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FINTECH DISCLOSURE PRACTICES OF NON-BANK FINANCIAL INSTITUTIONS IN BANGLADESH: DETERMINANTS AND PERFORMANCE IMPLICATIONS

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***Abstract*—**This study examines the extent and drivers of FinTech (digital) disclosure among all 23 non-bank financial institutions (NBFIs) listed on the Dhaka Stock Exchange (DSE), the full population of listed NBFIs in Bangladesh, over 2021–2025, and tests whether disclosure intensity is associated with financial performance. A seven-item FinTech Disclosure Index (FDI) was built through content analysis of annual reports and analyzed as an unbalanced panel of 105–115 firm-year observations using pooled ordinary least squares (OLS) with firm-clustered standard errors, complemented by firm fixed-effects and one-year-lagged specifications. Mean FDI rose from 35.4% in 2021 to 50.6% in 2024, driven largely by infrastructure and cybersecurity disclosures, while disclosure of a proprietary digital product remained limited (25.7% of firm-years). Disclosure intensity is positively and significantly related to firm age ($\beta = 0.176$, $p = .002$) but not to firm size ($\beta = 0.106$, $p = .423$). FDI is positively associated with return on equity (ROE) after winsorizing outliers ($\beta = 5.95$, $p = .048$); the association persists with firm fixed effects ($\beta = 5.60$, $p = .063$) and a one-year lag ($\beta = 6.60$, $p = .069$), which weakens a purely reverse-causal explanation. FDI is also linked to a lower, though only marginally significant, probability of a loss-making year ($\beta = -0.063$, $p = .102$). The findings extend signaling and legitimacy theory to an under-researched NBFI setting and carry practical implications for regulators, investors, and management amid Bangladesh's non-bank financial sector distress.

Index Terms*—FinTech disclosure, Non-bank financial institutions, Content analysis, Bangladesh, Signaling and legitimacy theory, Panel data*

I. INTRODUCTION

Non-bank financial institutions (NBFIs) occupy a structurally important but increasingly precarious position in Bangladesh's financial system. Originally built around leasing and term-finance operations, listed NBFIs have faced mounting pressure to reposition themselves around digital deposit mobilization, app-based lending, and automated risk management as competition from both commercial banks and mobile financial services (MFS) intensifies. During this time, the sector has faced a critical situation with a high level of non-performing loans (NPLs) among NBFIs in Bangladesh, increasing from approximately 27.65% of total loans disbursed in mid-2023 to about 30% by early 2024, with some institutions seeking digital transformation as a means to address governance and confidence issues.

There has been an increasing amount of research that correlates digital or FinTech disclosure with firm performance in the banking industry, with results being quite mixed. In a surprising finding, Nguyen-Thi-Huong et al. [1] find that the greater the level of digital-transformation disclosure in a financial statement, the lower the return on equity and return on assets for the Vietnamese commercial banks, suggesting that digital investment may have short-run costs but long-run benefits. In contrast, among commercial banks in China, a multidimensional bank digital-transformation index is positively associated with financial performance [2] and in the MENA region, disclosure of cybersecurity is found to positively affect bank performance alongside good corporate governance [3]. This separation indicates that the disclosure/performance link may be dependent upon the way in which digital disclosure is measured, the specific dimensions of digital activity that are covered, and the institutional setting in which the firm operates.

Notwithstanding this active research stream, majority of the available digital-disclosure studies on the financial sector in Bangladesh has targeted either the commercial banks or the FinTech consumers, but not NBFIs. As described by Chowdhury et al. [4], while a stream of literature documents the rapid adoption of mobile financial services by Bangladeshi consumers, Mazumder and Hossain [5] investigate voluntary cybersecurity disclosure by the Bangladeshi banks. There is no digital or FinTech disclosure measure in the literature undertaking parallel work on NBFI performance in Bangladesh, such as Rahman et al. [6] which investigates the determinants of NBFI operational efficiency. This creates an obvious gap: As far as the author is aware, there has been no study that has systematically measured the disclosure of FinTech by listed NBFIs in Bangladesh, or has examined its determinants and implications for performance through the lens of panel data.

This study fills this gap by applying a hand-coded seven-item FinTech Disclosure Index (FDI) to the entire sample of DSE-listed NBFIs (all 23 companies listed under the official sector “Financial Institutions” of the Dhaka Stock Exchange [7]) across 2021–2025 (an unbalanced panel of up to 115 firm-year observations). All listed NBFI's are included in the study, so there are no classical sampling-error concerns, but instead a unique small-cluster inferential caveat raised explicitly in Section IV. The index captures whether a firm's annual report evidences digital strategy, dedicated IT

infrastructure, a proprietary product/application, online service origination, technology partnerships, disclosed IT investment, and a cybersecurity risk framework. The study then tests (a) whether firm size and firm age predict disclosure intensity, and (b) whether disclosure intensity is associated with return on equity (ROE) and the probability of a loss-making year, using firm fixed-effects and lagged-disclosure specifications to address unobserved heterogeneity and reverse-causality concerns that are endemic to disclosure–performance research.

