



AI Disclosure, ESG Performance, and Tobin's Q in Southeast Asian Banking

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Abstract

Background: Banks increasingly disclose AI-related activities, but disclosure does not establish actual implementation or realized outcomes. Evidence remains limited regarding whether AI disclosure is associated with ESG performance and whether ESG performance subsequently has valuation relevance in Southeast Asian banking.

Objective: This study examines the associations among AI disclosure, ESG performance, and Tobin's Q.

Methods: A balanced panel of 1,230 bank-year observations covering 205 banking entities in 10 Southeast Asian countries from 2020 to 2025 was analyzed using bank and country-year fixed effects with bank-clustered standard errors. Robustness checks included lagged specifications, alternative variable definitions, ESG-pillar models, country exclusions, and cluster bootstrap analysis of the indirect association.

Results: AI disclosure was positively associated with contemporaneous ESG performance ($\beta = 0.0139$, $p = 0.006$; within $R^2 = 0.007$), with significant associations for social ($\beta = 0.0181$, $p = 0.004$) and governance ($\beta = 0.0096$, $p = 0.018$) performance. However, the disclosure–ESG association was not significant in lagged or one-year-ahead specifications. AI disclosure was not consistently associated with Tobin's Q, and the bootstrap confidence interval for the indirect association included zero.

Conclusion: AI disclosure is associated with ESG performance only contemporaneously and does not provide consistent evidence of valuation relevance through ESG. The findings support a cautious interpretation of AI disclosure as a potential signal and underscore the need for verifiable, outcome-linked reporting.

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INTRODUCTION

Artificial intelligence is no longer a peripheral topic in bank reporting (Abbas et al., 2026; Bouladasse et al., 2026). Annual and sustainability reports increasingly refer to machine learning, predictive analytics, automated credit assessment, conversational interfaces, fraud detection, and model governance. These disclosures matter because outsiders rarely see how deeply such systems are embedded in day-to-day banking operations. Managers can therefore use reporting to narrow information gaps and portray technology investment as a source of efficiency, resilience, or future competitiveness.

In Southeast Asia, this reporting incentive has grown alongside the policy debate on responsible AI. Both the ASEAN Guide on AI Governance and Ethics and the ASEAN Responsible AI Roadmap place transparency, accountability, security, and responsible deployment at the center of a trusted regional AI ecosystem (ASEAN, 2024, 2025). Recent evidence confirms this trend empirically. Onoja et al. (2026) document that AI-related disclosures have become increasingly prevalent in the annual reports of deposit money banks in Nigeria, while Lui (2026) observes growing AI reporting among Malaysian banks. In the broader Asian context, Long & Hao (2026) identify substantial cross-firm variation in AI disclosure intensity among Chinese listed firms, suggesting that disclosure practices differ considerably even within the same regulatory environment.

The important empirical distinction is between talking about AI and actually using it. Adoption concerns systems that are deployed and embedded in business processes, whereas disclosure concerns the account that management chooses to provide about those systems. An index based on corporate reports can show how extensively a bank communicates about AI, but it cannot reveal implementation depth, technical quality, financial materiality, or realized benefits without supporting operational evidence. Throughout this manuscript, the term “AI disclosure” refers exclusively to the extent of AI-related information communicated in corporate reports, whereas “AI adoption” and “AI implementation” denote the actual deployment of AI systems in business processes. This terminological distinction is maintained consistently to avoid conceptual conflation. Recent banking studies make this distinction explicit (Onoja et al., 2026). Work on AI washing and talk-action gaps goes further: sophisticated technological language may invite skepticism when observable commitments and outcomes do not follow (Long & Hao, 2026; X. Song et al., 2026).

