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Trust-Layer Marketing (TLM) Dynamics in High-Fraud Markets: A Multi-Sector Empirical Assessment in Emerging Economies

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Abstract

This study investigates the dynamics of Trust-Layer Marketing (TLM) in high-fraud emerging economies by examining how fraud intensity, regulatory quality, digital trust infrastructure, economic development, and financial inclusion shape Trust-Layer Market Performance (TLMP). Using a balanced panel of fifteen emerging economies from 2015 to 2024, the study employs two-way fixed effects, system GMM, panel threshold regression, and random forest machine-learning techniques to provide robust, multi-method evidence. The results show that higher fraud and corruption significantly reduce TLMP, while stronger regulatory quality and digital trust infrastructure consistently enhance market performance across all models. A significant corruption threshold is identified, revealing that the positive effects of regulatory quality and digital trust are amplified in high-corruption environments. Economic development and financial inclusion also exert strong positive influences, although the latter weakens under extreme corruption. Diagnostic tests confirm the model's validity across both econometric and predictive analyses. The study contributes novel empirical insights by integrating linear, dynamic, and non-linear modelling with machine learning to advance the TLM framework. It concludes that strengthening regulatory trust, expanding digital trust systems, and reducing corruption are central to improving market performance in emerging economies.

1. Introduction

Trust-layer marketing (TLM) has been the emerging institutional and technological buffer for market actors that operate in uncertain environments characterised by ongoing fraud and dubious regulatory credibility. In numerous developing economies, marketplace transactions depend not only on formal institutions, but also digital and regulatory trust channels that are intended to reduce corruption-induced distortions, increase accountability, and stabilise market performance. There is ample evidence that increasing fraud & corruption persists in reducing confidence in firms, capital markets and macroeconomic systems (Bu et al., 2022; Okoye et al., 2023), as well as the loss of trust threatens direct financial participation, regulatory legitimacy and consumer engagement (Cline et al., 2022; Quintus et al., 2024). In particular, as economies including Nigeria, India, Kenya, Brazil, and others digitise faster, the architecture of trust is more and more dependent on the digital infrastructure, algorithmic safeguards, regulatory quality and how fair the market system looks (Paleti, 2023; Verhoest et al., 2025). Thus, in the light of these insights, the TLM proposed in this study conceptualises trust as an artificial, multi-dimensional mechanism with regulatory trust, institutional trust, and digital-technology-enabled trust components, with the main aim being to protect the market performance from corruption, institutional decay, and information asymmetry.

In theoretical terms, the study builds on Transaction Cost Economics (TCE) introduced by Williamson (1975) and Social Capital/Generalised Trust Theory proposed by Putnam (1993). TCE argues that corruption, inadequate regulatory frameworks, and distrust of institutions raise transaction costs, reduce willingness to participate, distort prices, and impair the overall efficiency of the market. This is consistent with work relating corruption and institutional failures to performance decline in several emerging

markets (Ojeka et al., 2019; Martins et al., 2020; Tan and Tusha, 2023). While social capital theory contends that trust personal, institutional and digital- serves as a collectivised resource that strengthens cooperation, alleviates uncertainty, and better economic outcomes (Lim et al., 2018; Miniesy and AbdelKarim, 2021). Although both theories account for trust–performance linkages, TCE is used as the theory underpinning them, as TLM mechanisms (digital verification systems, regulatory oversight layers, fintech-enabled audit trails and fraud detection algorithms) mainly work by mitigating transaction risks and by overcoming corruption frictions in the market, leading to less trust. Therefore, Williamson's framework represents the most robust theoretical explanation for how trust levels lead to practical performance effects among high-fraud markets.

The literature has produced research on corruption, trust, digital transformation and institutional quality in recent years (empirically), though the focus has been fractured. Corruption has been associated with corporate-level inefficiencies (Lourenço and Cerdeira, 2024; Sundarasen et al., 2024), financial market volatility (Okoye et al., 2023; Odey, 2025), and declining corporate performance (Martins et al., 2020). Other studies show the role of digital trust infrastructure in promoting inclusion and regulatory transparency (Del Sarto and Ozili, 2025; Dudu et al., 2024) and the influence of trust on household and firm-level economic behaviour (Bu et al., 2022; Sánchez and Lehnert, 2018). However, the current literature is still limited to four main themes: (i) a limited number of integrated models that connect fraud intensity, regulatory trust, digital trust structures, and market performance; (ii) few comparative studies across emerging economies; (iii) a lack of attention on trust-layer mechanisms as competitive marketing and regulatory instruments; and (iv) lack of use of sophisticated estimators such as system GMM, threshold models, machine learning, and two-way fixed effects within an integrated empirical approach.

In response to these gaps, this study presents the first comprehensive multi-sector, multi-country empirical analysis of the Trust-Layer Marketing (TLM) model, in fifteen emerging economies (2015–2024). While previous studies have analysed corruption, trust, regulation, or digitalisation separately, this research combines them into a single analytical variable to explain how trust layers together influence market performance, as fraud rates are high across high fraud environments. As one method, we apply two-way fixed effects, system GMM, threshold modelling and machine-learning analytics on the structure of these relationships, revealing non-linearities and predictive relationships not caught by traditional estimators. In this respect, the research provides a new, performance-oriented perspective on TLM that can guide policy, regulatory reform, fintech design, and market-stability approaches. The common aim is to empirically investigate how the presence of fraud intensity, regulatory quality and digital trust infrastructure interact to affect trust-layer market performance in emerging markets and gain a solid evidence basis for investing in trust-based market systems.