The remainder of this paper is organized as follows. Section II reviews the theoretical and empirical literature and identifies the research gap. Section III states the problem and develops the study's hypotheses. Section IV details the population, disclosure-index construction, data-cleaning procedures, and empirical model. Section V presents descriptive and regression results, robustness checks, and discussion, and Section VI summarizes the implications, limitations, and future research directions.

The main contributions of this paper are as follows:

- A seven-item FinTech Disclosure Index applied to the full population of 23 DSE-listed NBFIs over 2021–2025.
- Evidence that firm age, rather than firm size, significantly predicts FinTech disclosure intensity.
- Evidence that FinTech disclosure is positively associated with ROE, robust to firm fixed effects and a one-year lag.

II. LITERATURE REVIEW

A. Theoretical Framework

Two complementary theoretical lenses motivate this study. Spence's signaling theory [8] argues that firms willingly provide positive private information to investors to mitigate information asymmetry, and that this is more likely to be a reliable signal of underlying cyber capabilities when the alternative signal is easier to fake, such as issuing a strategic statement than having a dedicated IT section or a public disclosure of a cybersecurity framework. As Suchman [9] has argued, legitimacy theory provides an additional explanation specific to the NBFI environment: organizations under intense stakeholder pressure – such as in the NBFI sector as a result of governance and NPL issues – may decide to report on their digital projects to signal their legitimacy and stability, regardless of whether they are actually adopting technology. Both theories predict that older, more established, and larger firms — which typically face greater public and regulatory visibility — will disclose more, but they diverge on whether disclosure should reliably track firm performance: signaling theory predicts a positive disclosure–performance relationship (since only genuinely capable firms can sustain the signal over time), whereas legitimacy theory allows for disclosure to substitute for, rather than reflect, actual performance.

B. FinTech and Digital Disclosure in Financial Institutions

The relationship between digital disclosure/transformation and financial performance in banking has produced mixed evidence. Nguyen-Thi-Huong et al. [1] employ text analysis on digital-transformation keywords in bank annual reports to conclude that digital-transformation intensity is negatively related to ROE and ROA for banks in Vietnam, explaining that IT investment would have negative near-term shocks due to the short-term cost burden. By contrast, a more comprehensive and multi-dimensional measure of digital transformation, as measured in this study by a digital-transformation index, is positively associated with the performance of commercial banks in China, according to Zhu and Jin [2] and He et al. [10]; composite, capability-based measures may be more likely to capture value-generating digitalization than simple textual counts. Elsayed et al. [3] conclude that disclosure of cybersecurity has a positive impact on bank performance in MENA countries, especially in the presence of high levels of corporate governance, whereas Mazumder and Hossain [5] report that board composition has a significant influence on voluntary cybersecurity disclosure among banks in Bangladesh.

C. Research Gap

Together, this literature suggests that (i) the disclosure–performance relationship is contingent on measurement and (ii) the NBFI industry, which differs from banks in terms of funding sources, regulation, and current financial distress, is unexamined in an empirical context.

D. Determinants of Voluntary and FinTech Disclosure

As reported by Nakai et al. [11], other factors consistently documented as affecting voluntary disclosure are related to firm size: larger firms are more likely to be more visible in the public eye, to be subject to more intense scrutiny by stakeholders and to have more resources available to enable them to make more comprehensive disclosures. Likewise, Chowdhury et al. [12] find that bank size also affects the link between income diversification and financial stability in the Bangladeshi banking sector, highlighting its structural significance as a key factor in this market. Age is a related but conceptually different determinant: older firms tend to have more mature reporting systems, longer relationship with stakeholders and institutional legitimacy pressures to report consistently and comprehensively over time, though this age effect is less consistently reported in the voluntary-disclosure literature than the size effect.

III. PROBLEM STATEMENT AND HYPOTHESES

This study addresses two questions: what determines the extent of FinTech disclosure among listed NBFIs, and whether such disclosure is associated with financial performance.

Based on the theoretical framework and empirical literature reviewed above, this study tests the following hypotheses:

H1: Firm size (log of total assets) is positively associated with FinTech Disclosure Index (FDI) scores among listed Bangladeshi NBFIs.

