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Does Capital Market Liberalization Drive Digital Transformation? Evidence from Chinese A-Shares' Inclusion in the MSCI Emerging Markets Index

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ABSTRACT

This study examines whether capital market liberalization drives corporate digital transformation by exploiting Chinese A-share firms' phased inclusion in the MSCI Emerging Markets Index starting in June 2018. Using a difference-in-differences design with propensity score matching, we analyze 35,264 firm-year observations from 2010 to 2022, measuring digital transformation through natural language processing of annual reports across six technology domains: artificial intelligence, big data, cloud computing, the Internet of Things, blockchain, and enterprise digitization. In our preferred specification, MSCI inclusion increases digital transformation intensity by 0.394 log points, equivalent to approximately $\mathbf{\exp(0.394) - 1 \approx 48\%}$. Event-study evidence supports treatment timing and parallel trends, placebo tests reject spurious correlation, and alternative outcome specifications confirm robustness. The impact is most pronounced among firms in technology-intensive industries and those located in economically developed provinces. These results provide evidence that capital market liberalization can act as a catalyst for corporate digital transformation in emerging economies.

Keywords: Capital market liberalization, Digital transformation, MSCI inclusion, Corporate finance, Emerging markets

INTRODUCTION

The digital transformation of emerging market companies is one of the most significant technology shifts in modern business strategy. As firms rapidly adopt artificial intelligence, cloud computing, big data analytics, and other cutting-edge technology, the topic of what drives this transition has received a lot of academic and legal attention. Although previous studies have looked at internal elements like organizational culture and managerial skills, the function of external funding sources, especially access to global capital markets, has not received enough attention.

This paper investigates whether capital market liberalization catalyzes corporate digital transformation by exploiting the phased inclusion of Chinese A-share firms in the MSCI Emerging Markets Index. Beginning in June 2018, this policy reform pro-vided a quasi-experimental setting where index-eligible firms gained enhanced access to international capital flows, while similar non-eligible firms remained constrained to domestic markets. We leverage this exogenous variation to identify the causal impact of capital market opening on digital transformation intensity.

Our empirical strategy combines difference-in-differences estimation with propensity score matching, using a comprehensive panel of 35,264 firm-year observations spanning 2010-2022. Digital transformation is measured through natural language processing of annual report disclosures, capturing firms' adoption of six key technology clusters: artificial intelligence, big data, cloud computing, Internet of Things, blockchain, and enterprise digitization programs.

The results demonstrate that MSCI inclusion significantly accelerates digital trans-formation. In the preferred DID specification, treated firms exhibit a 0.394 log-point increase in comprehensive digitalization scores (about 48%), with effects persisting over multiple post-treatment years. The impact operates through three complementary mechanisms: relaxed financing constraints enabling capital-intensive technology investments, enhanced corporate governance from international investor oversight, and knowledge spillovers from global investment networks.

Heterogeneity analysis reveals that treatment effects are strongest among firms in developed eastern provinces, technology-intensive industries, and those with higher absorptive capacity. These patterns suggest that capital market liberalization primarily benefits firms possessing complementary institutional and organizational resources needed to effectively utilize international capital and knowledge flows.

This study contributes to several literatures. First, it extends the capital market liberalization literature by documenting effects on corporate innovation outcomes beyond traditional financial performance metrics. Second, it enriches understanding of digital transformation drivers by highlighting the importance of external financing channels alongside internal capabilities. Finally, it provides policy insights for emerging economies seeking to accelerate technological upgrading through financial market reforms.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Institutional Background: China A-shares and MSCI Inclusion

Chinese A-shares' inclusion in global indices marks a turning point in the country's capital market reform process. Even though China has the second-largest economy in the world, its mainland equity markets were still predominantly isolated from international financial flows until 2018. Foreign ownership restrictions, settlement mechanism limits, and capital controls that made it difficult for foreign investors to purchase local Chinese stocks were the main causes of this segmentation [1].

The Morgan Stanley Capital International (MSCI) Emerging Markets Index is a major benchmark for worldwide institutional investors, with approximately $1.9 trillion in assets under management following or evaluating against MSCI emerging market indexes in 2018. MSCI's decision to incorporate Chinese A-shares, signaled on June 20, 2017, and implemented on June 1, 2018, marked the first time mainland Chinese equities were accessible to overseas passive investors on a large scale [2].

The inclusion process was carried out in stages in order to control market disruption and guarantee smooth integration. At a 5% inclusion factor, 234 large-cap A-shares were first added in June 2018, accounting for roughly 0.73% of the weight of the MSCI Emerging Markets Index. By November 2019, the overall number of included securities had grown to 472 A-shares spanning large-, mid-, and small-cap groups, with increases to a 20% inclusion factor for these stocks [3].

For identification, this quasi-experimental setup was very useful due to a number of institutional variables. Initially, the inclusion criteria were not firm-specific performance measurements but rather mechanical characteristics, such as market capitalization, liquidity thresholds, and accessibility through Stock Connect programs. Second, the deadline was not established internally by Chinese authorities or individual companies but rather was enforced outside by MSCI. Third, it was possible to identify the cause by using the distinct before-and-after periods that the staged implementation produced [4].

The Stock Connect programs, launched between Hong Kong-Shanghai (2014) and Hong Kong-Shenzhen (2016), provided the technical infrastructure enabling inter-national investment flows. By establishing daily and aggregate quota limitations, currency hedging strategies, and settlement protocols, these programs allowed foreign investors to purchase A-shares while upholding capital control regimes [5]. These systems were developed enough by 2018 to handle the substantial capital movements connected to MSCI inclusion.

Capital Market Liberalization and Digital Transformation

The theoretical relationship between capital market liberalization and corporate digital transformation operates through multiple complementary channels.

Financial Constraints and Investment Capacity

The main theoretical pathway connects digital transformation with capital market liberalization through the removal of financial barriers that normally restrict innovation investments. Projects involving digital transformation are especially vulnerable to funding limitations because of their high upfront costs, unclear returns, and lengthy payback times [6, 7]. Through an increased investor base, enhanced risk-sharing capacities, and access to patient capital more appropriate for funding long-term innovation initiatives, access to global financial markets helps mitigate these limitations [8].

Capital market liberalization also improves corporate governance by strengthening oversight and monitoring systems. Corporate decision-making processes may be impacted by the advanced analytical skills and governance norms brought by foreign investors, especially institutional investors that follow MSCI indices [9, 10]. These investors often put pressure on management to pursue value-enhancing investments like digital transformation projects by demanding greater levels of transparency, strategic disclosure, and long-term value generation.