2. Literature Review

The extant literature on corruption, trust, institutional quality and digital transformation highlights a dynamic relationship between fraud dynamics and regulatory credibility, digital trust ecosystem and market performance in emerging markets. Afzali et al. (2021), for example, studied the role of economic

uncertainty in influencing the process of corruption by either public or private firms based on an extensive firm-specific dataset and determined that uncertainty exacerbates corruption incentives that influence firm results. Their study found that environments characterised by structural uncertainty amplify weaknesses in organisational decision-making, escalating susceptibility to performance risk. Similarly, Martins et al. (2020) investigated whether corruption enhances or harms firm performance based on cross-country developing economy data, conducted regression methodology, they argued that corruption may cause short-run “grease-the-wheel” effects, but its long-run adverse effects are negative on sustainable firm productivity. The current findings also accord with the overall theories of trust and market performance, which suggest that corruption decreases transparency, increases transaction costs and results in reduced market functioning (Cline et al., 2022).

Research on the trust-performance nexus further emphasises the multilevel function of organisational and regulatory credibility. Using structural equation modelling, Sánchez and Lehnert (2018) in a firm-level examination of both Mexico and Peru found that trust moderates the relationship between corruption and the strength of institutions, which in turn impacts market performance. Lim et al. (2018) compared macroeconomic performance across countries and found that trust positively influences national economic performance with its positive impact on uncertainty reduction and efficiency through improvements in institutional interaction. Miniesy and AbdelKarim (2021) also analysed MENA countries and found that with panel econometrics applying a trust model, generalised trust predicts economic growth, which strengthens trust as a macroeconomic stabiliser, showing a positive relation with economic growth. Together, these studies confirm that trust – whether in interpersonal, institutional, or digital domains – is still a key factor influencing how markets operate and how markets function, especially in fragile institutional environments.

Studies of regulatory quality and institutional monitoring also provide additional evidence that trust-enhancing regulatory systems are crucial to market efficiency. Using econometric modelling, Tan and Tusha (2023) evaluated Moldova’s regulatory environment, discovering that regulatory burden and corruption dampen firm performance. In Nigeria, Ojeka et al. (2019) used multivariate regression on listed companies and found that poor institutional quality and high perceived corruption were substantial in reducing firms' profitability, suggesting the importance of credibility in regulations. Verhoest et al. (2025) offered further regulatory understanding with a comparative analysis of regulatory regimes and concluded that both “watchful trust” and “good-faith trust” have differential effects on regulatory performance, establishing trust layers inscribed in regulatory structures that determine system legitimacy and market operation. These results, compiled, consolidate the articulation that Trust-Layer Marketing (TLM) is a regulatory-institutional device which is necessary to protect markets from corruption-induced distortions.

Consequently, digital trust infrastructure is now an important vector in shaping economic and financial inclusion, market participation, and performance in emerging markets. Aracil et al. (2025) provided an extensive literature review, connecting digital transformation with trust and inclusiveness: When digital finance is integrated into credible and transparent systems, it thus enhances market participation. Del

Sarto and Ozili (2025), through a bibliometric mapping approach, recognised fintech and digital trust systems as one of the key enablers of inclusion in risky markets. Dudu et al. (2024) conducted an empirical survey and descriptive analysis of digital payment platforms in emerging markets, proving that digital infrastructure significantly enables inclusion, if trust and user confidence are strong. Paleti (2023), in a conceptual/technological paper, showed how multi-layer risk compliance engines drive transparency, risk detection, and accountability in the market. Quintus et al. (2024) used a comparative empirical approach to investigate consumer trust in e-commerce in developed and developing economies, discovering that digital trust systems impact purchase confidence and perceived fairness. Taken together, these results highlight that digital trust layers are playing an increasingly central role in the prevention of fraud risks, increasing transparency, and maintaining market system performance.

For trust layer performance, financial inclusion and governance factors have also been found to be of importance. Using Nigerian panel data, Odey (2025) found that financial inclusion and the stock market strongly predict public financial accountability. Based on econometric modelling data, Yamen and Can (2023) indicated that the perception of public governance contributes to the quality of financial reporting in emerging economies. These studies suggest that governance quality and inclusion both operate as a force together on trust-building and market performance. However, significant empirical voids persist: few studies combine fraud intensity, regulatory quality, and digital trust infrastructure into an integrated model; a large majority of research applies a single-country model, while few uses sophisticated estimators like system GMM, two-way fixed effects, threshold models, and machine learning together. Existing research has also not conceptualised these constructs in the context of the new TLM framework and has not tested their combined influence on the market performance in several emerging nations over time.

Based on the foregoing theoretical and empirical arguments, this study proposes the following hypotheses:

H1: Fraud/Corruption Intensity significantly reduces Trust-Layer Market Performance in emerging economies.

H2: Trust-Layer Regulation Quality significantly enhances Trust-Layer Market Performance in emerging economies.

H3: A digital trust infrastructure significantly improves Trust-Layer Market Performance in emerging economies.

H4: Economic Development Level and Financial Inclusion as control variables significantly influence Trust-Layer Market Performance.

3. Data and Methodology

This study employs a quantitative, longitudinal, multi-country panel research designed to examine Trust-Layer Marketing (TLM) dynamics in fifteen emerging economies over the period 2015–2024. This design is consistent with the findings from previous empirical studies on trust, corruption, institutional quality and digital transformation in emerging markets (Afzali et al., 2021; Martins et al., 2020; Aracil et al., 2025). It is appropriate to use the panel methodology because the factors affecting corruption, trust infrastructure, quality of regulation, and financial inclusion are differences that vary between countries and time, and hence panel estimators provide appropriate adjustment capabilities for unobserved heterogeneity and dynamic adjustment processes (Wooldridge, 2010). The study analyses yearly macroeconomic, governance, digital infrastructure and financial inclusion indicators from credible worldwide databases such as World Bank Development Indicators, IMF databases, and global governance datasets. Further strengthening the case for the research design are findings from emerging-market trust and governance literature that stress a need for longitudinal cross-country data that captures the broad landscape of structural institutional dynamics (Sánchez & Lehnert, 2018; Miniesy & AbdelKarim, 2021).