This is where signaling theory becomes useful. Signals matter when receivers believe they reveal an underlying attribute that would be costly or difficult for a lower-quality sender to imitate (Spence, 1978). Later work in management shows that observability alone is not enough; credibility also depends on cost, consistency, fit, and the way receivers interpret the message (Connelly et al., 2011). The credibility of AI disclosure as a signal depends on several conditions. First, substantive AI reporting requires technical specificity—such as details concerning system purposes, governance structures, validation procedures, and performance metrics—that may be costly for institutions without genuine AI capabilities to produce convincingly (Huang, 2022). Second, verifiable disclosure creates reputational risk for banks whose claimed capabilities are subsequently found to be exaggerated, potentially functioning as a bonding mechanism that distinguishes substantive from symbolic communication. Third, consistency between AI disclosure and independently observable outcomes, such as ESG performance improvements, provides an additional credibility check. AI disclosure may indicate innovation readiness, but investors have no reason to value every mention of AI equally. They may instead look for evidence that the claimed technological orientation is reflected in ESG performance, risk discipline, cost efficiency, or profitability. From a signaling perspective, AI disclosure may function as a credible signal when it is costly to produce, difficult for lower-quality institutions to imitate, and observable to market participants (Connelly et al., 2011). In the banking context, AI disclosure becomes economically meaningful when it reflects genuine organizational investment in technology that subsequently manifests in measurable ESG outcomes—such as enhanced social inclusion through AI-driven financial access or improved governance through automated compliance monitoring. ESG performance thus serves as an organizational translation of the AI signal, converting a disclosed technological orientation into verifiable sustainability outcomes. If investors recognize this translation, ESG should function as a transmission channel linking AI disclosure to market valuation. This three-stage mechanism—signal production, organizational translation, and market recognition—provides the theoretical foundation for the hypothesized pathway.

ESG performance offers one possible test of that translation. AI can be used to monitor energy consumption, widen access to financial services, and strengthen fraud detection, compliance, and model oversight. Much of the empirical literature reports a positive association between AI-related capabilities and corporate ESG performance. Yet most of that evidence comes from China and relies on policy shocks, patents, adoption measures, or text-based proxies that are not equivalent to disclosure intensity (Liu et al., 2025; Song et al., 2025; Zhang & Yang, 2024).

Salem et al. (2026) and Yang and Yang (2025) studying ASEAN-5 banks, find that AI adoption mediates the relationship between ESG activity and risk-taking. The proposed direction—from AI disclosure to ESG performance—rests on the premise that a disclosed AI orientation reflects an organizational strategic commitment that subsequently materializes in sustainability outcomes. Banks that publicly commit to AI-driven initiatives in social inclusion, risk management, and governance transparency create accountability expectations that may accelerate the integration of these technologies into ESG-relevant operations. This mechanism differs from prior AI-adoption-ESG studies in that it emphasizes the informational and strategic role of disclosure itself, rather than the direct operational effects of AI deployment. The reverse sequence considered here—AI disclosure, then ESG, then market value—has received much less direct scrutiny.

The final market response is far from settled. Onoja et al. (2026) find that some dimensions of AI disclosure improve profitability and Tobin's Q among Nigerian banks, while Lui (2026) reports positive associations with profitability and efficiency in Malaysia. These studies show that AI communication can carry economic information; they do not establish that markets price it uniformly. Sustainability information faces the same problem. Investor reactions to entry into a global sustainability index can be limited Hawn et al. (2018), reports no significant relationship between ESG scores and abnormal returns in ASEAN-5 markets. ESG performance is expected to function as a transmission mechanism—rather than merely a correlated outcome—because it represents a tangible organizational manifestation of the capabilities that AI disclosure signals. While disclosure itself may be perceived as cheap talk, improved ESG performance provides independently verifiable evidence that the claimed technological orientation has produced real operational consequences. Investors who observe this organizational translation may then incorporate it into their valuation assessments, creating the hypothesized indirect pathway from AI disclosure through ESG to Tobin's Q (Zhou et al., 2022). Disagreement among ESG ratings, arising from differences in scope, measures, and weights, adds another layer of uncertainty for investors (Berg et al., 2022).

Against that background, the paper focuses on a translation gap. Does greater AI disclosure coincide with stronger ESG performance? Does it relate to Tobin's Q? And, more demanding still, does ESG carry the AI signal into market valuation? The evidence comes from a reconstructed balanced panel of 1,230 observations for 205 banking entities in Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam between 2020 and 2025. The panel structure accounts for bank-level heterogeneity and country-year conditions through appropriate fixed-effects specifications, as detailed in the Methods section. The principal gap addressed here is therefore theoretical and relational: whether AI disclosure, as a signal of technological orientation, translates into observable ESG outcomes and whether those outcomes subsequently carry valuation relevance for market participants.

Three aspects of the analysis are intended to move the discussion forward. The first is conceptual discipline: the explanatory variable is treated as AI disclosure, not as proof of AI adoption. The second is a more granular signaling argument. A bank may produce a signal, fail to translate it into durable organizational outcomes, or fail to persuade market participants even when such outcomes are visible. The third is contextual scope. The Southeast Asian panel is examined through lagged models, alternative variable definitions, separate ESG pillars, country-exclusion tests, and a cluster-bootstrap analysis of the indirect association.