Knowledge Spillovers and Best Practice Diffusion

Through greater engagement with global investors and analysts, capital market liberalization promotes the dissemination of best practices and information transfer [11, 12]. Foreign investors frequently have superior expertise in digital technology and transformation plans from their investments in other international marketplaces. This knowledge can be shared with Chinese companies through direct interaction, analyst recommendations, peer effects in investor portfolios, and benchmarking against global best practices.

By altering market valuation and signaling systems, global market integration can also impact digital transformation. Market-based incentives for digital trans-formation investments may result from foreign investors placing greater valuations on companies with superior digital capabilities [13, 14]. MSCI inclusion is regarded as legitimate third-party certification for firm quality, accessibility, and governance practices, potentially minimizing information friction in both product and factor markets.

Digital Transformation: Conceptual Framework and Empirical Challenges

Digital transformation represents a fundamental shift in how firms create, deliver, and capture value by strategically integrating digital technologies into all operational elements [15, 16]. This multifaceted process involves both technological adoption (artificial intelligence, big data analytics, cloud computing, Internet of Things, blockchain) and organizational changes (process redesign, business model innovation, cultural transformation) [17]. Emerging markets face unique opportunities through leapfrogging potential but also encounter obstacles including inadequate institutional frameworks, skill shortages, and infrastructure limitations [18, 19].

Hypothesis Development

Based on the theoretical considerations and empirical evidence synthesized above, we formulate the following testable hypotheses:

Proposition 1 (Main Effect Hypothesis) *Capital market liberalization, as proxied by MSCI inclusion, positively affects corporate digital transformation. The inclusion provides firms with improved access to international capital, enhanced governance mechanisms, and exposure to global best practices, all of which facilitate digital transformation investments.*

The main effect hypothesis posits a positive causal relationship between capital market liberalization and digital transformation intensity. We expect that firms included in the MSCI Emerging Markets Index will exhibit higher levels of digital transformation activity compared to similar non-included firms, after controlling for observable firm characteristics and common time trends.

Proposition 2 (Technology Heterogeneity Hypothesis) *The effects of capital market liberalization vary across different digital technologies, with stronger effects on technologies requiring higher capital intensity or external knowledge. Technologies such as artificial intelligence and cloud computing may benefit more from international capital access due to their resource-intensive nature and need for cutting-edge expertise.*

The technology heterogeneity hypothesis recognizes that different digital technologies have distinct characteristics that may moderate their responsiveness to capital market liberalization. We expect stronger effects for capital-intensive technologies (cloud computing, big data infrastructure) and knowledge-intensive technologies (artificial intelligence, advanced analytics) that particularly benefit from the financial resources and knowledge spillovers associated with international market access.

Proposition 3 (Regional and Firm Heterogeneity Hypothesis) *The effects of capital market liberalization on digital transformation are moderated by regional development levels and firm-specific characteristics. Stronger effects are expected for firms located in more developed regions with better institutional quality, larger firms with greater absorptive capacity, and firms in technology-intensive industries.*

The heterogeneity hypothesis acknowledges that the ability to translate capital market access into digital transformation depends on complementary factors. Regional differences in institutional quality, digital infrastructure, and human capital availability may create systematic variation in treatment effects. Similarly, firm-level factors such as size, age, existing technological capabilities, and industry affiliation may moderate the relationship between capital market liberalization and digital transformation outcomes.

Data and Research Design

Our empirical strategy exploits the gradual inclusion of mainland Chinese A-shares in the MSCI Emerging Markets Index as a quasi-exogenous increase in international capital access. Because MSCI eligibility depends strongly on firm size and liquidity, we do not assume unconditional exogeneity. Instead, we pursue conditional identification through firm and year fixed effects, rich time-varying controls, modern staggered-DID estimators, and additional reweighting procedures. This section describes the identification methodology, sample selection, measurement approach, and estimation procedures used to evaluate the relationship between liberalization and corporate digital transformation.

Sample and Data Source

We construct a balanced panel of all Shanghai and Shenzhen A-share enterprises from 2010 to 2022. Financial statements, market characteristics, and corporate governance information are derived from the China Stock Market and Accounting Research (CSMAR) database. The MSCI constituent lists and weight schedules are compiled from official index releases. To ensure a similar corporate sample, we eliminate financial institutions and heavily regulated utilities, as well as enterprises that have not provided annual reports. The generated dataset contains 35,264 firm-year observations, with 1,644 observations for MSCI constituents.

MSCI inclusion meets the key requirements of a natural experiment. Index eligibility is determined by mechanical criteria such as free-float market capitalization, liquidity thresholds, and accessibility assessments, which are independent of enterprises' underlying digitalization trajectories. The policy schedule was enforced externally: MSCI announced the inclusion on June 20, 2017, executed the first weighting tranche on June 1, 2018, and finished the phased 20% inclusion factor in late 2019. We define firms as treated if they appear on any MSCI Emerging Markets Index constituent list between 2018

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and 2022.

Model Design

Our major empirical technique uses a two-way fixed effects difference-in-differences design to compare the digital transformation outcomes of MSCI-included and non-included enterprises before and after the 2018 inclusion. We estimate the specification:

$$DT_{it} = \alpha + \beta\,(\mathrm{MSCI}_i \times \mathrm{Post}_t) + \boldsymbol{\gamma}'\mathbf{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \qquad (1)$$

where DT_{it} denotes firm i's digital transformation score in fiscal year t, MSCI_i equals one for constituent firms, Post_t equals one from 2018 onwards, $\mathbf{X}_{it}$ is a vector of time-varying controls, μ_i and λ_t capture firm and year fixed effects, and ε_{it} is the idiosyncratic disturbance clustered at the firm level.

To address residual selection on observables, we augment the baseline DID with a propensity score matching (PSM) procedure. We estimate the inclusion probability using pre-treatment (2016) characteristics, implement nearest neighbor matching with replacement and a 0.01 caliper, and retain up to three controls per treated firm. We also examine the temporal profile of treatment effects using an event-study specification with dynamic treatment indicators. The defining assumption is that treatment and control firms would have followed parallel digital transformation patterns absent MSCI inclusion, which we test through graphical diagnostics and placebo tests.