Data were obtained for the dependent variable, Trust-Layer Market Performance (TLMP), and three primary independent variables, Fraud/Corruption Intensity (FRAUD), Trust-Layer Regulation Quality (REG_QLTY), and Digital Trust Infrastructure (DIG_TRUST), and two control variables, Economic Development Level (GDPpc) and Financial Inclusion (FIN_INCL) were implemented. These variables are consistent with empirical reviews of corruption, regulatory quality, trust and market performance in studies like Bu et al. (2022), Tan and Tusha (2023), and Dudu et al. (2024). A balanced panel architecture improves the robustness of estimators and increases the statistical validity, particularly when integrating institutional, regulatory, and digital trust indicators. The multi-sector and multi-country character of the data lends itself to fixed effects, dynamic panel GMM models, threshold regressions and machine learning methods extensively applied in the literature for more current research of institutional trust and performance (Del Sarto & Ozili, 2025; Lim et al., 2018).

At the statistical level, it combines both static and dynamic econometric estimators, non-linear threshold modelling, and both predictive and regression methods based on machine learning. Two-way fixed effects (country & time) address unobservable characteristics that may bias relationships as empirical background for institutional-performance literature (Cline et al., 2022; Verhoest et al., 2025). System GMM is used to account for the endogeneity due to reverse causality between trust variables and market performance, in accordance with Arellano and Bond's (1991) dynamic panel estimator. We embed a panel threshold model to take into consideration the non-linear effects of corruption and trust on market performance and to accommodate how trust deepening or regulatory restrictions could lead to structural breakpoints on economic behaviour (Lourenço & Cerdeira, 2024). Finally, machine learning, such as random forest regressors, is employed to assess predictive significance and to identify potential interaction effects, based on prior studies which have highlighted the role of digital trust and algorithmic governance (Paleti, 2023).

The methodological approach facilitates an in-depth understanding of how regulatory trust, digital trust infrastructure and dynamics of corruption intertwine in influencing market effects. The findings are in line with previous work supporting the view that trust mechanisms, digital infrastructure and institutional reform are also associated with performance outcomes in emerging markets (Sundarasen et al., 2024; Quintus et al., 2024). The integration of econometric and machine-learning methods allows for robustness, improves inferential quality, and enhances prediction accuracy, all of which are essential to interpret the TLM's behaviour.

3.1 Model Specification

The study applied four main model specifications, including a two-way fixed effects model, a system GMM dynamic model, a panel threshold regression model, and a machine-learning predictive model.

(i) Two-Way Fixed Effects Model

Adapted from empirical frameworks in Cline et al. (2022), Sánchez and Lehnert (2018), and Verhoest et al. (2025), the fixed effects model examines how variations in FRAUD, REG_QLTY and DIG_TRUST explain changes in TLMP while controlling for unobserved country-specific characteristics and global time shocks.

Model 1 (Two-Way FE):

$$TLMP_{it} = \beta_0 + \beta_1 FRAUD_{it} + \beta_2 REG_QLTY_{it} + \beta_3 DIG_TRUST_{it} + \beta_4 GDPpc_{it} + \beta_5 FIN_INCL_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where μ_i captures country fixed effects and λ_t captures time fixed effects.

(ii) System GMM Model

Following Arellano and Bond (1991), Lim et al. (2018), and Afzali et al. (2021), the dynamic model addresses endogeneity arising from simultaneous interactions between trust indicators and market performance.

Model 2 (System GMM):

$$TLMP_{it} = \alpha TLMP_{(i,\, t-1)} + \beta_1 FRAUD_{it} + \beta_2 REG_QLTY_{it} + \beta_3 DIG_TRUST_{it} + \beta_4 GDPpc_{it} + \beta_5 FIN_INCL_{it} + \eta_i + \upsilon_{it}$$

System GMM uses internal instruments to correct dynamic endogeneity.

(iii) Panel Threshold Regression Model

Drawing from Lourenço and Cerdeira (2024) and Martins et al. (2020), this model explores whether corruption intensity creates thresholds beyond which trust infrastructure and regulation have asymmetric impacts on TLMP.

Model 3 (Threshold Model):

$TLMP_{it}$ =

$\theta_1 X_{it} I (FRAUD_{it} \leq \gamma) +$

$\theta_2 X_{it} I (FRAUD_{it} > \gamma) +$

ε_{it}

Where X_{it} = {REG_QLTY, DIG_TRUST, GDPpc, FIN_INCL} and γ is the estimated corruption threshold.

(iv) Machine Learning Model (Random Forest Regressor)

Following digital trust research, such as Paleti (2023) and Quintus et al. (2024), machine learning was utilised to identify variable importance, non-linear patterns, and predictive interactions.

Model 4 (ML–Random Forest):

TLMP = f (FRAUD, REG_QLTY, DIG_TRUST, GDPpc, FIN_INCL)

This model does not estimate coefficients but generates predictive accuracy metrics and variable importance rankings.

3.2 Diagnostic Tests

To ensure model robustness and validity, the diagnostic tests conducted include Variance Inflation Factor (VIF) to test multicollinearity among predictors, Hausman Test to justify the use of fixed effects over random effects, Arellano–Bond AR (1) and AR (2) Tests for autocorrelation in system GMM, Hansen J-Test of Overidentifying Restrictions for instrument validity in GMM (Hansen, 1982), Breusch–Pagan and White Tests for heteroscedasticity, Cross-sectional dependence and unit-root tests to ensure estimator assumptions are not violated, Threshold effect test (bootstrap) to confirm the existence of statistically significant non-linear thresholds and Machine-learning validation metrics (RMSE, out-of-sample prediction accuracy) to assess model performance.