The study contributes to the growing literature on AI governance in banking by providing the first multi-country panel evidence on whether AI disclosure produces a signal that is organizationally substantive and market-relevant in the Southeast Asian context.

METHOD

The analysis followed a quantitative longitudinal panel design. The research dataset contains separate country sheets and a consolidated sheet named DATA ALL, which records 1,230 complete bank-year observations for 205 named banking entities across 10 Southeast Asian countries from 2020 to 2025. Each entity appears once in each year, producing a balanced six-year panel with no duplicate entity-year records. The reconstructed sample therefore consists of observations with complete data for all study variables throughout the observation period. Because the available dataset does not fully document the original population, sampling frame, or

complete inclusion and exclusion process, the sample is treated as the complete-data panel available for analysis rather than as a statistically representative sample of all banking institutions in Southeast Asia.

The original study identifies Refinitiv/LSEG, annual reports, sustainability reports, and author-coded AI disclosure as data sources. Reconstruction was confined to the values available in the research dataset: no observations were added, reported values altered, or missing values imputed. The dataset includes heterogeneous banking-related entities, while listing status and digital-bank classification are not independently documented in the available file. Accordingly, the manuscript uses the term “Southeast Asian banking entities” and treats institutional heterogeneity as a limitation. The reported country-exclusion tests assess whether the aggregate findings are sensitive to omitting individual countries; they should not be interpreted as direct validation of entity classification.

As Table 1 shows, Indonesia contributes 30 entities and 180 observations, Brunei Darussalam contributes 17 entities and 102 observations, and the remaining countries contribute 19 or 20 entities each. The coverage is geographically broad but should not be interpreted as statistically representative of every national banking system. Because the available dataset does not document the reason for the different country counts, the uneven distribution is treated as a limitation of external validity. Country-exclusion tests are used to assess whether the aggregate findings are sensitive to the inclusion of any single country.

Table 1

Sample distribution by country

Country	Banking entities	Observations
Brunei Darussalam	17	102
Cambodia	20	120
Indonesia	30	180
Laos	20	120
Malaysia	20	120
Myanmar	19	114
Philippines	19	114
Singapore	20	120
Thailand	20	120
Vietnam	20	120
Total	205	1,230

Variable measurement

AI disclosure

The AI Disclosure Index ranges from 0.01 to 1.00. According to the original study, the measure was coded from annual and sustainability reports and captures AI-related disclosure concerning applications such as machine learning, customer service, credit scoring, and fraud detection. However, the available research file does not contain the underlying checklist, item-level scores, source-page references, complete coding rules, or inter-coder reliability evidence. Therefore, the analysis treats the index as an existing measure of AI-related disclosure intensity and does not reinterpret it as evidence of AI adoption, implementation depth, expenditure, or technological maturity. This limitation should be considered when interpreting the reproducibility and measurement validity of the AI Disclosure Index.

ESG performance

Environmental, social, and governance pillar scores are recorded on a 0–1 scale, and their unweighted arithmetic mean is used as the primary composite. The supplied aggregate ESG field contains 60 Malaysian observations above 1, reaching 58.4, whereas almost all other records use a 0–1 scale. Because the available research file does not independently document the source of this unit inconsistency, the transparent pillar composite is used as the primary measure. As a robustness check, values above 1 in the original aggregate are divided by 100; the resulting normalized measure correlates strongly with the pillar composite ($r = 0.875$). Pillar-specific

regressions are also reported to show whether the aggregate association is concentrated in a particular ESG dimension.

Market valuation

The Tobin's Q field is taken directly from the research dataset. The primary level measure is winsorized at the 1st and 99th percentiles, while raw Q and log Q are used as alternative outcomes. An audit using the stated Chung & Pruitt (1994) approximation, (market capitalization + total liabilities) / total assets, reproduces the supplied Q for only 53.3% of observations. Accordingly, Tobin's Q remains only partially reconciled, and the valuation results should be interpreted cautiously. Winsorization and logarithmic transformation assess sensitivity to extreme values and functional form but do not resolve the underlying measurement discrepancy. Complete validation would require traceable fiscal-year market capitalization, liabilities, and total assets for all observations.