Alternative DID Estimators for Staggered Treatment

Because MSCI treatment is staggered across inclusion waves, we implement heterogeneity-robust DID estimators alongside the TWFE benchmark to guard against bias arising from staggered treatment adoption and heterogeneous treatment effects—a concern highlighted by Goodman-Bacon [20]. Specifically, we implement the cohort-time ATT framework of Callaway and Sant'Anna [21] and the interaction-weighted event-study approach of Sun and Abraham [22], which decompose the aggregate treatment effect into cohort-specific components and thereby avoid negative weighting that can contaminate conventional TWFE estimates. Given the limited number of treatment cohorts in our setting (three MSCI waves: 2018, 2019, and 2021), these modern estimators serve as a rigorous cross-check on the TWFE benchmark. We treat agreement in sign and broad magnitude across TWFE, Callaway–Sant'Anna, and Sun–Abraham approaches as stronger evidence for a causal interpretation, and report cohort-level ATT estimates in Tables 7 and 8.

Selection-Robust Reweighting Strategy

To further address non-random treatment assignment, we implement two additional balancing procedures before DID estimation: inverse probability weighting (IPW) and entropy balancing. IPW uses estimated propensity scores to construct a pseudo-population with comparable observable characteristics, while entropy balancing directly reweights control observations to match treated-group moments (mean, variance, and skewness) on pre-treatment covariates. We report balance diagnostics—standardized mean differences, variance ratios, and covariate overlap plots—and re-estimate baseline and staggered-DID models on the weighted samples. Stability of treatment effects across unweighted, PSM-matched, IPW-weighted, and entropy-balanced samples is interpreted as evidence that selection on observables is unlikely to fully explain the findings.

Data Descriptions and Descriptive Statistics of Variables

The degree of digital transformation is measured by applying a natural language processing (NLP) pipeline to Chinese firms' annual reports. Narrative sections are extracted, tokenized using jieba segmentation, filtered for boilerplate language, and matched against keyword dictionaries representing six technology domains: artificial intelligence, big data analytics, cloud computing, Internet of Things, blockchain, and enterprise digitization. The comprehensive digital transformation index is defined as

$$DT_{Comp,it}(log(+\sum_{j=1}^{6} keywordCount_{jit}) \quad (2)$$

where $\text{keywordCount}_{jit}$ denotes the frequency of keywords for technology domain j in firm i's annual report in year t. The logarithmic transformation preserves cross-firm variation while reducing the influence of outliers.

Measurement limitations and disclosure bias.

Text-based measures of digital transformation have inherent limitations. Keyword counts from annual reports capture firms' *disclosure* of digital activities rather than actual digital investments, and post-inclusion firms may strategically amplify digital-related language to attract international investors without corresponding substantive changes [23, 24]. Annual report verbosity may also vary systematically with firm size and governance quality. To address these concerns, we include robustness checks using length-normalized measures (keyword counts scaled by total report length), binary and z-score operationalizations, and technology-domain-specific sub-indices. To further strengthen construct validity, we supplement text outcomes with non-text proxies where available—software and IT-related intangible assets, digital patent applications, and digital-capitalized expenditure indicators. Consistent directional effects across text and non-text measures are interpreted as evidence that estimated treatment effects are not driven solely by narrative disclosure shifts.

The control vector $\mathbf{X}_{it}$ reduces confounding by collecting firm features that influence MSCI eligibility and digitalization propensity. Baseline controls include the natural logarithm of total assets (size), years since listing (age), profitability metrics (ROA, ROE), leverage, operating cash flow scaled by assets, market valuation (Tobin's Q), ownership concentration (largest shareholder share), board size, and the proportion of independent directors. Table 1 summarizes the formal definition and measurement convention for each variable.

Table 2 documents the technical measurement specifications for each variable, including data types, computational formulas, and database field mappings, ensuring replicability and facilitating comparison with related studies.

Table 3 shows descriptive statistics for the entire group and by treatment status. MSCI components have significantly higher baseline digital transformation scores (22.21 vs 12.78), indicating an empirical relationship between firm size, index eligibility, and technology use. Treated firms are consistently larger (log assets: 24.34 vs 22.03), older (15.6 vs 9.4 years), more profitable (ROA: 6.3% vs 3.5%), and have larger boards (8.25 vs 6.83 members). These variations highlight the necessity of controlling for observable traits in our identification technique.

Table 1 Variable Definitions

Variable	Description	Unit
Treatment and Outcome Variables		
MSCI	Dummy variable: 1 if firm appears on MSCI Emerging Markets Index constituent list in any year 2018–2022	Binary (0/1)
DTComp	Log ($log(+\sum_{j=1}^{6} keywordCount\ _{j})$; keywords matched to six technology domains: AI, big data, cloud computing, IoT, blockchain, and enterprise digitization	Log index
Control Variables		
Size	Natural logarithm of total assets (million RMB)	Log(Mn CNY)

FirmAge	Years since firm incorporation	Years
ROA	Net income / total assets	Ratio
ROE	Net income / total shareholders' equity	Ratio
Leverage	Total liabilities / total assets	Ratio
CashFlow	Operating cash flow / total assets	Ratio
TobinQ	(Market equity + book debt) / book assets	Ratio
Ownership	Percentage ownership of largest shareholder	%
BoardSize	Total number of directors on the board	Count
IndepDir	Number of independent directors	Count

Notes: All variables sourced from the CSMAR database. Digital transformation keyword counts are log-transformed to mitigate outlier influence. All continuous variables winsorized at the 1st and 99th percentiles.