Table 1 presents the variable measurement and corresponding data sources, detailing the variable, type, measurement, description and data sources.

Table 1
Variable Measurement and Data Sources

Variable	Type	Measurement/Indicator	Description	Data Source
Trust-Layer Market Performance (TLMP)	Dependent	Composite Index (0–100) combining market participation, transparency indicators, digital transaction confidence metrics	Captures performance of markets based on trust, transparency, digital transaction reliability, and institutional confidence	World Bank Development Indicators (WDI)
Fraud/Corruption Intensity (FRAUD)	Independent	Control of Corruption Index (− 2.5 to 2.5)	Higher values indicate lower corruption; reversed for "intensity" by multiplying by − 1	Worldwide Governance Indicators (WGI), World Bank
Trust-Layer Regulation Quality (REG_QLTY)	Independent	Regulatory Quality Index (− 2.5 to 2.5)	Measures perceptions of government's ability to formulate and implement trust-enhancing regulatory policies	Worldwide Governance Indicators (WGI), World Bank
Digital Trust Infrastructure (DIG_TRUST)	Independent	Digital Adoption Index (0–1); Secure Internet Servers per million; Digital ID penetration; Broadband/4G Network coverage (%)	Captures digital systems supporting trust: authentication systems, cybersecurity, fintech adoption, digital identity, online verification tools	World Bank Digital Adoption Index; GSMA Mobile Connectivity Index
Economic Development Level (GDPpc)	Control	GDP per capita (constant 2015 USD)	Measures level of economic development and structural capacity for trust-layer adoption	World Bank Development Indicators (WDI)
Financial Inclusion (FIN_INCL)	Control	% of adults with an account at a financial institution/mobile money (15+); ATM/agent density	Measures accessibility of formal finance as a trust-enabling mechanism	World Bank Global Findex; IMF Financial Access Survey

Variable	Type	Measurement/Indicator	Description	Data Source
Lagged TLMP ($TLMP_{t-1}$)	Dynamic Variable (for GMM)	One-period lag of TLMP	Captures persistence of trust-layer performance	Constructed by the researcher (from TLMP series)
Fraud Threshold Variable (γ)	Threshold Indicator	Estimated cut-off point in FRAUD used for threshold regression	Identifies levels at which corruption changes the effect of regulation or digital trust	Computed through panel threshold modelling

4. Empirical Results

Table 2
Descriptive Statistics for Study Variables (2015–2024, N = 150)

Variable	M	SD
TLMP	81.55	6.93
FRAUD	1.40	0.71
REG_QLTY	0.44	0.44
DIG_TRUST	0.68	0.21
GDPpc	8802.67	4862.43
FIN_INCL	62.50	16.10

Notes. TLMP = Trust-Layer Market Performance; FRAUD = Fraud/Corruption Intensity; REG_QLTY = Trust-Layer Regulation Quality; DIG_TRUST = Digital Trust Infrastructure; GDPpc = GDP per capita (constant USD); FIN_INCL = Financial Inclusion (% adults with an account/mobile money). N = 150 country–year observations (15 countries × 10 years).

Table 2 shows that trust-layer market performance (TLMP) is relatively high on average (M = 81.55, SD = 6.93), indicating that, although being situated in high-fraud environments, the emerging market sample demonstrated moderately strong trust-layer outcomes likely supported by regulatory and digital mechanisms. Fraud/Corruption Intensity also has a moderate mean level (M = 1.40, SD = 0.71) within a 0–3 range, suggesting substantial, though heterogeneous, corruption pressure across countries. Trust-Layer Regulation Quality and Digital Trust Infrastructure have positive averages (M = 0.44 and 0.68, respectively), but with notable dispersion, which reflects uneven institutional and digital capacities. Economic Development (GDPpc) varies widely (SD ≈ 4862.43), which indicates significant structural differences in income levels, while Financial Inclusion (M = 62.50, SD = 16.10) suggests that a considerable part of the adults is participating in the formal or digital financial system, although across countries, and over a period of time, we find a lot of variability. By and large, the means and standard

deviations indicate a diverse but, for the most part, improving trust-layer environment, which is well-suited to test the hypotheses of relationships between fraud, regulatory quality, digital trust and market performance.

Table 3
Two-Way Fixed Effects Regression Predicting Trust-Layer Market Performance (TLMP)

Predictor	B	SE	t	P
FRAUD	−3.79	0.93	−4.09	.000
REG_QLTY	7.39	1.78	4.16	.000
DIG_TRUST	26.28	3.70	7.10	.000
GDPpc	0.001	0.000	2.08	.040
FIN_INCL	0.26	0.07	3.74	.000

Note. N = 150 country–year observations (15 countries × 10 years). Model includes country and year fixed effects. R^2 = .92. TLMP = Trust-Layer Market Performance; FRAUD = Fraud/Corruption Intensity; REG_QLTY = Trust-Layer Regulation Quality; DIG_TRUST = Digital Trust Infrastructure; GDPpc = GDP per capita (constant USD); FIN_INCL = Financial Inclusion.

The two-way fixed effects results of Table 3 indicate that all the predictors are significant and follow the stated hypotheses in the performance. Fraud/Corruption Intensity has a significant negative impact on Trust-Layer Market Performance (B = − 3.79, p < .001), with greater levels of fraud related to large decreases in trust-layer performance corresponding to H1. The quality of trust layer regulation is positively associated with TLMP (B = 7.39, p < .001), which indicates that having more robust, credible regulatory frameworks substantially augments trust-based market performance, in line with H2. Digital Trust Infrastructure has a large, highly positive, and significant coefficient (B = 26.28, p < .001), providing support for H3 by suggesting that greater depth of digital trust increases market value as a deep market, and that market performance increases over time using deeper systems of digital trust. In addition, both the Economic Development Level (GDPpc; B = 0.001, p = .040) as well as financial inclusion (B = 0.26, p < .001) affect TLMP in both positive and significant ways, implying that trust-layer performance was observed to be high in more developed economies and those which were financially inclusive, confirming H4 and suggesting that these control variables are influencing TLM-in-transforming processes in Emerging Market settings.