Control variables

Bank size is the natural logarithm of total assets, and leverage is total liabilities divided by total assets. Both variables are winsorized at the 1st and 99th percentiles. Fixed effects absorb stable differences in reporting currency and scale. Price-to-book value is omitted because, as another valuation measure, it overlaps conceptually with Tobin's Q. The NPL and ROA fields are also omitted: unresolved unit inconsistencies produce implausible maxima. Excluding them is preferable to allowing unreliable controls to shape the estimates. Bank size (log total assets) was included because larger banks typically have greater resources for both AI development and ESG reporting, creating a potential confounding pathway. Leverage was included because capital structure influences both strategic technology investment and market valuation, making it a necessary control in models examining AI disclosure-valuation relationships. The omission of ROA and NPL, while potentially introducing omitted-variable bias from uncontrolled profitability and asset-quality effects, was necessitated by the unresolved measurement inconsistencies that would have introduced greater bias through unreliable control variables.

Econometric specification

The primary ESG equation is:

$$ESG_{it} = \beta_1 AI_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + bank_i + country-year_{ct} + error_{it}.$$

The valuation equation is:

$$Q_{it} = \gamma_1 AI_{it} + \gamma_2 ESG_{it} + \gamma_3 Size_{it} + \gamma_4 Leverage_{it} + bank_i + country-year_{ct} + error_{it}.$$

Bank fixed effects account for persistent differences in business model, ownership, organizational culture, and disclosure style. Country-year fixed effects absorb macroeconomic, market, regulatory, and institutional shocks shared by entities in a given country and year. Identification therefore comes from changes within a bank after those common country-year movements are removed. Variance decomposition confirms that sufficient within-bank variation exists for fixed-effects identification. For AI disclosure, the between-bank standard deviation is 0.198 and the within-bank standard deviation is 0.132, indicating that approximately 31% of total variance occurs within banks over time. For the ESG composite, within-bank variation accounts for approximately 22% of total variance (between SD = 0.112, within SD = 0.064). Although the between-bank component dominates, the within-bank variation is sufficient to support meaningful fixed-effects estimation over the six-year panel. Standard errors are clustered by bank to allow for heteroskedasticity and serial dependence within entities (Colin Cameron & Miller, 2015). For a short-balanced panel, this is more defensible than treating repeated observations of the same bank as independent (Wooldridge, 2002).

Sensitivity was examined in several ways. The valuation analysis first estimates the total association between disclosure and Tobin's Q, then adds ESG to estimate the direct association. Further models lag disclosure by one year, relate disclosure in year t to ESG and valuation in t+1, substitute raw and logged Q for winsorized level Q, and replace the pillar composite with the normalized original ESG score. The three ESG pillars are also modeled separately, and each country is excluded in turn. Finally, the indirect association is defined as the product of the lagged

disclosure-to-ESG path and the ESG-to-Q path. Its uncertainty was evaluated using 1,000 bank-cluster bootstrap resamples, preserving the bank-level sampling structure and avoiding the normality assumption of a Sobel test (Preacher & Hayes, 2008).

These specifications estimated conditional associations. Fixed effects address time-invariant omitted characteristics, but not reverse causality, time-varying confounding, or measurement error. Lags improve temporal ordering; they do not convert the design into a causal one.

Research integrity and reproducibility boundary

Reconstruction changed the scope of the sample and the econometric specification, but it did not manufacture new observations. The original workbook was left untouched. Rescaling, composite construction, logarithmic transformation, and winsorization were carried out only in the analysis layer and are described above. No undocumented instrument, coding-reliability statistic, or additional source is assumed to exist. Equally, unresolved questions about entity identity, listing status, the disclosure instrument, and the traceability of Tobin's Q are stated openly rather than hidden behind the re-estimation.

RESULTS AND DISCUSSION

Results

Descriptive statistics

Table 2 provides the descriptive statistics. AI disclosure averages 0.575 and varies considerably across banks and years. The mean ESG composite is 0.651; among the pillars, social records the highest mean (0.684), followed by governance (0.667) and environmental performance (0.601). Tobin's Q is strongly right-skewed. Its raw mean is 2.216, compared with a median of 1.206 and a maximum of 14.588. Winsorization retains every observation while reducing the range to 0.180-9.156.

Variance decomposition reveals that for AI disclosure, the between-bank standard deviation (0.198) exceeds the within-bank standard deviation (0.132), indicating that most variation is cross-sectional. For Tobin's Q (winsorized), the between-bank SD is 1.874 and the within-bank SD is 1.082. These decompositions confirm that while cross-bank differences dominate, meaningful temporal variation exists within banks to support the fixed-effects identification strategy.

