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Original Article

Digital Infrastructure Integration and Capital-Market Resilience in a Frontier Exchange: A Longitudinal Panel and Coefficient-Decomposition Analysis of the Nairobi Securities Exchange

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Abstract

Digital infrastructure has become the backbone of commerce across Sub-Saharan Africa, yet evidence on whether firm-level integration protects listed companies' capital-market outcomes during macroeconomic stress remains scarce, dominated by studies of Chinese firms. This study examines whether sectoral digital infrastructure exposure is associated with market-based resilience (lower equity price volatility and stronger returns, not organizational resilience) among the 53 companies continuously traded on the Nairobi Securities Exchange over the turbulent 2021-2025 cycle, and tests the financial channel involved.

Daily transactional records are aggregated into a balanced firm-year panel and analysed with three estimators: random effects (REs), two-way fixed effects (FEs), and correlated REs (CREs, Mundlak), all with firm-clustered standard errors. A Hausman test rejects REs for the time-varying regressors ($\chi^2(3) = 41.11$, $p < 0.001$). Because the exposure tier is a coarse, sector-based proxy correlated with firm size and liquidity, five additional identification checks extend the robustness battery: an unbalanced panel reintroducing previously excluded, thinly traded counters (including a bank omitted from the original classification, which is assigned Tier 2 but contributes no usable observation); a lagged, predetermined liquidity specification; a quarterly-frequency replication; a continuous market-wide shock index; and a traded-value size/turnover proxy, given the absence of market-capitalization data.

Market liquidity, not digital exposure directly, carries the association. A coefficient-decomposition analysis, distinguished from causal mediation, identifies the channel: between-firm market liquidity (firm-mean log volume) is strongly and negatively associated with volatility (−0.510, $p < 0.01$), and a Gelbach (2016) decomposition within a single model family attributes essentially all of the small RE-CRE coefficient gap to this liquidity term (−0.120 of −0.099 total). The association survives every extension: an unbalanced 58-firm sample (−0.448), quarterly aggregation (−0.384), 1-year-lagged liquidity (−0.433), a continuous shock index (−0.482), and an independent traded-value proxy (−0.380). Descriptively, digitally integrated banking and telecommunications firms trade with materially lower volatility (2.02% versus 3.01-3.42%) and higher mean returns (14.73%) than traditional-sector counterparts, but this raw tier-level pattern does not stand as a direct digital-exposure effect: the linear digital-exposure index is not itself a significant predictor of volatility, any resilience signal is concentrated in the high-exposure tier, and it does not survive controlling for between-firm liquidity in the preferred CRE model (direct effect 0.097, n.s.). Digital exposure does not steepen the liquidity-return relationship; a minimum-detectable-effect calculation shows the design can reliably detect interaction effects only above roughly 4.5-5.3 at 80% power, several times the observed estimates, a bounded, power-limited null. Market liquidity and scale are therefore the proximate, measurable channel linking digital infrastructure to capital-market resilience here, though the design is associational, single-market, and limited by a coarse sector-level exposure measure.

Categories: Corporate Governance & Business Ethics, Digital business, Banking and financial services

Keywords: digital infrastructure, market-based resilience, market liquidity, panel data econometrics, coefficient decomposition, nairobi securities exchange, frontier markets, g14, g15, g12

Introduction

Global commerce has been reshaped over the past two decades by the rapid expansion of digital infrastructure (Myovella et al., 2020) (Aghion et al., 2021). In Sub-Saharan Africa this evolution did not replicate the linear developmental stages of advanced economies: the region leapfrogged legacy networks to establish mobile-first digital rails as a backbone of macroeconomic activity (Ndung'u and Signé, 2020). The scale is now considerable. Mobile money processed more than USD 2 trillion globally in 2025, of which roughly USD 1.4 trillion was transacted in Sub-Saharan Africa, with East Africa alone accounting for USD 806 billion (GSMA, 2026), and account ownership across developing economies has risen sharply on the back of mobile payments (Demirgüç-Kunt et al., 2022). Kenya is the canonical case: mobile money demonstrably improves household risk-sharing and shock absorption (Jack and Suri, 2014) (Suri et al., 2021), and digital finance is credited with broad inclusion and stability effects (Ozili, 2018) (Ahmad et al., 2020).