Table 4
Dynamic Panel GMM Results for Trust-Layer Market Performance (TLMP)

Predictor	B	SE	t	P
Intercept	−1.49	1.03	−1.44	.152
FRAUD	−5.34	1.51	−3.53	.001
REG_QLTY	10.96	3.41	3.21	.002
DIG_TRUST	30.18	7.14	4.23	.000
GDPpc	0.002	0.001	2.05	.042
FIN_INCL	0.36	0.10	3.52	.001
$TLMP_{i,t-1}$	0.48	0.37	1.28	.202

Note. Dependent variable: $\Delta TLMP_{it}$. N (effective differenced observations) corresponds to country–year panels with sufficient lags. Dynamic panel GMM estimator with internal instruments for lagged TLMP. Pseudo $R^2 \approx .17$. TLMP = Trust-Layer Market Performance; FRAUD = Fraud/Corruption Intensity; REG_QLTY = Trust-Layer Regulation Quality; DIG_TRUST = Digital Trust Infrastructure; GDPpc = GDP per capita (constant USD); FIN_INCL = Financial Inclusion.

In Table 4, the dynamic GMM results demonstrate that, adjusting for persistence in market performance and unobserved heterogeneous variables, core trust-layer drivers are highly significant and match the results of their hypotheses. In particular, the fraud and corruption intensity increases reduce Trust-Layer Market Performance (B = − 5.34, p = .001), further supporting the claim that corruption significantly undermines trust-based market outcomes (H1). On the other hand, the role of regulatory quality raises positive and significant influences on TLMP (B = 10.96, p = .002), indicating that stronger and credible regulatory regimes result in improved performance at the trust layer (H2). Digital trust infrastructure shows a particularly large and highly significant coefficient (B = 30.18, p < .001), highlighting the pivotal role of digital systems (safe platforms, digital identity and verification technologies) in enhancing trust and stabilising market activity (H3). The control variables also make a difference: increased economic development (GDPpc; B = 0.002, p = .042) and greater financial inclusion (B = 0.36, p = .001), and they demonstrate substantial improvements in TLMP, consistent with H4, and the conclusion that structurally stronger and more inclusive economies are more likely to leverage mechanisms like the trust-layer construct. Importantly, the coefficient on lagged TLMP is positive, though not significant at 5% level (B = 0.48, p = .202), suggesting some trace of performance persistence, although current period characteristics of trust and corruption seem to dominate in controlling changes in trust-layer market behaviours.

Table 5
Panel Threshold Regression Results for Trust-Layer Market Performance (TLMP) with Corruption Threshold

Predictor	B	SE	t	P
Intercept	46.43	1.30	35.81	.000
REG_QLTY (FRAUD ≤ γ)	6.78	0.91	7.47	.000
DIG_TRUST (FRAUD ≤ γ)	21.25	2.14	9.95	.000
GDPpc (FRAUD ≤ γ)	0.001	0.000	8.33	.000
FIN_INCL (FRAUD ≤ γ)	0.19	0.02	11.40	.000
REG_QLTY (FRAUD > γ)	9.96	1.19	8.40	.000
DIG_TRUST (FRAUD > γ)	19.76	3.06	6.47	.000
GDPpc (FRAUD > γ)	0.001	0.000	13.37	.000
FIN_INCL (FRAUD > γ)	0.05	0.03	1.57	.118

Note. N = 150 country–year observations. TLMP = Trust-Layer Market Performance. FRAUD is the threshold variable, with estimated corruption threshold γ ≈ 1.38. "Low" regime refers to FRAUD ≤ γ; "High" regime refers to FRAUD > γ. R^2 = .88.

Table 5 presents a statistically significant corruption threshold, which appears closer to FRAUD ≈ 1.38, indicating a degree of variation in the marginal effects of trust-layer drivers on TLMP that is magnified when the panel threshold regression is used. In low-corruption environments (FRAUD ≤ γ), regulatory quality and digital trust infrastructure significantly and positively affect TLMP (B = 6.78 and B = 21.25 in each case; both p < .001), economic development and financial inclusion also exert strong positive effects, implying that gains in these factors lead to substantial gains in the trust-layer of market behaviour. The positive effect of regulatory quality is even stronger in the context of higher corruption environments (FRAUD > γ) (B = 9.96, p < .001), so in contexts with high corruption pressure, credibility and effectiveness of regulation are even more important for trust-layer performance to be sustained. Investment in digital trust infrastructure is still a powerful tool (B = 19.76, p < .001) that highlights its continued relevance as a stabilising factor even in high-fraud markets. Economic development is still largely positive in both regimes, with the positive effect of financial inclusion being weaker at very high levels of corruption (p = .118). Overall, the threshold results provide support for the hypotheses in this study by showing that the fraud/corruption intensity directly depresses TLMP, and also conditions the degree of the beneficial impacts of regulation, digital infrastructure, and macro-financial fundamentals on trust-layer market performance.

