research.

The estimated magnitude of the *ML* association is comparatively modest. Using the reported standard deviation of *ML* (0.033), a one-standard-deviation increase corresponds to an estimated change in *ROA* of approximately −0.0047, calculated as (-0.1438 \times 0.033). Relative to the mean *ROA* of 0.146, this is approximately 3.3%. This calculation is a scale-based illustration of the fitted linear relationship, not a causal effect. Its interpretation is further constrained by the constructed nature of *ML* and the limited time dimension of the panel.

The evidence provides limited support for a negative association between the constructed money-laundering risk indicator and LFC profitability. It is directionally consistent with the compliance-cost and financial-risk mechanisms discussed in the literature, but it does not establish the size of those mechanisms or demonstrate that actual money laundering reduces the profits of individual LFCs.

4.4 Firm Size and LFC Profitability

Firm size is not statistically significant in either fixed-effects specification. The coefficient is negative in Model 1 (β = -0.0869, p = 0.427) and Model 2 (β = -0.0785, p = 0.395). Accordingly, the within-firm estimates do not provide evidence of a statistically significant association between changes in firm size and changes in profitability over the observation period, conditional on the other included variables.

The reported standard deviation of *FCSIZE* is 0.120, indicating limited overall dispersion on the reported measurement scale. Nevertheless, the overall standard deviation alone does not establish the extent of within-company variation. A decomposition of within-company and between-company variation would provide a stronger basis for explaining the insignificant fixed-effects coefficient.

The results do not establish that firm size is irrelevant to LFC profitability. Rather, they indicate that the present fixed-effects specifications do not identify a statistically significant within-company association between firm size and *ROA* over the seven-year period. Table 6 summarises the main findings in relation to the theoretical framework and the empirical literature.

Table 6: Findings compared with earlier studies

Finding	Agrees with	Differs from	Main reasons
Management efficiency: positive, strong	Hendeniya et al. (2023); agency theory (Jensen & Meckling, 1976)	None	Cost control and income quality turn directly into profit; the effect is the same under every estimator
Corruption: positive, weak	Aburime (2009); Aish et al. (2021); Bolarinwa & Soetan (2019); "grease the wheels" view (Leff, 1964; Huntington, 1968)	Hendeniya et al. (2023); Ben Ali et al. (2020); Ho et al. (2019); "sand the wheels" view (Shleifer & Vishny, 1993; Mauro, 1995)	Secured, small-ticket LFC lending; CPI changes only by year so it may carry crisis-period effects; different sector and period
Money laundering: negative, weak	Takáts (2011); Hussain et al. (2021); Shah et al. (2022); economics of crime (Becker, 1968)	Hendeniya et al. (2023); partly Aish et al. (2021)	Compliance cost weighs more on small LFCs; banks may gain from laundered deposits and fees; possible under-reporting (Nobanee & Ellili, 2018)
Firm size: not significant	Pooled results match Hendeniya et al. (2023)	Hendeniya et al. (2023) in the fixed-effects model	Size differences between firms are absorbed by company effects

5. Conclusions

This study examines the relationships between country-level corruption, money-laundering risk, and the profitability of 26 Licensed Finance Companies (LFCs) in Sri Lanka over the period 2018–2024. Fixed-effects estimates with Driscoll–Kraay standard errors show that the corruption indicator is positively associated with Return on Assets (*ROA*), whereas the money-laundering risk indicator is negatively associated, with both relationships significant only at the 10% level. H1 and H2 are supported only at the 10% level and are not supported at the 5%

level. Management efficiency shows a consistent, statistically significant positive association with profitability across both models. However, these findings establish associations rather than causal effects.

From a managerial perspective, the results highlight the relevance of operational efficiency and effective resource utilisation to LFC profitability. Maintaining robust anti-money laundering controls remains essential despite the limited statistical evidence concerning profitability. For regulators, including the Central Bank of Sri Lanka and the Financial Intelligence Unit, access to firm-level data on compliance expenditure, suspicious transaction reporting, regulatory findings, and internal controls would strengthen the empirical assessment of institutional risk and financial performance.

The study has several limitations. The explanatory variables are derived from country-level indices rather than direct measures of company-specific corruption or money-laundering exposure. The seven-year observation period also limits the reliability of statistical inference, particularly under Driscoll–Kraay estimation. Furthermore, the models do not examine lagged effects or fully isolate common macroeconomic and regulatory influences.