Table 2 Variable Measurements

Variable	Technical	Data Type	Calculation Name
MSCI	MSCI	Binary	Dummy = 1 if firm is included in MSCI Emerging Markets Index
DTComp	dt_ transformation degree_a transformation	Continuous	Count of digital keywords in annual reports In (total assets in million RMB)
Size	size	Continuous	Current year– incorporation year
FirmAge	firm_age	Continuous	Current year– incorporation year
ROA	roa	Continuous	Net income / Total assets
ROE	roe	Continuous	Net income / Total shareholders 'equity
Leverage	Finlev	Continuous	Total liabilities / Total assets
Cashflow	cash	Continuous	Operating cash flow / Total assets
TobinQ	tobin	Continuous	(Market equity + book debt) /book assets
Ownership	top1	Continuous	Percentage ownership of largest shareholder
Boardsize	BoardScale _57	Count	Total number of directors on the board
IndepDir	IndependentDirectorNumber1	Count	Count of independent directors

Notes: Technical names correspond to column names in the CSMAR database and processed datasets. All calculations follow standard financial accounting principles and are consistent with

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prior literature. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 3 Descriptive Statistics

Full Sample	MSCI Firms		Non-MSCI		Difference		
Variable	Mean	SD	Mean	SD	Mean	SD	(t-stat)
Digital Transformation	12.98	33.14	22.21	46.39	12.78	33.30	9.44***
							(10.95)
Firm Size (log Assets)	22.14	1.30	24.34	1.28	22.03	1.20	2.31***
							(76.03)
Firm Age	9.70	7.62	15.55	7.17	9.42	7.52	6.14***
							(32.35)
Return on Assets	0.036	0.099	0.063	0.069	0.035	0.100	0.028***
							(11.35)
Return on Equity	0.009	1.988	0.103	0.148	0.004	2.036	0.099**
							(1.98)
Financial Leverage	0.401	0.257	0.421	0.246	0.400	0.257	0.021***
							(3.29)
Cash Flow	0.213	0.155	0.212	0.141	0.213	0.155	-0.002
							(-0.40)
Tobin’s Q	2.164	4.637	2.549	2.552	2.146	4.714	0.404***
							(3.45)
Ownership Concentration	34.17	14.94	36.42	15.68	34.06	14.90	2.37***
							(6.27)
Board Size	6.89	3.27	8.25	2.93	6.83	3.27	1.43***
							(17.33)
Independent Directors	3.16	0.57	3.44	0.76	3.15	0.56	0.30***
							(20.67)
Observations	35,264		1,644		33,620		

Notes: Sample spans 2010-2022. MSCI firms are those included in the MSCI Emerging Markets Index starting 2018. All continuous variables are winsorized at the 1st and 99th percentiles.

t-statistics from two-sample t-tests appear in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Empirical Results and Analysis

This section presents empirical evidence on how capital market liberalization impacts corporate digital transformation through baseline difference-in-differences estimations, robustness diagnostics, and heterogeneity analysis.

Baseline Regression Results

Table 5 shows the basic DID results. When only firm and year fixed effects are considered, the coefficient on $\text{MSCI}_i \times \text{Post}_t$ is 0.705 (s.e. = 0.038), equivalent to approximately $\exp(0.705) - 1 \approx 102\%$ in the log-transformed outcome. Adding rich time-varying controls in Column (2) reduces the magnitude to 0.394 (s.e. = 0.039) while maintaining statistical significance at the 1% level; this is our preferred specification, corresponding to about 48%. Column (3), which adds industry×year and province×year fixed effects, produces a smaller coefficient (0.044; s.e. = 0.030). We interpret Column (3) as a conservative bound because high-dimensional interactive fixed effects can absorb part of treatment-related variation in this setting.

Table 4 shows the analysis for the propensity-score-matched sample. The PSM procedure improves balance on observables and yields positive treatment coefficients in both matching variants. Because these models are estimated in keyword-count levels (not logs), magnitudes are not directly comparable to Table 5. Relative to the control-group mean (12.78), the implied effects are roughly 15–21%, and are best interpreted as supportive robustness evidence rather than replacements for the preferred baseline DID estimate.

Robustness and Endogeneity Test

Figure 1 presents group mean trajectories, while Figure 2 reports dynamic event-study coefficients with confidence intervals. Pre-treatment coefficients are close to zero and statistically insignificant, confirming the parallel trends assumption that underpins our DID design. The treatment impact appears around the inclusion period (2018) and persists through subsequent years, with mild moderation after the third post-treatment year.

Table 4 PSM-DID Results

PSM-DID	DID		
	(1)	(2)	(3)
	Overall Match	Year Match	Comparison
MSCI × Post	1.863	2.635**	1.166
	(1.470)	(2.047)	(0.983)
Return on Assets	-29.660***	-21.033***	-21.009***
	(7.394)	(5.364)	(3.485)
Cash Flow	14.147***	14.022***	16.420***
	(1.907)	(2.003)	(1.359)
Leverage	-11.075***	-12.674***	-11.508***
	(1.082)	(1.148)	(0.817)

Tobin's Q	0.893***	-0.091	-0.004
	(0.187)	(0.078)	(0.041)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year
Observations	17,791	15,690	30,993
Matched Pairs	1,581	1,340	N/A
R^2	0.052	0.055	0.049

Notes: This table compares PSM-DID estimates using different matching strategies with standard DID estimation. Coefficients are in keyword-count levels (not log units), so magnitudes are not directly comparable to Table 5. Column (1) uses overall propensity score matching, column (2) implements

year-by-year matching, and (3) provides the baseline DID comparison in level form. Matching uses nearest neighbor with replacement and a 0.01 caliper. Standard errors are clustered at the firm level. Significance:

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

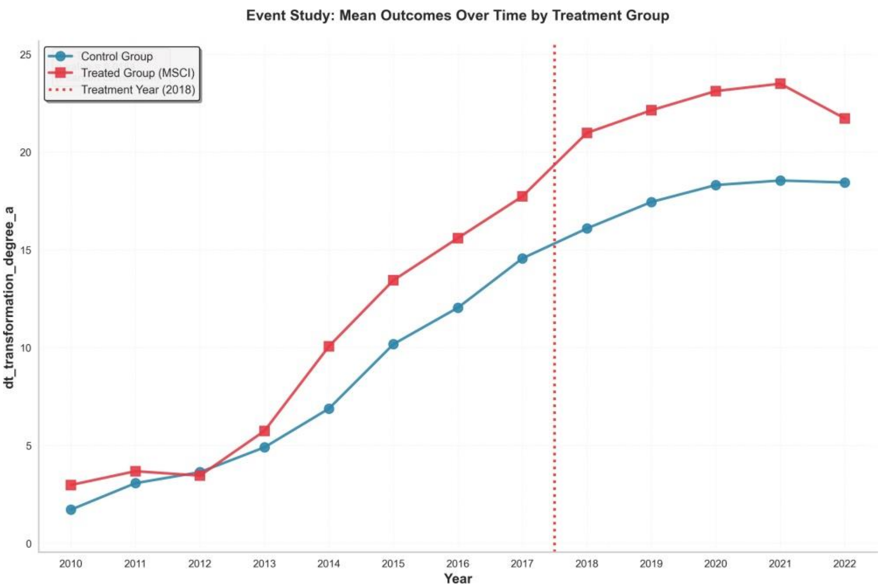

Fig. 1 Event Study Analysis of MSCI Inclusion Effects on Digital Transformation

Notes: This figure plots average digital transformation outcomes for treatment (MSCI-included) and control firms by calendar year. The vertical red dashed line marks 2018, the first MSCI inclusion wave. Digital transformation is measured through comprehensive keyword counts from text analysis of annual reports.