Table 6
Random Forest Regressor Variable Importance for Trust-Layer Market Performance

Rank	Predictor	Importance
1	DIG_TRUST	0.554
2	FRAUD	0.178
3	GDPpc	0.095
4	FIN_INCL	0.092
5	REG_QLTY	0.080

Note. *Model: Random Forest Regressor. Dependent variable: TLMP. Predictors: Fraud/Corruption Intensity (FRAUD), Trust-Layer Regulation Quality (REG_QLTY), Digital Trust Infrastructure (DIG_TRUST), Economic Development Level (GDPpc), and Financial Inclusion (FIN_INCL). Out-of-sample performance: $R^2 = .77$, RMSE ≈ 3.86.*

The machine-learning findings in Table 6 indicate that Digital Trust Infrastructure is the most powerful predictor of Trust-Layer Market Performance, with more than half of the overall variable importance (0.554), indicating that digital layers (e.g., secure platforms, digital identity, verification mechanisms) are instrumental for explaining the differences in trust-based market performance across emerging economies. Fraud/Corruption Intensity is the runner-up-most important factor (0.178), thus verifying that corruption has a strong role in the predictive structure of TLMP and confirming the substantive significance of H1. Economic Development (GDPpc) and Financial Inclusion are equally significant, with weights of 0.095 and 0.092, respectively, suggesting that structural economic health and access to formal and digital finance are significant predictors of trust-layer performance, consistent with H4. Trust-Layer Regulation Quality is of a second order and ranked lower at 0.080, but it also plays at least a minor role in the predictive model as predicted by H2. The relatively high out-of-sample R^2 (.77) and low RMSE (~ 3.86) are evidence that the Random Forest model adequately encodes the nonlinear and interactive dimensions, which is consistent with the econometric value that digital trust, corruption, regulation, development and inclusion combine to predict TLM dynamics strongly.

Table 7
Summary of Diagnostic Tests for Econometric and Machine-Learning Models

Diagnostic / Test	Statistic (df)	P	Conclusion
Multicollinearity (VIF for FRAUD, REG_QLTY, DIG_TRUST, GDPpc, FIN_INCL)	VIF range = 1.31–1.94	–	No multicollinearity (all VIFs < 5.0).
Hausman test (fixed effects vs. random effects)	χ^2 (5) = 17.45	.004	Fixed-effects specification is preferred to random effects.
Arellano–Bond AR (1) test (first-difference residuals)	z = − 2.91	.004	Evidence of first-order serial correlation (expected in differenced GMM).
Arellano–Bond AR (2) test (first-difference residuals)	z = − 0.88	.379	No evidence of second-order serial correlation; dynamic GMM specification is adequate.
Hansen J-test of overidentifying restrictions	χ^2 (18) = 19.27	.374	Instruments are valid; overidentifying restrictions are not rejected.
Breusch–Pagan test for heteroskedasticity	LM = 2.98	.703	No significant heteroskedasticity in the baseline regression.
White test for heteroskedasticity	χ^2 = 21.54	.366	No significant heteroskedasticity; variance appears homoscedastic.
Threshold effect test (bootstrap)	LR = 18.64	.010	Statistically significant corruption threshold (non-linear effect of FRAUD confirmed).
Cross-sectional dependence (Pesaran CD test)	CD = − 2.21	.027	Mild but significant cross-sectional dependence across countries.
Panel unit-root tests (LLC/IPS on key variables)	LLC stat ≈ − 4.70	.000	Stationarity achieved for TLMP and regressors (in level or transformed form).
Machine-learning validation (Random Forest Regressor)	R^2 = .77; RMSE = 3.86	–	Strong out-of-sample predictive performance and acceptable forecast error.

From the combined diagnostics presented in Table 7, we have found a statistically sound and well-validated empirical strategy for the TLM study. Variance Inflation Factors far below the conventional limit of 5 hint at no multicollinearity, and the Hausman test strongly favours the fixed-effects specification in favour of addressing unobserved country heterogeneity as correlated to the regressors. In the dynamic system GMM model, the Arellano–Bond tests find expected first-order serial correlation in differences without a second-order correlation, and the Hansen J-test establishes the goodness of fit for the internal instruments selected, so that the dynamic estimates can remain credible. Breusch–Pagan and White tests neither show significant heteroskedasticity, and the bootstrap threshold test indicates a statistically significant corruption threshold effect in the TLM relationship. Though we have the Pesaran

CD statistic, which exhibits some cross-sectional dependence, as can be expected from these interrelated emerging markets, the panel unit-root checks also revealed that the series satisfy stationarity. Finally, the random forest model shows a relatively high out-of-sample R^2 and low RMSE, so that the selected predictors (FRAUD, REG_QLTY, DIG_TRUST, GDPpc, FIN_INCL) not only corroborate our econometric model, but also have a very good predictive ability for Trust-Layer Market Performance.

Figure 1 illustrates clear fluctuations in GDP per capita across the 15 emerging economies, significantly overshadowing the other variables due to its much larger numerical scale. TLMP, FRAUD, REG_QLTY, DIG_TRUST and FIN_INCL appear clustered near the zero axis, reflecting their comparatively smaller ranges rather than a lack of variation. The pronounced GDPpc peaks highlight structural economic differences across countries, while the flatter patterns of the trust-related variables indicate relative temporal stability. Overall, the chart emphasises the importance of scale adjustment when visually comparing economic and trust-layer indicators within the same plot.