Table 2

Descriptive statistics

Variable	Mean	SD	Minimum	Median	Maximum
AI Disclosure Index	0.575	0.238	0.010	0.607	1.000
ESG composite	0.651	0.128	0.272	0.667	0.920
Environmental score	0.601	0.141	0.108	0.610	0.900
Social score	0.684	0.114	0.133	0.690	0.920
Governance score	0.667	0.166	0.108	0.700	0.950
Tobin's Q, raw	2.216	2.235	0.001	1.206	14.588
Tobin's Q, winsorized	2.195	2.143	0.180	1.206	9.156
Log total assets, winsorized	15.140	3.186	6.222	15.909	19.932
Leverage, winsorized	0.693	0.190	0.011	0.715	0.962

In the pooled data, AI disclosure correlates 0.502 with ESG. Its correlation with winsorized Tobin's Q is 0.144, while ESG correlates 0.210 with Q. These figures mix differences between banks with changes within banks, so they are descriptive rather than tests of the hypotheses. This contrast between the pooled correlation ($r = 0.502$) and the small fixed-effects coefficient (within $R^2 = 0.007$) is informative. It indicates that the observed disclosure-ESG relationship is predominantly cross-sectional, driven by persistent differences between banks that disclose extensively and those that do not, rather than by changes occurring within individual banks over time. The fixed-effects estimates thus provide a more conservative but methodologically appropriate assessment of the within-bank association. The fixed-effects estimates provide the

more relevant evidence.

Primary fixed-effects results

The main estimates appear in Table 3. In Model 1, greater AI disclosure is associated with a higher ESG composite (beta = 0.0139, SE = 0.0050, $p = 0.006$). Moving across the full 0-1 disclosure range corresponds to an increase of 0.0139 in the 0-1 ESG composite. This is a modest relationship, and the within R-squared is only 0.007. The very limited within R^2 warrants explicit interpretation. It indicates that AI disclosure explains a negligible share of the within-bank variation in ESG performance, meaning that other time-varying factors not captured by the model—such as regulatory changes, management turnover, strategic reorientation, or external ESG rating methodology shifts—account for the vast majority of ESG variation within banks. AI disclosure should therefore not be characterized as an important determinant of ESG performance; the statistical significance reflects the precision afforded by the large panel rather than strong explanatory relevance. The 95% confidence interval for this coefficient is [0.0041, 0.0237], confirming that while statistically distinguishable from zero, the upper bound implies a maximum plausible effect of approximately 2.4 percentage points across the full disclosure range. H1 is therefore supported only in the contemporaneous specification and should not be interpreted as evidence of a strong or temporally persistent relationship.

Model 2 excludes ESG and estimates the total association with Tobin's Q. The AI coefficient is positive but imprecise (beta = 0.1158, SE = 0.2803, $p = 0.680$). Adding ESG in Model 3 leaves the disclosure coefficient nonsignificant (beta = 0.1549, SE = 0.2783, $p = 0.578$); ESG is also nonsignificant (beta = -2.8120, SE = 1.8855, $p = 0.137$). The primary valuation models thus do not support H2. Leverage is positively related to Q in both specifications, but that coefficient is not given a substantive interpretation while the valuation field remains unreconciled.

Table 3

Fixed-effects estimates

Predictor	Model 1: ESG composite	Model 2: Tobin's Q, total	Model 3: Tobin's Q, with ESG
AI disclosure	0.0139*** (0.0050)	0.1158 (0.2803)	0.1549 (0.2783)
ESG composite	--	--	-2.8120 (1.8855)
Log assets	-0.0007 (0.0020)	-0.2266 (0.1759)	-0.2285 (0.1751)
Leverage	-0.0046 (0.0071)	1.3345*** (0.3637)	1.3215*** (0.3637)
Observations	1,230	1,230	1,230
Banks	205	205	205
Within R-squared	0.0070	0.0405	0.0443

*Notes: Bank and country-year fixed effects are included. Bank-clustered standard errors are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.*

Temporal, pillar, and robustness results

Once time is introduced, the contemporaneous ESG result becomes less persuasive. Lagged AI disclosure has a small, nonsignificant association with ESG (beta = 0.0021, $p = 0.403$), and the estimate is similar when disclosure in year t is related to ESG in $t+1$ (beta = 0.0020, $p = 0.422$). The data therefore do not show that increased disclosure reliably comes before improved ESG performance.

The level-Q results are more stable. Neither lagged disclosure (beta = 0.2487, $p = 0.344$) nor the one-year-ahead specification (beta = 0.2736, $p = 0.338$) is significant. Using raw Q yields beta = 0.1765 ($p = 0.534$), and the contemporaneous log-Q coefficient is -0.0135 ($p = 0.925$). There is one notable exception: lagged disclosure is positively associated with log Q (beta = 0.2468, $p = 0.036$). Yet the corresponding one-year-ahead log-Q estimate is weaker and misses the 5% threshold (beta = 0.2785, $p = 0.082$). Taken together, these models indicate inconsistent valuation evidence, not an association that is literally zero under every specification.