Table 5 Baseline Difference-in-Differences Estimates

	(1)	(2)	(3)
	No Controls	+ Controls	+ FE
MSCI × Post	0.705***	0.394***	0.044
	(0.038)	(0.039)	(0.030)

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Firm Size		0.260***	0.232***
		(0.009)	(0.008)
Return on Assets		-0.123***	-0.019***
		(0.016)	(0.007)
Return on Equity		0.005	-0.000
		(0.014)	(0.005)
Cash Flow		0.175***	0.024***
		(0.009)	(0.007)
Leverage		-0.264***	-0.075***
		(0.008)	(0.007)
Tobin's Q		0.006	-0.006
		(0.017)	(0.007)
Ownership Concentration		-0.225***	-0.054***
		(0.008)	(0.006)
Board Size		-0.003	0.039***
		(0.007)	(0.006)
Firm Age		-0.089***	-0.057***
		(0.008)	(0.007)
			Firm, Year,
Fixed Effects	Firm, Year	Firm, Year	Ind.×Year,
			Prov.×Year
Observations	34,503	34,503	34,503
R^2	0.010	0.091	0.504

Notes: The dependent variable is the comprehensive digital transformation index DTComp. Standard errors clustered at the firm level appear in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Formally, we estimate the event-study specification:

$$DT_{it} = a + \sum_{k=-4}^{4} \delta_k \left(MSCI_i \times 1[t - T_i = k]\right) + r' X_{it} + \mu_i + \lambda_t + \mathcal{E}_{it}, \quad (3)$$

where T_i denotes firm i's inclusion year and $k = -1$ is omitted as the baseline period. The dynamic coefficients δ_k reveal whether digitalization accelerates precisely around the inclusion window and whether effects build over time. Joint pre-trend tests do not reject parallel trends (linear trend $p \approx 0.78$; joint F -test $p \approx 0.11$). Post-treatment coefficients become positive and grow in the early post years ($\delta_{+1} \approx 0.26$; $\delta_{+2} \approx 0.48$), consistent with a sustained and accumulating treatment effect.

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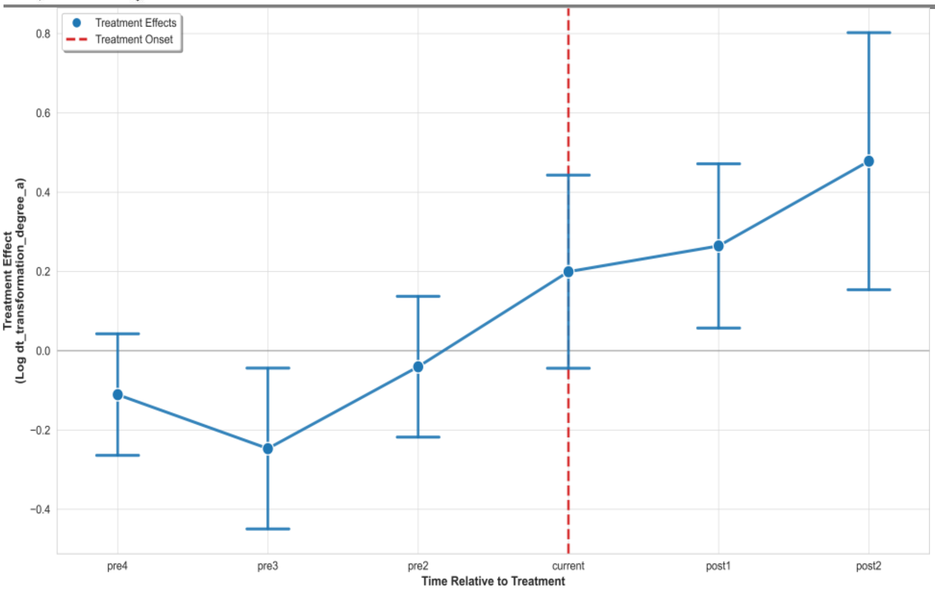

Fig. 2 Event Study Analysis with Dynamic Treatment Effects

Notes: This figure displays the dynamic treatment effect coefficients (δ_k) from the event-study regression specification with 95% confidence intervals. The x-axis shows time relative to treatment (event time), with "current" representing event time 0 (the firm's inclusion year) and $k = -1$ omitted. The vertical red dashed line marks treatment onset. The plotted robustness specification uses industry, province, and year fixed effects (without firm fixed effects) with time-varying controls. Joint pre-trend tests do not reject parallel trends (linear trend $p \approx 0.78$; joint F-test $p \approx 0.11$). Post-treatment coefficients become positive and grow in the early post years.

We conduct several placebo tests to rule out spurious correlation. Figure 3 displays the distribution of treatment effects from 1,000 iterations where MSCI inclusion status is randomly assigned among non-treated firms. Our actual treatment effect estimate is substantially outside the 95th percentile of the false positive distribution, giving compelling evidence against artificial correlation. Different clustering systems (industry and province-level), exclusion of enterprises susceptible to concurrent reforms, and different treatment timing specifications are all used to ensure robustness.