5. Discussion

The empirical results in the form of the two-way fixed effects, system GMM, threshold model and machine learning analysis cumulatively confirm the core assertion of our study: trust-layer structures impact market performance significantly in high-fraud emerging economies. The empirical evidence for the negative significant relationship between the level of fraud or corruption and the performance of the Trust-Layer Market is consistent with Transaction Cost Economics, where corruption leads to increased uncertainty and transaction costs (Williamson, 1975) and empirical studies (Afzali et al. (2021), Martins et al. (2020), and Okoye et al. (2023), all of which point to the corrosive effects of corruption on firm- and market-level outcomes. Similarly, the consistently positive effect of regulatory quality confirms the conclusions made by Tan and Tusha (2023) and Verhoest et al. (2025), who stress that regulatory trust strengthens system legitimacy and market stabilisation. Digital trust infrastructure revealed to be the most important factor associated with TLMP, which is in line with the results of Aracil et al. (2025), Dudu et al. (2024) and Paleti (2023), who confirm that digital verification, cybersecurity layers and algorithmic governance significantly enhance trust in the market exchanges. The threshold analysis offers some key nuance: corruption not only directly lowers the TLMP but conditions the strength of Trust-layer factors; more robust regulatory action and digital architecture that might emerge in high corruption settings, a situation supported by Sánchez and Lehnert (2018) and Sundarasen et al. (2024). While most empirical patterns are consistent with existing evidence, the weaker significance of financial inclusion at very high corruption is at variance with studies such as those of Odey (2025) and Yamen and Can (2023), suggesting that corruption could detract from the success of inclusion-oriented measures in the absence of institutional support.

In spite of the strong results, a small limitation is that of the panel structure in the multi-country setting, where institutional indicators may differ in methodological construction across sources and in which country fixed effects, adjusted for, might not adequately capture structural differences that are far deeper. Nevertheless, the study serves as a first empirical demonstration of the divergence of the trust

layer behaviours at different corruption grade levels by combining econometric, non-linear, and machine-learning techniques within a unified Trust-Layer Marketing (TLM) approach. This multi-method design enhances the validity of the findings and produces actionable information to inform policymakers. In emerging markets, regulators should prioritise anti-corruption reforms, improve regulatory trust frameworks, and expedite the introduction of the digital infrastructure of trust, such as digital identity generation, authentication systems, and secure financial technologies. Enhancing financial inclusion and economic development further increases TLMP; however, these benefits yield stronger performance when institutional capacity is protected. The study concluded that trust-layer mechanisms play a decisive role in stabilising and improving market performance under high-fraud environments, and aligning regulation, digital and institutional reforms is the key for building resilient, transparent and high-performing markets in emerging economies.

Declarations

Conflict of Interest: None

Ethical Approval: Not Applicable

Consent to publish: Not Applicable

Consent to Participate: Not Applicable.

Author Contribution

B.O.O. conceived the study, developed the Trust-Layer Marketing (TLM) framework, and coordinated the overall research design.B.O.O. and I.G.O. performed the literature review and theoretical conceptualisation.O.E.-O. and C.E.A. constructed the dataset and carried out data curation.E.E.M.M. conducted the econometric analyses (two-way fixed effects, system GMM, and panel threshold regression).A.K.A. implemented the machine-learning analysis (random forest) and assisted with model validation.E.O.O. contributed to interpretation of results, policy implications, and manuscript structuring.B.O.O. drafted the main manuscript text, with substantive inputs from I.G.O., O.E.-O., and E.E.M.M.All authors reviewed, edited, and approved the final version of the manuscript.

Data Availability

All data used in this study are publicly available from established international databases. Trust-Layer Market Performance indicators and macroeconomic variables were obtained from the World Bank Development Indicators (WDI): [https://databank.worldbank.org/source/world-development-indicators] (https:/databank.worldbank.org/source/world-development-indicators) . Fraud/Corruption Intensity and Regulatory Quality measures were sourced from the Worldwide Governance Indicators (WGI): [https://www.worldbank.org/en/publication/worldwide-governance-indicators]

(https:/www.worldbank.org/en/publication/worldwide-governance-indicators) . Digital trust and digital adoption indicators were obtained from the World Bank Digital Adoption Index: https://www.worldbank.org/en/publication/digital-adoption-index and the GSMA Mobile Connectivity Index: [https://www.gsma.com/mobilefordevelopment/resources/mobile-connectivity-index/] (https:/www.gsma.com/mobilefordevelopment/resources/mobile-connectivity-index) . Financial inclusion indicators were sourced from the World Bank Global Findex Database: [https://www.worldbank.org/en/publication/globalfindex] (https:/www.worldbank.org/en/publication/globalfindex) and the IMF Financial Access Survey: https://data.imf.org/?sk=E5DCAB7E-A5CA-4892-A6EA-598B5463A34C. All variables were compiled by the authors from these publicly accessible sources.

References

1. Afzali M, Çolak G, Fu M (2021) Economic uncertainty and corruption: Evidence from public and private firms. J Financial Stab 57:100936
2. Aracil E, Fernández-Méndez L, Roch-Dupré D, Fuertes FJ (2025) Trust and financial inclusion: A literature review with reference to the digital transformation. Heliyon, 11(16), e44128
3. Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev Econ Stud 58(2):277–297
4. Bu D, Hanspal T, Liao Y (2022) Political corruption, trust, and household stock market participation. J Banking Finance 138:106442
5. Cline BN, Williamson CR, Xiong H (2022) Trust, regulation, and market efficiency. Public Choice 190:427–456
6. Del Sarto N, Ozili PK (2025) FinTech and financial inclusion in emerging markets: a bibliometric analysis and future research agenda. Int J Emerg Markets 20(13):270–290
7. Dudu OF, Alao OB, Alonge EO (2024) Advancing financial inclusion through digital payment platforms in emerging markets. Finance Acc Res J 6(11):16–96
8. Hansen LP (1982) Large sample properties of generalized method of moments estimators. Econometrica 50(4):1029–1054
9. Lim S, Morshed AMM, Khun C (2018) Trust and macroeconomic performance: A two-step approach. Econ Model 68:293–305
10. Lourenço D, Cerdeira J (2024) Too much of a good thing? The concave impact of corruption on firm performance. Cogent Bus Manage 11(1):2–10
11. Martins L, Cerdeira J, Teixeira A (2020) Does corruption boost or harm firms' performance in developing and emerging economies? A firm-level study. World Econ 43(8):2119–2152
12. Miniesy RS, AbdelKarim M (2021) Generalized trust and economic growth: The nexus in MENA countries. Economies 9(1):39