Whether this macro-level infrastructure translates into firm-level capital-market resilience in African capital markets is far less clear. As elaborated below, capital-market resilience (lower price volatility, steadier returns) is a narrower and more specific claim than organizational resilience in the broader management sense (Duchek, 2020) (Hillmann and Guenther, 2021). The rapidly growing firm-level literature on digital transformation and resilience is concentrated almost entirely on Chinese listed firms, where evidence is mixed: digital transformation has been linked to greater risk-taking (Tian et al., 2022), to bank stability through diversification (Khattak et al., 2023), and to an inverted U-shaped rather than monotonic resilience effect (Yan et al., 2024). Survey-based work links digital capabilities to performance only indirectly, through mediating capabilities (Heredia et al., 2022), and meta-analytic evidence shows that the information and communications technology (ICT) performance relationship is contingent on a country's ICT development status (Karim et al., 2022). No study that we are aware of tests these propositions with capital-market data from an African frontier exchange, nor identifies the financial channel through which any protective association operates. This matters because frontier markets differ from China's deep, liquid exchanges on precisely the dimension most likely to carry the effect: liquidity is scarce, unevenly distributed, and priced (Bekaert et al., 2007) (Hearn, 2012).

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This study addresses that gap with a longitudinal panel analysis of the Nairobi Securities Exchange (NSE) over 2021-2025, a window spanning the global inflationary surge of 2022, the severe depreciation of the Kenyan shilling, 20.4% year-on-year against the US dollar in 2023, under aggressive monetary tightening (International Monetary Fund, 2024), and the recovery of 2024-2025. The NSE offers a stark sectoral bifurcation between digitally integrated banking and telecommunications conglomerates and traditional asset-heavy agricultural and manufacturing issuers, together with extreme dispersion in trading activity, making it an unusually clear setting to separate a digital-integration effect from a liquidity effect, while also, as the additional analyses show, making the two difficult to fully disentangle with sector-level data alone.

Two research questions guide the inquiry. First, is a higher degree of structural integration into national digital infrastructure associated with lower equity price volatility during systemic macro shocks in a frontier market? Second, through which financial channel does any such association operate, in particular, is it carried by market liquidity, and does digital integration moderate the liquidity-return relationship?

The paper makes three contributions, each qualified in light of the identification concerns addressed below. First, it extends the digital transformation-resilience literature (Tian et al., 2022) (Khattak et al., 2023) (Yan et al., 2024) beyond China to an African frontier market, using transparent capital-market data rather than survey measures, while being explicit that the exposure measure is a structural, sector-level proxy and not a firm-level digitalization index. Second, it moves beyond documenting an association to decomposing it: a coefficient-decomposition analysis (Gelbach, 2016), deliberately distinguished from causal mediation (Baron and Kenny, 1986), identifies market liquidity as the dominant statistical channel carrying the small cross-sectional association, and this decomposition is now stress-tested with a predetermined (lagged) liquidity specification, an unbalanced-panel check for survivorship, and a quarterly-frequency replication. Third, it grounds the socio-technical account of digital resilience in the market-microstructure literature on liquidity in thin markets (Amihud, 2002) (Lesmond, 2005) (Fong et al., 2017), yielding falsifiable, mechanism-level propositions for future replication across African exchanges.

Literature review and hypothesis development

Theoretical Framework: Resources, Dynamic Capabilities and Socio-Technical Systems

The Resource-Based View (RBV) holds that capabilities generate durable advantage when they are valuable, rare, imperfectly imitable and non-substitutable (Wernerfelt, 1984) (Barney, 1991), and its information-systems application treats digital assets as internal resources that optimize firm-specific efficiency (Wade and Hulland, 2004). Digital transformation research has extended this static view in two directions relevant here. Dynamic-capability accounts show that the value of digital assets lies in ongoing sensing, seizing, and reconfiguring rather than in ownership per se (Warner and Wäger, 2019) (Vial, 2019) (Verhoef et al., 2021), and meta-analytic evidence confirms that ICT capabilities translate into performance contingently, depending on the surrounding technological environment (Karim et al., 2022). Socio-Technical Systems (STS) theory supplies the second extension: the enterprise is an open system whose internal technical layers are structurally intertwined with external institutional and financial networks (Trist, 1981) (Mumford, 2006). In frontier markets, digital integration is therefore not merely a localized corporate choice but a structural alignment between the firm and macro-level rails such as national mobile-money networks, central clearing systems and telecommunications capacity (Ndung'u and Signé, 2020).

Under this combined lens, digital infrastructure integration is a relational capability: a firm that embeds its transaction pipelines and data flows in a regional digital infrastructure can preserve core functions when physical channels are disrupted (Jack and Suri, 2014). For capital markets, specifically, the same alignment should manifest as superior informational visibility and tradability, an implication that the empirical design below tests directly rather than assuming. As the construct-validity discussion below makes explicit, this sector-level structural alignment is a coarser and more indirect construct than firm-level digital adoption, so the empirical claims that follow are scoped accordingly.