The alternative, normalized aggregate ESG measure produces a positive AI coefficient (beta = 0.0140, $p < 0.001$). The contemporaneous ESG estimate also remains positive and significant when countries are omitted one at a time. In contrast, the disclosure coefficient in the

primary Q equation is nonsignificant in every country-exclusion test, with all p-values above 0.30. Thus, no single country accounts for either the broad contemporaneous disclosure-ESG pattern or the absence of a stable market association.

The pillar estimates provide qualified support for H1a. Disclosure is positively associated with social performance ($\beta = 0.0181$, $p = 0.004$) and governance performance ($\beta = 0.0096$, $p = 0.018$). The environmental coefficient is positive but narrowly misses the conventional 5% threshold ($\beta = 0.0140$, $p = 0.0501$). These coefficients should not be ranked because no formal cross-equation equality test was conducted. The defensible conclusion is narrower: the contemporaneous aggregate result is clearest in the social and governance equations.

Table 4

Temporal, alternative-outcome, and pillar results

Test	AI coefficient	p-value	Interpretation
ESG, AI lagged one year	0.0021	0.403	No temporal association
ESG in $t+1$, AI in t	0.0020	0.422	No sequential association
Tobin's Q, lagged AI	0.2487	0.344	Nonsignificant
Tobin's Q in $t+1$	0.2736	0.338	Nonsignificant
Raw Tobin's Q	0.1765	0.534	Nonsignificant
Log Tobin's Q, contemporaneous	-0.0135	0.925	Nonsignificant
Log Tobin's Q, lagged AI	0.2468	0.036	Significant exception
Log Tobin's Q in $t+1$	0.2785	0.082	Weak, not significant at 5%
Environmental pillar	0.0140	0.050	Borderline
Social pillar	0.0181	0.004	Positive and significant
Governance pillar	0.0096	0.018	Positive and significant

Indirect association through ESG

The indirect-association analysis uses 1,025 observations because the first year for each bank is lost when disclosure is lagged. The lagged disclosure-to-ESG path is not significant ($\beta = 0.0021$, $p = 0.403$). ESG is likewise nonsignificant in the valuation equation that includes lagged disclosure and the controls ($\beta = -2.5689$, $p = 0.111$). Multiplying the two coefficients gives an indirect estimate of -0.0055. Its 95% percentile interval across 1,000 bank-cluster bootstrap resamples is [-0.0292, 0.0112]. Because the interval spans zero, H3 is not supported.

This approach improves on the original study's normal-theory Sobel test by preserving the bank-level sampling structure and allowing the indirect effect to have a nonnormal distribution. It remains, however, an associational exercise. A null indirect estimate may reflect the absence of the proposed mechanism, error in the disclosure or ESG measures, a poorly matched annual interval, or the limitations of applying Tobin's Q across all entities in this panel.

The null indirect-association result should also be interpreted in the context of unresolved measurement uncertainties. If the AI Disclosure Index contains substantial measurement error, the first-stage coefficient would be attenuated toward zero, mechanically weakening the indirect-effect estimate. Similarly, if Tobin's Q is measured with error for a substantial share of observations, the second-stage coefficient would be less precisely estimated. The null result may therefore reflect either the genuine absence of the proposed transmission mechanism or the combined effect of measurement limitations in the principal variables.

Discussion

From disclosure to ESG: visible association but weak temporal evidence

The contemporaneous estimates are consistent with the idea that banks which disclose more about AI also report stronger ESG performance. That result broadly resembles studies connecting AI capability with sustainability outcomes Song et al. (2025), although the present measure captures disclosure rather than capability. Social and governance performance provide the clearest associations. This is credible in a banking setting: customer-facing automation, accessibility, service responsiveness, transaction monitoring, fraud detection, and compliance

analytics map readily onto those two reporting domains. Environmental consequences are likely to be slower and more indirect, involving energy use, climate data, financed emissions, and portfolio choices.

There are good reasons not to read too much into the positive coefficient. It is small, the within-model fit is low, and neither the lagged nor the sequential estimate is significant. One explanation is mundane but important: AI and ESG passages may be produced by the same reporting function in the same reporting cycle. A bank that documents one topic extensively may document the other extensively as well. Reverse ordering is also possible; stronger ESG governance may make a bank more willing and better equipped to discuss AI. Finally, an annual lag may simply be the wrong interval if technological change reaches ESG outcomes within a few months or only after several years.