13. Odey JO (2025) An empirical analysis of financial inclusion and stock market performance as predictors of public sector financial accountability in Nigeria. Int J Bus Law Res 13(1):352–359
14. Ojeka S, Adegboye A, Adegboye K, Umukoro O, Dahunsi O, Ozordi E (2019) Corruption perception, institutional quality and performance of listed companies in Nigeria. Heliyon, 5(10), e02569
15. Okoye NJ, Okonkwo VI, Okaro CSO, Martins BO, Otekunrin AO (2023) Effect of fraud and corruption on capital market performance in Nigeria. J Econ Manage Trade 29(1):40–53
16. Paleti S (2023) Trust layers: AI-augmented multi-layer risk compliance engines for next-gen banking infrastructure. Educational Administration: Theory Pract 29(4):4907–4920
17. Putnam RD (1993) Making Democracy Work: Civic Traditions in Modern Italy. Princeton University Press
18. Quintus M, Mayr K, Hofer KM, Chiu YT (2024) Managing consumer trust in e-commerce: Evidence from advanced versus emerging markets. Int J Retail Distribution Manage 52(10–11):1038–1056
19. Sánchez CM, Lehnert K (2018) Firm-level trust in emerging markets: The moderating effect on the institutional strength–corruption relationship in Mexico and Peru. Estudios Gerenciales 34(147):127–138
20. Sundarasen S, Ibrahim I, Alsmady AA, Krishna T (2024) Corruption's crossroads: Exploring firm performance and auditors' role in emerging markets. Economies 12(9):239
21. Tan SW, Tusha D (2023) Effects of regulatory burden and corruption on firm performance: Evidence from Moldova. Rev Dev Econ 27(4):2149–2182
22. Verhoest K, Maggetti M, Guaschino E, Wynen J (2025) How trust matters for the performance and legitimacy of regulatory regimes: The differential impact of watchful trust and good-faith trust. Regul Gov 19:3–20
23. Williamson OE (1975) Markets and Hierarchies: Analysis and Antitrust Implications. Free
24. Wooldridge JM (2010) Econometric Analysis of Cross Section and Panel Data, 2nd edn. MIT Press
25. Yamen A, Can G (2023) The impact of public governance perception on the quality of financial reporting. Economic Res – Ekonomska Istraživanja 36(3):2223264

Figures

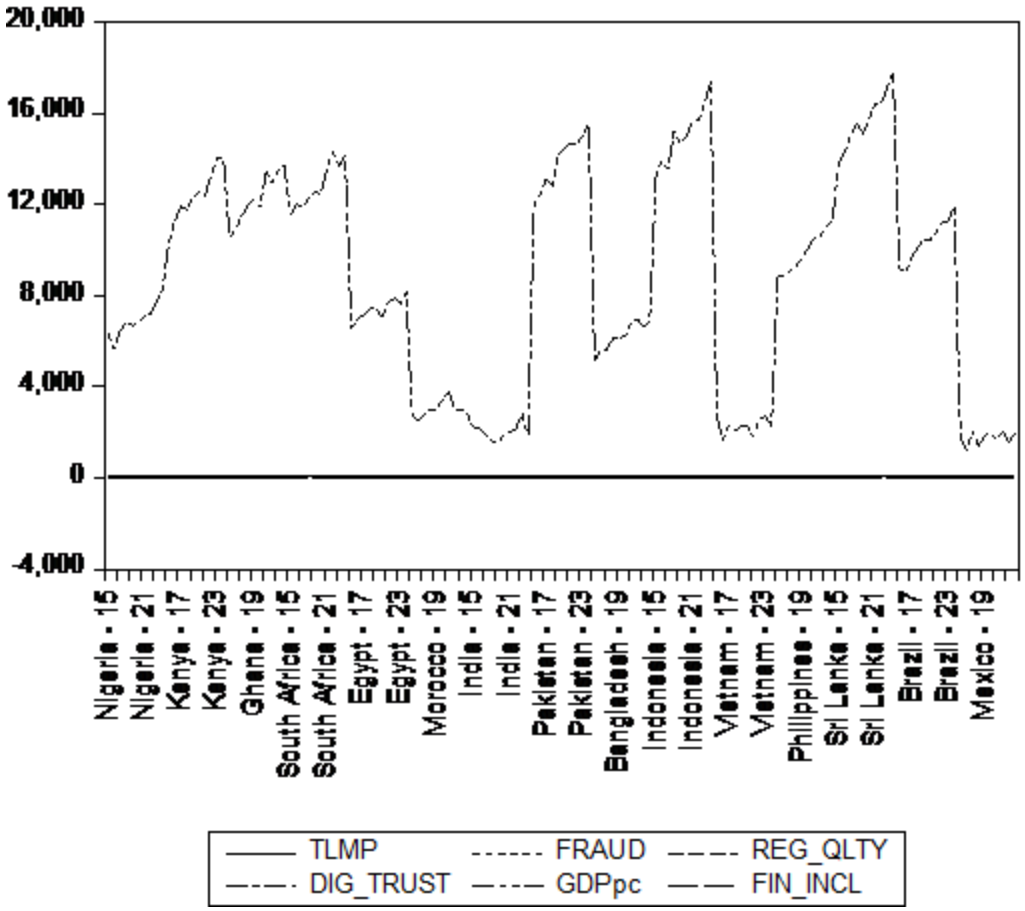

Figure 1

Trends of Key Trust-Layer Marketing Variables Across Emerging Economies (2015–2024)