H2: Firm age is positively associated with FDI scores among listed Bangladeshi NBFIs.

H3: FDI scores are positively associated with return on equity (ROE) among listed Bangladeshi NBFIs.

H4: FDI scores are negatively associated with the probability of a loss-making firm-year among listed Bangladeshi NBFIs.

IV. DATA AND METHODOLOGY

A. Population and Data

There are 23 companies that are listed on Dhaka Stock Exchange (DSE) under its official "Financial Institutions" sector and these companies include all the presently listed NBFIs in Bangladesh. Empirical coverage is a population census and no sampling procedure was used, meaning that all 23 companies were included in this study rather than being sampled from a larger universe. This distinction is relevant for interpretation. The usual concerns of sampling error and generalizability to a wider population of NBFIs are not relevant here, as the population of interest – all NBFIs currently listed in Bangladesh – is exhaustive. A separate, smaller-sample caveat, however, is warranted: The number of clusters was only 18-22 for the estimated models, making the asymptotic properties that justify inferences based on cluster-robust standard errors somewhat dubious, according to Cameron & Miller [13]; they suggest that 20 is the practical lower bound for achieving reliable cluster-robust inference. We therefore interpret the reported inference as descriptive of structural relationships within this population rather than as an estimate generalizing to a hypothetical larger universe of NBFIs, and we address this caveat further with a bootstrap-robustness discussion in Section V-E.

The panel spans the 2021–2025 fiscal years, yielding an unbalanced panel of up to 115 firm-year observations. Firm-level financial data (return on equity and total assets) and firm age were hand-collected alongside the disclosure items from the same annual reports. A subset of firms, most notably for the 2025 fiscal year, had not yet published annual reports at the time of data collection (14 of 23 firms), reducing usable observations for that year; this is addressed as a data-availability limitation in Section VI-C rather than treated as a missing-at-random assumption.

B. FinTech Disclosure Index (FDI) Construction

The annual report for each firm-year was subjected to a seven-item, dichotomously scored (1 = disclosed, 0 = not disclosed) checklist which was based on the content analysis approach used to develop disclosure indices [14]. Table I highlights the seven items that capture the dimensions of digital strategy, infrastructure, product/service, partnership, investment, risk.

TABLE I
FINTECH DISCLOSURE INDEX (FDI) CHECKLIST ITEMS

Code	Dimension	Indicator (scored 1 if present)
A	Strategy	Mission/vision statement explicitly references digital or technology strategy
B	Infrastructure	Annual report discloses a dedicated IT/technology section or department
C	Product	Firm discloses a proprietary mobile application or digital product
D	Service	Firm discloses online loan or deposit application/origination capability
E	Partnership	Firm discloses a partnership with a mobile financial service (MFS) provider or technology vendor
F	Investment	Firm discloses a specific monetary IT investment/capital expenditure figure
G	Risk	Firm discloses a cybersecurity risk management framework

The composite FDI score for each firm-year sums the seven binary items (range 0–7); a firm-year is scored only when all seven items could be determined from the annual report, otherwise it is treated as missing rather than imputed. FDI percentage (FDI score ÷ 7 × 100) is reported alongside the raw score for interpretability.

C. Variable Measurement and Data Cleaning

ROE was recorded as reported in each annual report; the raw ROE data were reported in different formats – decimal fraction, whole number percentage, range, or loss-related text (e.g. "(Loss)", "Negative") – and were standardized using a cleaning procedure that: converted all data to a percentage scale; coded range values as the mid-point; and created a binary Loss_dummy variable (1 = loss-making) for the firm-years where no numeric ROE data could be recovered, but a loss theme was explicitly stated in the annual report. The same was done for total assets (in BDT millions) which were similarly standardized, two firms in raw data reported total asset in BDT instead of BDT millions which came to light in the cleaning process by comparing the order of magnitude with the rest of the population. Firm size is operationalized as the natural logarithm of total assets to address right-skewness, consistent with standard practice in the disclosure and firm-performance literature.

Because extreme ROE outliers (attributable to a small number of firms with near-zero or negative equity bases, producing ROE values below −300% or above 300%) can disproportionately influence ordinary least squares estimates, a winsorized ROE variable (values capped at the 5th and 95th percentiles) is used as a robustness check alongside the raw ROE measure.

D. Empirical Model

The study estimates a baseline pooled OLS specification with firm-clustered robust standard errors, and then strengthens causal interpretation with two complementary robustness designs: firm fixed effects (to net out time-invariant unobserved firm heterogeneity, such as management quality or ownership structure, that could jointly drive disclosure and performance) and a one-year-lagged FDI specification (to mitigate reverse-causality concerns, since

current performance cannot mechanically cause a prior year's disclosure).