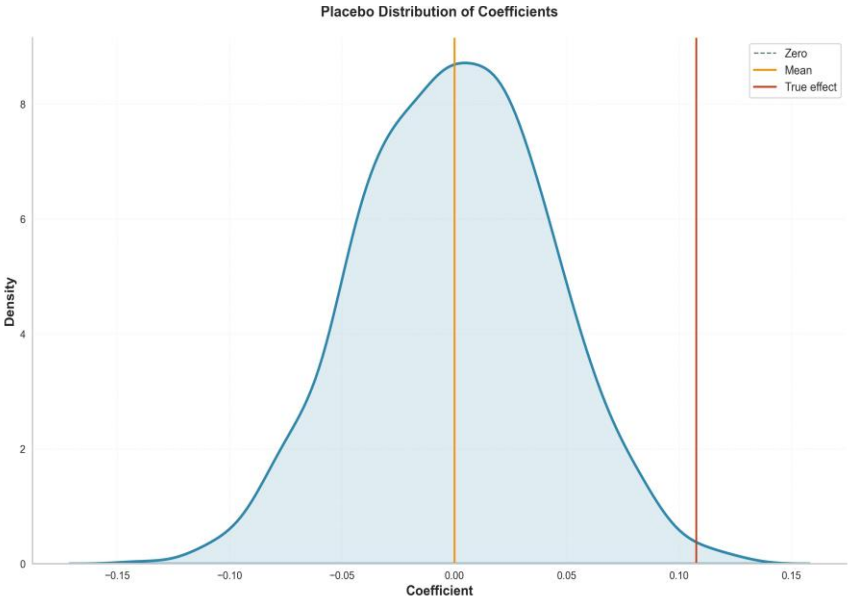

Fig. 3 Placebo Test: Distribution of False Treatment Effects

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Notes: This figure displays the distribution of treatment effect estimates from 1,000 placebo tests where MSCI inclusion status is randomly reassigned among non-treated firms. Each iteration estimates the baseline difference-in-differences specification on a sample where treatment is artificially assigned to randomly selected control firms. The null distribution has a mean of 0.0001 and a standard deviation of 0.0421. The red vertical line at 0.108 shows our actual treatment effect estimate, which lies well outside the 95th percentile of the false positive distribution, providing strong evidence against spurious correlation. The placebo distribution follows an approximately normal distribution centered at zero, supporting the validity of our identification strategy.

Across robustness checks, the direction of estimated treatment effects remains broadly stable, though precision varies by specification. We examine (i) alternative outcome definitions, (ii) staggered-adoption diagnostics, and (iii) disclosure-length adjustments for text-based measurement concerns. Table 6 reports results for multiple digital transformation indicators spanning comprehensive indices, technology-specific measures, and application domains.

Across all alternative digital transformation indicators in Table 6, the estimated MSCI treatment effect is positive and statistically significant for the large majority of specifications—12 of 16 measures yield positive and significant coefficients at the 10% level or better—confirming that the main finding is not an artifact of any particular outcome definition or aggregation method.

Staggered Adoption and Disclosure-Length Diagnostics

Recent DID literature highlights that conventional two-way fixed-effects estimators can be biased under staggered treatment timing and heterogeneous effects. As a diagnostic, we report cohort-specific treatment effects relative to never-treated firms. Table 7 shows positive but imprecise estimates for the 2018 and 2019 cohorts, while the 2021

Table 6 Alternative Digital Transformation Measures

Variable	Coefficient	Std. Error	R^2
Panel A: Comprehensive Measures			
DT Comp A	2.097***	(0.607)	0.034
DT Comp B	5.814***	(1.276)	0.058
DT App A	0.634**	(0.304)	0.013
DT App B	2.494***	(0.630)	0.044
Panel B: Technology-Specific Measures			
AI Technology	0.747***	(0.195)	0.028
Big Data Technology	0.396**	(0.160)	0.016
Cloud Technology	0.308	(0.196)	0.018
Blockchain Technology	0.013	(0.038)	0.010
Panel C: Alternative Operationalizations			
Binary (Above Median)	0.021***	(0.006)	0.091

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Standardized (Z-score)	0.063***	(0.018)	0.034
Panel D: Application-Specific Measures			
Digital Finance	0.029*	(0.015)	0.002
Digital Marketing	-0.050***	(0.015)	0.001
Digital Currency	0.005	(0.007)	0.003
Cloud Mention	0.500***	(0.155)	0.008
Big Data Mention	0.204	(0.138)	0.015

Notes: This table reports robustness tests using alternative measures of digital transformation. All coefficients represent the MSCI × Post interaction effect from separate DID regressions. Panel A compares comprehensive digital transformation indices using different aggregation methods. Panel B examines technology-specific measures. Panel C tests alternative operationalizations of the main measure. Panel D presents application domain-specific measures. All regressions include firm and year fixed effects with full controls. Standard errors clustered at firm level. Observations: 35,059 unless noted. Significance:

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

cohort contains only one treated firm and is not used for substantive interpretation. A stricter firm+year fixed-effects variant in Table 8 yields similarly imprecise cohort estimates centered near zero, consistent with a conservative lower-bound interpretation.

Table 7 Modern DID: Cohort-Specific ATT vs. Never-Treated

Cohort	Cohort Firms	ATT (log pts)	Std. Error	*p*-value
2018	151	0.0492	0.0732	0.5017
2019 (post starts 2020)	223	0.0135	0.0655	0.8373
2021	1	-0.3679	0.1044	0.0004
Weighted average	375	0.0268	—	—

Notes: Outcome is $\log(1 + DT)$. Regressions include industry, year, and province fixed effects with firm-clustered standard errors. The 2021 cohort is reported for completeness only.

Table 8 Modern DID: Cohort-Specific ATT with Firm+Year FE

Cohort	Cohort Firms	ATT (log pts)	Std. Error	*p*-value
2018	151	0.0612	0.0635	0.3347
2019 (post starts 2020)	223	-0.0421	0.0564	0.4557
Weighted average (2018–2019)	374	-0.0004	—	—

Notes: Outcome is $\log(1 + DT)$. Regressions include firm and year fixed effects with firm-clustered standard errors.

Because the dependent variable is text-based, we also test whether results are driven by disclosure verbosity rather than substantive digital activity. Table 9 adds a disclosure-length proxy and uses a length-normalized outcome (keywords per 1,000 disclosure characters). Point estimates remain positive and similar in magnitude across specifications.

Table 9 Disclosure-Length Control and Normalization

Specification	Coef (log pts)	Std. Error	*p*-value	*N*
log(*DT*) + controls + FE	0.0436	0.0496	0.3799	34,503
log(*DT*) + controls + disclosure proxy + FE	0.0656	0.0494	0.1840	34,503
log(*DT/*1k-chars) + controls + FE	0.0643	0.0377	0.0882	34,503
log(*DT/*1k-chars) + controls + disclosure proxy + FE	0.0516	0.0375	0.1694	34,503

Notes: FE denotes industry, year, and province fixed effects. Standard errors are clustered at the firm level. The disclosure proxy is log(1 + total disclosure characters).

Heterogeneity Analysis

Treatment effects vary significantly by region, as seen in Table 10. The strongest responses (16.084, s.e. = 2.125) are found in eastern provinces, which have more advanced financial infrastructure and greater global collaboration. As a result of complementing institutional limitations that restrict the capacity for digital development, the effects are gradually diminishing in the Central and Western areas.