Future research should incorporate firm-level governance and compliance indicators, extend the observation period, examine lagged relationships, and compare financial institutions across sectors. Further investigation of compliance costs, credit quality, and governance mechanisms would clarify the channels through which institutional risks relate to profitability. Overall, this study extends the evidence on Sri Lanka's non-bank financial sector and identifies management efficiency as the most consistent statistically significant correlate of LFC profitability within the estimated models.

References

Aburime, T. U. (2009). Impact of corruption on bank profitability in Nigeria. *Euro Economica, 23*(02), 50–57.

Aish, K., Hassan, M. K., Zaman, Q. U., Ehsan, S., Abbas, K., & Shah, I. H. (2021). Do Islamic banks gain from corruption and money laundering (ML)? *Journal of Money Laundering Control, 25*(4), 909–929. https://doi.org/10.1108/JMLC-09-2021-0094

Basel Institute on Governance. (2023). *Basel AML Index: Assessing money laundering risks around the world*. https://index.baselgovernance.org/

Baum, C. F. (2001). Residual diagnostics for cross-section time series regression models. *The Stata Journal, 1*(1), 101–104.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy, 76*(2), 169–217. https://doi.org/10.1086/259394

Ben Ali, M. S., Fhima, F., & Nouira, R. (2020). How does corruption undermine banking stability? A threshold nonlinear framework. *Journal of Behavioral and Experimental Finance, 27*, 100365. https://doi.org/10.1016/j.jbef.2020.100365

Bolarinwa, S. T., & Soetan, F. (2019). The effect of corruption on bank profitability. *Journal of Financial Crime, 26*(3), 753–773. https://doi.org/10.1108/JFC-09-2018-0102

Central Bank of Sri Lanka. (2023). *Financial system stability review*. Central Bank of Sri Lanka.

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics, 80*(4), 549–560.

Financial Intelligence Unit of Sri Lanka. (2022). *Annual report*. Central Bank of Sri Lanka.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica, 46*(6), 1251–1271.

Hendeniya, H. G. G. M. N., Premarathna, W. G. I. D., & Tennekoon, S. T. M. S. (2023). The effect of corruption and money laundering on banking profitability and stability of licensed commercial banks in Sri Lanka. *Journal of Business and Technology, 7*(2), 33–56. https://doi.org/10.4038/jbt.v7i2.98

Ho, K.-C., Ma, J. Z., Yang, L., & Shi, L. (2019). Do anticorruption efforts affect banking system stability? *The Journal of International Trade & Economic Development, 28*(3), 277–298. https://doi.org/10.1080/09638199.2018.1522661

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal, 7*(3), 281–312.

Huntington, S. P. (1968). *Political order in changing societies*. Yale University Press.

Hussain, N., Sheikh, S. M., & Shah, I. H. (2021). Exploring the role of corruption and money laundering (ML) on bank's loan portfolio quality: A cross-country investigation. *Journal of Financial Regulation and Compliance, 30*(3), 265–281. https://doi.org/10.1108/JFRC-10-2021-0086

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Leff, N. H. (1964). Economic development through bureaucratic corruption. *American Behavioral Scientist, 8*(3), 8–14.

Mauro, P. (1995). Corruption and growth. *The Quarterly Journal of Economics, 110*(3), 681–712.

Méon, P.-G., & Sekkat, K. (2005). Does corruption grease or sand the wheels of growth? *Public Choice, 122*(1–2), 69–97.

Nobanee, H., & Ellili, N. (2018). Anti-money laundering disclosures and banks' performance. *Journal of Financial Crime, 25*(1), 95–108. https://doi.org/10.1108/JFC-10-2016-0063

Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels* (CESifo Working Paper No. 1229). CESifo.

Shah, W. U. H., Hao, G., Yan, H., & Yasmeen, R. (2022). Efficiency evaluation of commercial banks in Pakistan: A slacks-based measure Super-SBM approach with bad output (Non-performing loans). *PLOS ONE, 17*(7), e0270406. https://doi.org/10.1371/journal.pone.0270406

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika, 52*(3–4), 591–611.

Shleifer, A., & Vishny, R. W. (1993). Corruption. *The Quarterly Journal of Economics, 108*(3), 599–617.

Takáts, E. (2011). A theory of "crying wolf": The economics of money laundering enforcement. *The Journal of Law, Economics, and Organization, 27*(1), 32–78. https://doi.org/10.1093/jleo/ewp018

Transparency International. (2023). *Corruption Perceptions Index 2022*. https://www.transparency.org/en/cpi/2022

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.