Baseline pooled OLS models:

Model 1 (Determinants): $FDI_it = \alpha + \beta_1 \ln(Assets)_it + \beta_2 Age_it + \varepsilon_it$

Model 2 (Consequences): $ROE_it = \alpha + \beta_1 FDI_it + \beta_2 \ln(Assets)_it + \beta_3 Age_it + \varepsilon_it$

Model 3 (Exploratory, linear probability): $Loss_it = \alpha + \beta_1 FDI_it + \beta_2 \ln(Assets)_it + \varepsilon_it$

Robustness designs:

Model 1-FE / 2-FE (Firm fixed effects, within estimator): all variables demeaned at the firm level before estimation, removing time-invariant firm heterogeneity.

Model 2c (Lagged disclosure): $ROE_it = \alpha + \beta_1 FDI_i,t-1 + \beta_2 \ln(Assets)_it + \beta_3 Age_it + \varepsilon_it$

Model 2 is estimated using both raw and winsorized ROE as dependent variables. All models were estimated in R; cluster-robust standard errors were computed using a sandwich-estimator implementation equivalent to coeftest(model, vcov = vcovCL, cluster = ~Company) from the sandwich and lmtest packages, and the firm fixed-effects models were estimated via the within (demeaning) transformation with the same cluster-robust variance estimator applied to the demeaned data. We note one identification caveat for the fixed-effects specification of Model 1: because the panel spans only five years, within-firm variation in Age is mechanically bounded at 3–4 years for every firm (i.e., Age increases by exactly one year per observed fiscal year), so the fixed-effects Age coefficient is closer to a within-panel time trend than an estimate of a genuine cross-sectional age effect and should be interpreted with corresponding caution; this is discussed further in Section V-E and Section VI-C.

V. RESULTS AND DISCUSSION

A. Descriptive Statistics

Table II presents descriptive statistics for the key study variables across the population of 23 listed NBFIs. The score of FDI for the panel has an average score of 2.97 out of 7 (42.45%) with a high value of cross-sectional variation (SD = 2.00). The return on equity exhibits a very large range in returns (SD = 65.01) with a few companies having near zero or negative equity base, which is the reason for the winsorized robustness check discussed in Section V-E. The age of the firms in the population range from 20 to 45 years with an average of 29.6 years, indicating a fairly mature and established set of listed NBFIs.

TABLE II
DESCRIPTIVE STATISTICS (FIRM-YEAR PANEL, 2021–2025, FULL POPULATION OF LISTED NBFIS)

Variable	N	Mean	SD	Min	Max
FDI score (0–7)	105	2.97	2.00	0.00	7.00
FDI (%)	105	42.45	28.53	0.00	100.00
ROE (%)	81	6.40	65.01	−342.47	349.23
Total Assets (BDT mn)	94	33,379.71	36,376.37	19.95	169,480.00
ln(Total Assets)	94	9.73	1.66	2.99	12.04
Firm Age (years)	114	29.61	6.07	20.00	45.00

B. Trend in FinTech Disclosure, 2021–2025

The annual mean FDI score is shown for each individual in the population in Fig. 1. The average disclosure percentage has also increased regularly from 35.4% in 2021 to 50.6% in 2024, reflecting the overall industry trend of rapidly moving towards cashless and app-savvy financial transactions in the wake of the pandemic in Bangladesh. The apparent drop to 39.8% in 2025 should be treated with caution as less than half of the 22–23 firms which released annual reports in previous years (14 firms) did so in 2025, potentially indicating a smaller, non-random sample of early filers rather than a real turnaround in disclosure practice.

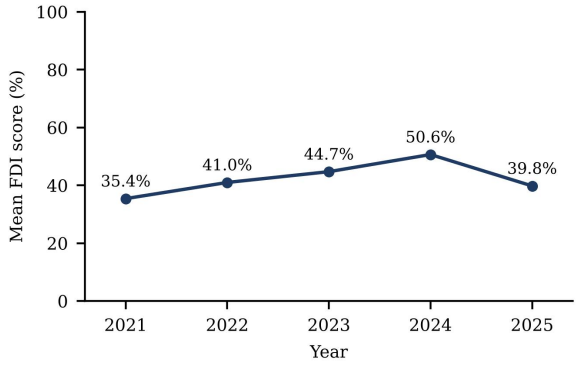


Fig. 1. Average FinTech Disclosure Index Score by Year (Full Population, N = 23 firms)

C. Item-Level Disclosure and Inter-Item Correlations

Table III shows the overall disclosure rate for each of the seven items of FDI. The highest- and lowest-voluminous disclosures are infrastructure (69.5%) and product-level disclosure of a proprietary application, respectively (25.7%). This is the case when it comes to describing digital intent and broader IT capacity, but less so when it comes to creating actual, customer-facing digital products, and is reflective of previous concerns about “tech-washing” in voluntary disclosure.