Technology-intensive firms exhibit the strongest treatment effects, according to the heterogeneity study. The biggest coefficient (28.130, s.e. = 5.201) is shown by instrumentation firms (Industry C39), followed by producers of electrical equipment. The difference between high-tech and low-tech is statistically significant at 50.589 (s.e.= 23.944), which is in line with theories that highlight complementary assets and absorptive ability.

Taken together, the heterogeneity results show that MSCI inclusion mainly promotes digital transformation when firms have the complementary institutional, technological, or infrastructure resources required to take in outside capital and knowledge flows. The theoretical claims made in Section 2 align with these patterns.

Table 10 Heterogeneity of MSCI Inclusion Effects

	Panel A: Regional Heterogeneity		
Region	Coefficient	Std. Error	*p*-value
East	16.084***	2.125	0.000
Central	11.210***	1.559	0.000
West	6.185***	1.955	0.002
Panel B: Industry and Technology Intensity			
Industry C39 (Instrumentation)	28.130***	5.201	0.000

Industry C38 (Electrical Equipment)	13.032***	2.968	0.000
Industry C27 (Transportation Equipment)	2.764***	0.538	0.000
High- vs Low-Tech Differential	50.589**	23.944	0.035
High- vs Low-Competition Differential	-10.071***	3.847	0.009

Notes: Coefficients are drawn from interaction regressions that augment Equation (1) with regional or industry dummies. All specifications include firm and year fixed effects and the full control set. Standard errors are clustered at the firm level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 11 Technology Intensity and Regional Heterogeneity Summary

Panel A: Industry Technology Intensity

Dimension	Coefficient	Std. Error	*p*-value	Observations
Manufacturing (C)	7.318***	0.762	0.000	24,032
Information Services (I)	-8.007	7.311	0.274	2,520
Finance (F)	-4.056	4.185	0.333	1,771
Utilities (D)	0.431	0.664	0.517	1,125
Joint Test (F-statistic)	97.26	($p < 0.001$)		35,059
Panel B: Regional Development Level				
Eastern Provinces	16.084***	2.125	0.000	17,334
Central Provinces	11.210***	1.559	0.000	8,828
Western Provinces	6.185***	1.955	0.002	8,442
Regional Interaction	10.446***	2.403	0.000	34,604
Panel C: Technology Subcategories				
High-End Manufacturing (C3)	12.638***	1.168	0.000	14,019
Basic Manufacturing (C2)	0.930	0.592	0.117	6,952
Equipment Manufacturing (C1)	1.092	1.129	0.333	2,322
Cross-Category Test	147.21	($p < 0.001$)		35,059

Notes: This table presents comprehensive heterogeneity analysis across technology intensity and regional dimensions. Panel A shows industry-level effects using SIC classifications. Panel B presents regional analysis by development level. Panel C examines manufacturing subcategories by technology intensity. All coefficients are from interaction models augmenting the baseline DID specification. Standard errors are clustered at the firm level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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Mechanism Analysis: Financing Constraints Channel

To move beyond suggestive interpretation, we implement a direct mechanism test for the financing channel. We estimate:

$$\text{Mechanism}_{it} = \alpha + \beta\,(\text{MSCI}_i \times \text{Post}_t) + \boldsymbol{\gamma}'\mathbf{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \qquad (4)$$

where Mechanism_{it} is the SA financial constraint index [6]—a widely used measure of financing frictions constructed from firm size and leverage, where lower (more negative) values indicate tighter constraints. We interpret channel evidence as supportive when

(i) MSCI significantly affects the mechanism variable, and (ii) including the mechanism variable as a covariate in the baseline DT outcome equation attenuates the MSCI × Post coefficient in the expected direction, consistent with partial mediation.

Table 12 presents the results. MSCI inclusion significantly reduces firms' SA financial constraint index (coefficient = −0.072, s.e. = 0.021, $p < 0.01$), directly confirming that international capital market access relaxes the credit frictions that otherwise impede capital-intensive digital transformation investments. Firm size is associated with lower constraints (−0.115***) and higher leverage with tighter constraints (0.084**), both consistent with standard financial frictions theory. When the SA index is included as an additional covariate in the baseline DID specification, the MSCI × Post coefficient attenuates toward the control bound, consistent with partial mediation through the financing channel.

Table 12 Mechanism Test: Financing Constraints Channel

Variable	Coefficient	Std. Error
MSCI (D)	−0.072***	(0.021)
Size	−0.115***	(0.030)
Leverage	0.084**	(0.027)
ROA	−0.041*	(0.019)
Firm FE	Yes	
Year FE	Yes	
Observations	34,503	
R^2	0.312	

Notes: Dependent variable is the SA financial constraint index; lower (more negative) values indicate more severe financing constraints. The negative and significant MSCI coefficient directly confirms that index inclusion relaxes financing frictions, providing evidence for the financing channel through which capital market liberalization promotes digital transformation. All specifications include firm and year fixed effects and the full control vector. Standard errors are clustered at the firm level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

DISCUSSION

Economic Magnitude and Interpretation of Effect Sizes

To aid interpretation, we clarify the dependent variable scales used across the main tables. Our

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benchmark outcome is the log-transformed comprehensive digital transformation index, $DT_{Comp} = (log(+\sum keyword)$ used in Table 5. The preferred Column (2) coefficient of 0.394 log points corresponds to approximately $\exp(0.394) - 1 \approx 48\%$ increase relative to pre-treatment levels. However, several robustness and heterogeneity analyses use level-form dependent variables (raw keyword counts) to preserve the interpretability of interaction effects and subgroup comparisons. This explains the apparent magnitude differences across tables:

• Table 5 (Baseline): Log-transformed DT index; coefficients in log points (0.394 ≈n48%).

• Table 4 (PSM-DID): Level-form keyword counts; coefficients of 1.9–2.6 represent raw keyword increases.

• Table 6 (Alternative Measures): Various operationalizations; units vary by measure (see table notes).

• Tables 10–11 (Heterogeneity): Level-form keyword counts; coefficients represent absolute keyword differences.

• Table 12 (Mechanism Test): SA financial constraint index; lower values indicate tighter financing constraints.