For signaling theory, the timing problem is consequential. Two reported constructs moving together in the same year does not show that a technological signal has become substantive sustainability performance. Credibility requires persistence and corroboration by outcomes that are harder to imitate than narrative disclosure. The evidence supports the more modest conclusion that AI disclosure and ESG performance move together contemporaneously after fixed effects; it does not show that disclosure precedes ESG improvement.

Why the signal does not consistently reach market valuation

The more revealing result is the break between what the organization reports and what the market appears to value. AI disclosure is not significantly associated with level Tobin's Q in the total, direct, lagged, raw-Q, or one-year-ahead models. ESG is also nonsignificant in the valuation equations, and the bootstrapped indirect estimate crosses zero. In short, the contemporaneous disclosure-ESG association does not translate into a consistent valuation premium.

This differs from the Nigerian evidence of value-relevant AI disclosure dimensions and the Malaysian evidence on profitability and cost efficiency (Lui, 2026). The difference is informative rather than necessarily contradictory. Profitability and efficiency are accounting or operating outcomes; Tobin's Q depends on investors noticing, believing, and pricing the information. Operational improvement can accompany disclosure without producing a market premium, particularly when materiality and credibility are hard to judge.

The pattern is closer to research showing that sustainability information is not priced uniformly. Investors can respond weakly to sustainability-index events Hawn et al. (2018), and ESG scores have not generated significant abnormal-return responses in ASEAN-5 evidence (Danila, 2026). Attention, reporting comparability, market development, regulation, and investment horizon may all shape reception. Those conditions vary sharply across the ten countries represented here. Country-year fixed effects absorb common shocks, but they cannot make an AI statement equally informative across very different institutions.

The significant lagged log-Q estimate deserves explicit attention. Logging Q reduces the influence of the right tail, and under that transformation the positive association emerges. It is absent, however, from the primary level-Q model, the total-association model, and the sequential log-Q specification at the 5% level. The fairest reading is that the valuation result is sensitive to specification. Accordingly, "fails" in the title describes the predominant and theoretically central evidence; it should not be read as a claim of a universal null.

ESG does not operate as the proposed transmission channel

For ESG to operate as the proposed channel, disclosure must precede ESG and ESG must carry valuation-relevant information. Neither requirement is met robustly. Lagged disclosure does not predict ESG, ESG does not predict Q in the indirect-effect equation, and the bootstrap interval includes zero. On this evidence, ESG cannot be presented as the mechanism through which AI disclosure creates market value.

The nonfinding helps distinguish a signal's content from its validation. ESG may seem to confirm a responsible technological orientation, yet an aggregate rating can be too broad, slow moving, or method-dependent to provide a credible bridge. Berg et al. (2022) document how different choices of scope, measurement, and weighting produce disagreement among ESG ratings. The unit inconsistency discovered in the supplied aggregate field offers a smaller but

concrete illustration of the same problem. Although the reconstructed composite and normalized aggregate yield similar contemporaneous estimates, neither produces a stable route to valuation.

Comparison with Salem et al. (2026) clarifies the boundary rather than resolving it. Their ASEAN-5 model starts from ESG activity, treats AI adoption as a mediating capability, and explains bank risk-taking. This paper starts from AI disclosure and asks whether ESG connects that disclosure to market value. Different constructs, directions, and outcomes make the models noninterchangeable. One implication is that AI may matter more as an operational capability supporting risk discipline than as a narrative expected to command a valuation premium.

Theoretical contribution

The first theoretical contribution is to unpack signaling into three stages. Management produces an AI disclosure; the organization may or may not convert the underlying capability into ESG outcomes; and market participants decide whether those outcomes merit a valuation response. Treating disclosure as adoption collapses these stages and assumes away the central empirical problem. The estimates show why that separation is necessary.

A second contribution concerns the evidence required for credibility. General AI language is relatively easy to imitate. More discriminating disclosure would report items that can be checked: investment, accountable governance roles, model inventories, performance measures, assurance, incidents, energy use, bias testing, and customer or risk outcomes. A quantity-oriented index may capture how visible AI is in a report while missing whether the claims are costly, specific, and credible. The absence of a stable valuation association is consistent with that distinction.

The regional setting adds a third qualification. Southeast Asian banking is digitizing rapidly, but institutional arrangements and AI and ESG governance remain heterogeneous. ASEAN guidance has established a shared direction for responsible AI without yet creating fully comparable bank-level reporting. Receiver interpretation is therefore likely to remain fragmented. When investors cannot compare the cost, content, and outcomes of AI initiatives, even frequent disclosure may fail to earn a stable premium.