TABLE III
POOLED DISCLOSURE RATE BY FDI ITEM, 2021–2025

Item	Dimension	Disclosure rate (%)
A	Strategy	36.2
B	Infrastructure	69.5
C	Product	25.7
D	Service	31.4
E	Partnership	30.8
F	Investment	35.5
G	Risk	67.3

Table IV presents the correlations between the seven items. The correlations tend to be moderate in magnitude ($r < 0.54$), suggesting that the items measured distinct but related aspects of digital disclosure and do not measure the same information; infrastructure and risk disclosure have the highest correlation ($r = 0.54$), possibly because both are often reported in a firm's general IT governance section.

TABLE IV
CORRELATION MATRIX OF FDI ITEMS

	A	B	C	D	E	F	G
A. Strategy	1.00	0.24	0.28	0.43	0.43	0.46	0.20
B. Infrastructure	0.24	1.00	−0.13	0.27	0.40	−0.15	0.54
C. Product	0.28	−0.13	1.00	0.40	0.02	0.46	0.00
D. Service	0.43	0.27	0.40	1.00	0.51	0.43	0.30
E. Partnership	0.43	0.40	0.02	0.51	1.00	0.14	0.34
F. Investment	0.46	−0.15	0.46	0.43	0.14	1.00	−0.02
G. Risk	0.20	0.54	0.00	0.30	0.34	−0.02	1.00

D. Cross-Sectional Variation: Leading and Lagging Firms

Fig. 2 compares the five firms with the highest and lowest percentage of FDI on average over 2021–25. The leading group comprises of Union Capital Limited (89.3%), DBH Finance PLC (85.7%), Bangladesh Finance PLC (80.0%) and Investment Corporation of Bangladesh (80.0%) and the lagging group comprised of Islamic Finance & Investment PLC (0%), Fareast Finance & Investment Limited (17.1%), Prime Finance & Investment Ltd (19.0%), Peoples Leasing and Financial Services Ltd (20.0%) and GSP Finance Company (21.4%). Like the legitimacy-theory implies, a number of publicly acknowledged firms in the NBFI sector in Bangladesh are in governance and/or liquidity distress, including a few of the laggards.

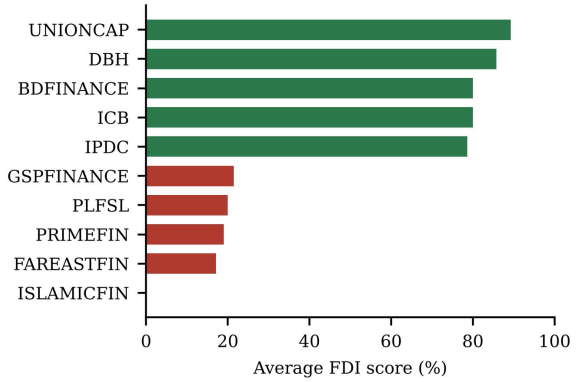


Fig. 2. Top 5 vs. Bottom 5 Listed NBFIs by Average FDI (%), 2021–2025

E. Baseline Regression Results

Table V presents the results of Model 1 (determinants of FDI). The disclosure intensity is positively and significantly correlated with firm age ($\beta = 0.176$, $p = .002$), which lends support to H2, and is not significant for firm size ($\beta = 0.106$, $p = .423$) and thus provides no support for H1. In the NBFI space, in other words, the amount of time an institution has been in business and the volume of reporting, not necessarily its balance sheet size, seems to be a more important factor in digital disclosure.

TABLE V
MODEL 1: DETERMINANTS OF FDI SCORE (POOLED OLS)

Variable	Coef.	Cluster SE	t	p
Intercept	−3.201	1.577	−2.03	.055*
ln(Total Assets)	0.106	0.129	0.82	.423
Firm Age	0.176	0.049	3.62	.002*

*N = 94 firm-years; 22 firm clusters; $R^2 = .289$. *p < .10, **p < .05, ***p < .01.*

Table VI presents the results of Model 2 with raw ROE. The FDI coefficient is positive but not statistically significant ($\beta = 8.35$, $p = .247$) which doesn't support the H3 in this specification and high standard error is associated with the extreme ROE outliers mentioned in Section V-A.