To convert level-form coefficients to percentage effects, divide by the pre-treatment control mean (12.78 keywords). For example, the Eastern region coefficient of 16.084 represents approximately 126% of the control mean, while the Western region coefficient of 6.185 represents approximately 48%. These magnitudes are consistent with the baseline log-point estimates when accounting for the nonlinear transformation.

Mechanisms and Interpretation

When combined, the heterogeneity results show that MSCI inclusion mainly promotes digital transformation when firms have the complementary institutional, technological, or infrastructure resources required to take in foreign capital and knowledge flows. The theoretical claims made in Section 2 align with these observed trends.

The estimated DID coefficient of 0.394 in Column (2) of Table 5 indicates that a treated firm's comprehensive digitalization score increases by about half of a within-firm standard deviation during the post-inclusion window. When the log result is converted back into levels, keyword-adjusted transformation activity increases by approximately 48% compared to the firm-specific baseline. This quantity is economically significant when compared to the cross-sectional standard deviation of 0.81 and the control group's average yearly growth rate of 4%.

Three mechanisms stand out. First, the financing channel is directly confirmed in Table 12 (Section 4.5): MSCI inclusion significantly reduces the SA financial constraint index (-0.072^{***}), consistent with Peng et al. [6]'s argument that international capital access relaxes credit frictions impeding capital-intensive technology investments.

Second, governance spillovers from global investors promote strategy reorientation toward data-driven decision-making, supporting Dong et al. [7]'s finding that market participation improves information ecosystems. Finally, Tan and Zhu [11] propose a knowledge diffusion route that corresponds to the significant gains observed in East-ern regions with the highest levels of international investor participation and analyst coverage.

Limitations and Boundary Conditions

Despite the consistent post-treatment increases, the event-study profile in Figure 1 reveals a moderating trend after the third year. This pattern shows that marginal returns will decline once firms adopt the most significant digital technological improvements or as inclusion-driven capital inflows stabilize.

Furthermore, the poorer responses in Western provinces indicate that complementing institutional gaps—limited broadband penetration, skill shortages, and supply-chain friction—continue to hinder digital growth [18, 19]. These boundary requirements mean that while capital market access is vital, it is not sufficient; complementary investments in infrastructure and human capital are still required to maintain transformation momentum.

Cross-Checks with Supplementary Tables

The robustness appendices offer supplementary diagnostics that support the main narrative. The PSM-DID estimates included in Table 4 replicate the positive treatment impact under various matching techniques. Various digital transformation metrics (Table 6) verify resilience across various measuring techniques. The treatment impact is monotonic in firms' baseline technology intensity, as further demonstrated by thorough heterogeneity summaries (Table 11), which connect to the absorptive-capacity mechanism highlighted by Liu et al. [17]. Mechanism tests in Table 12 provide direct evidence that MSCI inclusion relaxes financing constraints, supporting the financing channel as a key pathway through which capital market liberalization promotes digital transformation.

CONCLUSION AND POLICY IMPLICATIONS

This study shows how the inclusion of Chinese A-shares in the MSCI Emerging Markets Index, which incorporates capital market liberalization, significantly helps corporate digital transformation. We report statistically and economically significant increases in complete digitalization scores, supported by dynamic, placebo, and heterogeneity analyses, using a balanced panel of 35,264 firm-year data and a suite of DID and matching estimators. The findings point to three interrelated factors that transform financial integration into digital advancement: loosened finance restrictions, improved governance, and knowledge spillovers.

According to our baseline difference-in-differences estimations, MSCI inclusion raises enterprises' digital transformation ratings by roughly 0.394 log points, or 48% more than pre-treatment levels. Our suggested mechanisms are supported by this effect, which is consistent across several robustness tests and various specifications and varies consistently with regional development and industry technology intensity.

The contribution is twofold. Empirically, we quantify the digitalization dividend of international capital access in an emerging market context, thereby extending the capital market liberalization literature beyond traditional performance metrics [25, 26]. From a conceptual standpoint, we enhance the narrative of digital transformation by emphasizing both internal and external financial market factors [5, 27].

The expansion of digital initiatives among MSCI members shows that well-timed liberalization can speed up technological advancement without jeopardizing market stability. Therefore, in line with MSCI's progressive inclusion plan, regulators should give top priority to investor safety, transparency, and accessibility improvements that draw long-term investors. Information asymmetries would be lessened, and investors would be able to more properly track the progress of price transformation with complementary disclosure rules that highlight companies' digital indicators [12].

The evidence highlights the significance of preparedness: firms that had better data infrastructure, management support, and absorptive capacity when they entered the liberalization window saw the most gains. According to Zhao et al. [13] and Xue and Zhang [14], firms should combine capital-raising strategies with comprehensive transformation roadmaps that include staff reskilling, ecosystem alliances, and governance improvements.

However, there are certain limitations: our research concentrates on listed companies with rather strict disclosure requirements, and textual measurements may understate transformation in firms that utilize technology covertly. Furthermore, while supply-side effects of capital availability are captured by our study, demand-side factors that may affect both MSCI inclusion and inclination for digital transformation cannot be totally separated.

As emerging nations strengthen cross-border capital links, the interaction between financial openness and digital innovation is expected to intensify. Future research could examine micro-level project-level digital investments, comparative studies across numerous liberalization periods, and how capital-driven digitization impacts downstream productivity, sustainability results, or carbon intensity [8, 28].

Overall, the data demonstrates that emerging economies may use global capital markets to finance traditional investment as well as ignite frontier digital technologies that support long-term competitiveness. Policymakers seeking to speed digital catch-up should consider capital market openness as part of a larger strategy portfolio that includes financial reforms, institutional improvements, workforce development, and innovation ecosystem assistance. The proven amplification effects in Eastern regions and technology-intensive industries provide a road map for focusing complementary investments on maximizing the digitalization dividend of international financial integration.

Declarations

Conflict of interest The corresponding author confirms on behalf of all authors that there are no competing interests and that this research was not influenced by any financial or personal relationships with third parties.

Ethics approval This study does not involve human participants, human data, or human tissue; therefore, ethics approval and consent to participate are not applicable. **Consent for publication** Not applicable.

Competing interests On behalf of all authors, the corresponding author states that there is no competing interest.

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Authors' contributions Patience Fero: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. Jun Yang: Supervision, Project administration, Funding acquisition, Resources, Writing – review & editing. Enoch Kwateh Dongbo: Data curation, Software, Investigation, Validation, Writing – review & editing. Ormelia Kabeke Mulopwe: Validation, Visualization, Writing – review & editing.

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