Managerial and policy implications

For bank managers, the practical lesson is not to publish more AI sentences but to make the material ones testable. Each use case should be linked to an accountable owner, deployment stage, control framework, material risk, investment, and measurable outcome. A credit-scoring disclosure, for instance, could explain monitoring, fairness tests, human oversight, customer recourse, and portfolio implications. Reporting on fraud detection could address coverage, false positives, confirmed loss reduction, and escalation governance where legal and commercial constraints permit. Such detail is harder to imitate and gives readers a basis for judging credibility.

Sustainability teams should also avoid treating AI as a separate innovation narrative. The contemporaneous social and governance results suggest that the two reporting streams are already connected. Credible reporting would discuss adverse effects as carefully as benefits, including energy consumption, privacy, algorithmic bias, workforce transition, and model risk. A balanced account is more informative than uniformly promotional language.

Regulators and standard setters can improve comparability by distinguishing AI adoption, governance, risk, and outcomes within a structured reporting framework. The ASEAN Guide on AI Governance and Ethics offers a regional starting point. A banking template could add fields for system purpose, materiality, oversight, validation, third-party dependence, customer impact, incident management, and performance metrics. Standardization need not expose sensitive model details; its purpose would be to help users separate substantive implementation from AI washing. It is important to note that the empirical design measures disclosure quantity rather than signal quality, credibility, or investor perception. The signaling interpretation—that investors may discount AI disclosures perceived as inexpensive or easily imitable—is therefore offered as a theoretical explanation consistent with the observed pattern of results, rather than as an empirically demonstrated mechanism. Future research should directly operationalize signal credibility, verifiability, and specificity to test this interpretation.

The findings suggest that AI terminology in corporate reports, by itself, does not appear to constitute sufficient evidence of value creation from an investor perspective. Narrative claims are

more useful when compared with technology spending, senior oversight, workforce capability, operating efficiency, asset quality, customer outcomes, incidents, and ESG results. The specification-sensitive Q estimates make that need for corroboration especially clear.

CONCLUSION

This paper examined whether AI disclosure is associated with ESG performance and Tobin's Q using a reconstructed six-year panel of 1,230 observations for 205 banking entities across 10 Southeast Asian countries. The empirical strategy combined bank and country-year fixed effects with bank-clustered standard errors and subjected the main estimates to a series of robustness checks, including lagged specifications, sequential models, alternative outcome measures, pillar-level regressions, country exclusions, and a cluster-bootstrap analysis of the indirect association.

A clear but limited pattern emerges. Banks with greater AI disclosure also exhibit higher contemporaneous ESG composite scores, particularly in the social and governance pillars. However, this relationship does not survive a one-year lag and does not predict next-year ESG performance. Nor does AI disclosure show a stable association with the level of Tobin's Q across the primary, total, lagged, raw-Q, and sequential models. ESG performance does not appear to transmit the relationship into firm valuation. Although the positive coefficient on lagged log Tobin's Q prevents a blanket null conclusion, a single specification is insufficient to support the stronger claim that AI disclosure enhances firm value.

The theoretical implication is that AI disclosure should be viewed only as a potential signal. Its market value depends on whether the claimed capability produces observable organizational outcomes and whether market participants perceive those outcomes as credible. Visibility, translation, and reception are distinct empirical questions. Conflating them would turn "the bank discusses AI" into the unsupported assertion that "the bank has implemented valuable AI."

The same distinction guides practice. Banks should replace generic AI narratives with reporting tied to measurable outcomes and relevant controls. Regulators can make such disclosures easier to compare across institutions. Investors should assess AI claims against operational and sustainability evidence rather than relying on disclosure frequency or keyword counts alone.

The evidence also has important limitations. The workbook does not document the AI-index checklist, source pages, coding reliability, listing status, or digital-bank classification, and its entity labels cover a heterogeneous set of banking and related institutions. The reported Tobin's Q cannot be reproduced from the stated components for 46.7% of observations, while several other financial ratios have unresolved unit inconsistencies. Fixed effects cannot eliminate reverse causality or time-varying confounding. Ongoing verification of sample identities, market and accounting units, disclosure-coding procedures, and Tobin's Q calculations is therefore a priority for strengthening the empirical foundation of these findings. Future research could then compare substantive AI deployment with AI disclosure, examine market reactions to material AI announcements, or develop text-based measures that distinguish credible reporting from promotional language.

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