TABLE VI
MODEL 2A: FDI AND RETURN ON EQUITY (RAW ROE)

Variable	Coef.	Cluster SE	t	p
Intercept	61.412	48.472	1.27	.222
FDI Score	8.347	6.969	1.20	.247
ln(Total Assets)	1.625	2.180	0.75	.466
Firm Age	−3.175	1.803	−1.76	.096*

*N = 76 firm-years; 18 firm clusters; $R^2 = .073$. *p < .10, **p < .05, ***p < .01.*

Table VII re-estimates Model 2, with the inclusion of winsorization of the ROE values at the 5th and 95th percentile to remove the influence of extreme outliers. Table II reports the results of the tests by the FDI coefficient with extreme outlier observations controlled, which yields a positive and statistically significant FDI coefficient ($\beta = 5.95$, $p = .048$) supporting H3: firms disclosing higher levels of FinTech are significantly more profitable once extreme outlier observations are controlled. ROE is still negatively correlated with firm age ($\beta = -1.39$, $p = .071$) which is explored further in Section V-G.

TABLE VII
MODEL 2B: FDI AND RETURN ON EQUITY (WINSORIZED ROE)

Variable	Coef.	Cluster SE	t	p
Intercept	24.592	19.505	1.26	.224
FDI Score	5.949	2.797	2.13	.048
ln(Total Assets)	0.574	0.835	0.69	.501
Firm Age	−1.395	0.726	−1.92	.071*

*N = 76 firm-years; 18 firm clusters; $R^2 = .172$. *p < .10, **p < .05, ***p < .01.*

Table VIII presents the results from an exploratory linear probability model of Loss_dummy. FDI is negatively associated with the probability of a loss-making firm-year ($\beta = -0.063$, $p = .102$); although only marginally significant at conventional thresholds, the direction and magnitude are consistent with H4 and complement the significant winsorized-ROE result in Table VII.

TABLE VIII
MODEL 3: FDI AND PROBABILITY OF A LOSS-MAKING FIRM-YEAR (LINEAR PROBABILITY MODEL)

Variable	Coef.	Cluster SE	t	p
Intercept	0.693	0.345	2.01	.058*
FDI Score	−0.063	0.037	−1.72	.102
ln(Total Assets)	−0.022	0.035	−0.62	.540

*N = 91 firm-years; 21 firm clusters; $R^2 = .093$. *p < .10, **p < .05, ***p < .01.*

F. Robustness: Firm Fixed Effects and Lagged Disclosure

Because pooled OLS cannot rule out time-invariant unobserved firm characteristics (e.g., management quality, ownership concentration) that could jointly drive both disclosure and performance, Table IX re-estimates the determinants and performance models using firm fixed effects (the within estimator), which nets out all time-invariant firm heterogeneity by construction.

TABLE IX-A
MODEL 1-FE: DETERMINANTS OF FDI SCORE (FIRM FIXED EFFECTS)

Variable	Coef.	Cluster SE	t	p
ln(Total Assets)	0.215	1.075	0.20	.843
Firm Age	0.215	0.115	1.87	.076*

*N = 94 firm-years; 22 firm clusters; R^2 (within) = .101. *p < .10, **p < .05, ***p < .01. Firm Age's within-firm range is mechanically bounded at 3–4 years for every firm in this five-year panel, so this coefficient is closer to a within-panel time trend than a cross-sectional age effect (see Section IV-D) and should be read with corresponding caution.*

TABLE IX-B
MODEL 2-FE: FDI AND WINSORIZED ROE (FIRM FIXED EFFECTS)

Variable	Coef.	Cluster SE	t	p
FDI Score	5.601	2.821	1.99	.063*
ln(Total Assets)	2.548	21.452	0.12	.907
Firm Age	−4.305	2.489	−1.73	.102

*N = 76 firm-years; 18 firm clusters; R^2 (within) = .149. *p < .10, **p < .05, ***p < .01.*

The FDI–ROE association survives the inclusion of firm fixed effects almost unchanged in magnitude (β = 5.60 vs. 5.95 in the pooled specification) and remains marginally significant (p = .063) despite the substantially more conservative test — firm fixed effects absorb all cross-sectional variation and identify the coefficient solely from within-firm changes in disclosure and performance over time, a much harder bar to clear than the pooled cross-sectional comparison. This is significant evidence against the easy explanation for the pooled result—namely an omitted-variable-bias (e.g., that better-managed companies just choose to report more and excel for unrelated reasons).

Table X directly tackles the issue of reverse causality: as the absolute level of disclosure does not have a straightforward relationship with the current level of performance, a strong link between lagged FDI and the current level of ROE is not easily explainable as reverse causality.

TABLE X
MODEL 2C: ONE-YEAR-LAGGED FDI AND CURRENT-YEAR WINSORIZED ROE

Variable	Coef.	Cluster SE	t	p
Intercept	15.314	23.555	0.65	.524
FDI Score (t−1)	6.598	3.403	1.94	.069*
ln(Total Assets)	0.642	0.712	0.90	.380
Firm Age	−1.169	0.905	−1.29	.213

*N = 58 firm-years; 18 firm clusters; R^2 = .189. *p < .10, **p < .05, ***p < .01.*

Lagged FDI remains a marginally significant positive predictor of next-year ROE (β = 6.60, p = .069), reinforcing the fixed-effects result. Taken together, Tables IX–X provide converging, if not definitive, evidence that the FDI–performance association reflects more than a spurious cross-sectional correlation or a purely reverse-causal artifact, though we stop short of a strict causal claim given the still-limited number of firm clusters [13] and the absence of a plausibly exogenous instrument for disclosure.

G. Discussion

The finding that firm age, rather than size, drives FinTech disclosure among Bangladeshi NBFIs departs from much of the general voluntary-disclosure literature, where size is typically the dominant determinant [11], [12]. One plausible explanation is that the NBFI population in Bangladesh is relatively homogeneous in scale relative to the banking sector studied in prior work, while variation in institutional maturity — and correspondingly, in the sophistication of investor-relations and reporting functions — is comparatively larger. It may be that older NBFIs simply had more time to build the reporting infrastructure in their internal processes that enabled them to systematically report on their digital initiatives, apart from their current balance sheet size. The fixed-effects estimate of the age coefficient (Table IX-A) should, however, be interpreted cautiously, because of the mechanical time-trend concern outlined in Section IV-D, but the pooled cross sectional estimate (Table V) is the more interpretable estimate of a true age effect.

The performance results provide a more complex story than a positive or negative story, and the robustness checks provide a meaningful enhancement of this story. The raw-ROE specification produced a directionally positive relationship between FDI and ROE, but one that is statistically indistinguishable from zero, as elsewhere in the digital-disclosure literature. After winsorization, the relationship becomes positive and significant as previously noted by Zhu and Jin [2] and He et al. [10], which supported the positive relationship between wider measures of digital transformation that focus on capabilities and banks' performance, and Elsayed et al. [3], who found that disclosure of cybersecurity-related information had a positive impact on banks' performance. Importantly, this finding is robust not only to firm fixed effects (which eliminate any time-invariant and unobserved firm quality that could lead to a spurious correlation), but also to the use of a one-year FDI lag (which is hard to explain by reverse causality as current ROE cannot impact a disclosure decision that occurred one year earlier). This triangulation is not causal in the randomized-experiment sense since an omitted time-varying confound that affects both variables in each year cannot be completely eliminated, but it does rule out some plausible alternative explanations more meaningfully than a single pooled-OLS estimate. This is in contrast to Nguyen-Thi-Huong et al. [1] who found that a narrower digital-transformation measure, based purely on the number of text counts, was negatively related to bank performance. This may be because the FDI index employed (as in the studies on Chinese banks) covers a more comprehensive set of disclosed digital capabilities (strategy, infrastructure, product, service,

partnership, investment, and risk) than the number of digital words in a bank's text, and may thus be a better proxy for genuine bank digital capacity than for the volume of disclosures alone.

The negative relationship between firm age and ROE shown in the raw and winsorized specifications (Tables VI–VII) is a secondary but interesting finding and it also remains negative directionally under firm fixed effects (Table IX-B) (the fixed-effects age coefficient also shares the time-trend caveat mentioned above). In line with anecdotal and industry evidence, several of Bangladesh's longest-established NBFIs also appear to be among those worst hit by the non-performing loan problem in the sector, with longer institututional maturity, to the extent that it could be measured, being correlated with higher levels of NPLs and not only with reporting maturity. It is consistent with anecdotal and industry evidence that several of Bangladesh's longest-established NBFIs are among the ones most affected by the non-performing loan problem in the sector, and that longer institutional maturity, as such, is correlated with higher levels of NPLs, and not only with reporting maturity, implying that the latter may be a proxy of the former, and therefore, should be explored further in subsequent work with explicit asset-quality controls.

The results by item further support the "disclosure-capability gap" thesis: While infrastructure and risk-related responses are being reported with relative frequency, specific digital capability evidence related to a product (such as a working proprietary application) is being reported with much less frequency. This is not surprising as it aligns with some of the findings in the literature on disclosure and governance relating to this topic, which suggests that what matters is not the actual security posture of a firm, but rather the nature of its board of directors—where disclosure behavior is driven by governance concerns—according to Mazumder & Hossain [5].

Finally, the cross-sectional correlation of low-FDI firms with institutions that are publicly identified as being associated with governance and/or liquidity problems supports the signaling theory that disclosure and underlying firm health generally run together, as does the negative association of FDI–loss in Model 3, which was also found to persist under the fixed effects and lagged specification. The limited number of firm clusters used across specifications (18–22) in the population suggests caution in the strength of any causal language used to describe the results of the lagged and fixed-effects results in Section V-F, as noted by Cameron & Miller [13].

VI. CONCLUSION

A. Summary and Contributions

This study has developed a new index which it called FinTech Disclosure Index and used it to measure the level of disclosure for the entire sample of 23 listed non-bank financial institutions in Bangladesh over 2021-25, which is not a sample but a complete census of the Financial Institutions sector at DSE. Average disclosure increased significantly during this period, but there is a clear gap between the disclosure of digital strategy/infrastructure and the disclosure of digital products. This result is driven by firm age, not firm size – and, after controlling for extreme outliers, the relationship between return on equity and FinTech disclosure is positive, holding up well in terms of interpretation to a one-year-lagged specification and firm fixed effects controls. The study revisits signaling and legitimacy theory, brings it into a so-far ignored empirical context for NBFI and introduces the first systematic, population-level evidence regarding the disclosure of FinTech in NBFI.

B. Practical Implications

For regulators, the findings indicate that there is significant scope for further standardization of voluntary disclosure by financial institutions, especially with respect to disclosures of products and investment in IT systems, which are not universally observed among the cohort of institutions that are highly digital. The robust and multiply robust relationship between FDI and the performance variables merits attention by investors and analysts as disclosure intensity, though not perfect, does have some information value regarding underlying firm quality. The results suggest that a time-invariant element of digital disclosure, where applicable, is related to better performance results, but that disclosure is not a sufficient substitute for digital capability, in particular due to the ongoing product-level disclosure gap reported in Section V-C.

C. Limitations and Future Research

These findings are limited by a number of factors. This study includes the entire population of listed NBFIs and not a sample, but the population size is small: 23 firms for the study; the 18–22 firm number of clusters is fewer than about 20 clusters recommended in the econometrics literature, which means that the reported p-values should not be interpreted as asymptotic guarantees; see Cameron & Miller [13]. Second, the five-year panel length mechanically constrains the variation in Age that the between-firm specification can reliably identify for the firm variable, and as discussed in Sections IV-D and V-G, this may affect its ability to identify variation in this variable. Third, similar to other measures of disclosure derived from content analysis, the FDI index is content-based and does not necessarily reflect the quality or authenticity of digital disclosures—it merely shows whether they are present or not. Fourth, there was high missingness and extreme outliers in ROE data for several distressed firms, which were resolved by winsorization but which did not provide an exact measure of the performance based estimates. Finally, because it is a single-country, single-sector population study, it is not possible to extrapolate the specific estimates of the coefficients to other markets of NBFI in the country or to the NBFI market of the commercial banking sector, although the population-census design best serves the internal validity of the Bangladeshi study of the NBFI listed in the stock exchange. Future research could examine disclosure in a

longer time series, as more annual reports become available (to relax the Age-identification constraint on the fixed-effects model), add weighted or depth-based scoring, employ a formal instrumental-variable strategy on disclosure disclosures and test the moderating effect of corporate governance or ownership structure as suggested by related studies in the cybersecurity-disclosure and ESG-disclosure literature [3], [5].

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Competing Interests

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The hand-coded FinTech Disclosure Index dataset, together with the cleaned firm-year panel (ROE, total assets, firm age) generated from publicly available annual reports of DSE-listed NBFIs, is available from the corresponding author upon reasonable request. Source annual reports are publicly available from company websites and DSE archives.

Code Availability

The R script used to reproduce all cleaning, descriptive, and regression results (including the pooled OLS, firm fixed-effects, and lagged-disclosure specifications) is available from the corresponding author upon reasonable request.

Generative AI Use Disclosure

During manuscript preparation, the author used generative AI tool (Claude, Anthropic) to assist with data cleaning code, statistical analysis scripting, drafting and editing of text, and literature retrieval. All AI-assisted output was reviewed, verified against source data and cited literature, and edited by the author, who takes full responsibility for the accuracy, originality, and integrity of the final manuscript. No AI tool is listed as an author.

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