Digital Transformation and Firm Resilience: Recent Empirical Evidence

Organizational resilience research conceptualizes resilience as a multi-stage capability of anticipating, coping with, and adapting to adversity (Duchek, 2020), distinguishes severity of loss from time to recovery (DesJardine et al., 2019), and cautions that the construct must be measured through observable outcomes if it is to support cumulative research (Hillmann and Guenther, 2021) (Conz and Magnani, 2020). Meta-analytic work identifies digital and information-processing capabilities among the antecedents of firm resilience (Iftikhar et al., 2021), and case and survey evidence links digital tools, agility, and social-media capabilities to the survival of small and medium-sized enterprises (SMEs) through crises (Troise et al., 2022) (Martín-Rojas et al., 2023). This study adopts a narrower, market-based operationalization within that broader construct family (equity-price volatility and returns) and does not claim to measure organizational resilience directly; the distinction is discussed further in the variable-definitions subsection.

Firm-level financial evidence, however, is more equivocal than the capability literature implies. Among Chinese listed firms, digital transformation raises corporate risk-taking (Tian et al., 2022), and its relationship with resilience is inverted U-shaped, with over-digitalization associated with fragility (Yan et al., 2024). For banks, digitalization strengthens stability, operating partly through diversification (Khattak et al., 2023). Survey-based structural models find the digital-capability effect on performance to be indirect, mediated by technological capabilities (Heredia et al., 2022). Three features of this literature motivate the present design: the evidence is concentrated in one institutional setting (China); resilience is usually proxied by accounting or text-based measures rather than market behaviour; and the transmission channel is rarely identified. A market-based test in an African frontier setting, with an explicit decomposition design, addresses all three.

Evidence Beyond China: African, Frontier and Broader Emerging Markets

Because so much of the firm-level digitalization-resilience evidence originates in China, its portability to an African frontier exchange cannot be assumed; China's deep, liquid A-share market and its distinctive institutional environment differ from the NSE on precisely the dimensions this study isolates. Three bodies of non-Chinese evidence therefore frame the analysis. First, research on African equity markets documents that these exchanges are thin, segmented, and only partially integrated with global markets, so that liquidity and size are first-order priced characteristics and returns behave differently from those in developed markets (Allen et al., 2011) (Alagidede, 2011) (Hearn, 2012) (Smith, 2008). Second, the frontier- and emerging-market asset-pricing literature shows that liquidity risk commands a large premium and that frontier markets offer diversification precisely because they are weakly integrated (Bekaert et al., 2007) (Berger et al., 2011). Third, Sub-Saharan evidence on digital finance links mobile-money and digital-payment infrastructure to household resilience (Jack and Suri, 2014) (Suri et al., 2021), to firm financing and development (Beck et al., 2018), and to bank stability across the region (Chinoda and

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Kapingura, 2023). Taken together, this non-Chinese evidence motivates a liquidity-centred reading of digital resilience in frontier markets and cautions against transplanting the Chinese findings directly. The present study contributes the first firm-level capital-market test of the digital exposure-resilience association on an African frontier exchange and explicitly identifies the liquidity channel.

Digital Finance and the Sub-Saharan African Context

Sub-Saharan Africa is the global centre of mobile money, transacting roughly USD 1.4 trillion in 2025 (GSMA, 2026), and digitalization contributes measurably to the region's growth (Myovella et al., 2020). Micro-evidence from Kenya shows that mobile money improves household risk-sharing (Jack and Suri, 2014) and that digital credit increases household resilience to shocks (Suri et al., 2021); reviews link mobile money to inclusion and development outcomes across the continent (Ahmad et al., 2020) and digital finance to financial stability (Ozili, 2018); recent panel evidence shows that digital financial inclusion strengthens bank stability across Sub-Saharan African banking systems (Chinoda and Kapingura, 2023). The Global Findex confirms the step-change in account ownership and digital payments through 2021 (Demirgüç-Kunt et al., 2022). This literature, however, is anchored at the household and macro levels. The firm-level capital-market consequences of operating on these rails, for the volatility, liquidity, and returns of listed companies, remain essentially undocumented, which is the gap this study fills.

Market Microstructure: Liquidity, Volatility and Returns in Thin Markets

Liquidity is a priced characteristic: expected returns compensate illiquidity (Amihud and Mendelson, 1986) (Amihud, 2002), and in emerging markets liquidity effects on returns are first-order (Bekaert et al., 2007). Emerging-market liquidity is scarce and heterogeneous, with substantial zero-return and non-trading days (Lesmond, 2005); in African markets specifically, thin trading impairs informational efficiency (Smith, 2008) and liquidity is a dominant priced factor (Hearn, 2012). Low-frequency proxies (the Amihud ratio, zero-return-day shares and high-low ranges) measure these constructs credibly when intraday data are unavailable (Fong et al., 2017), though the high-low range is also mechanically related to the realized-volatility outcome used here, a point taken up explicitly in the variable-definitions subsection. Transparency interacts with liquidity: transaction-cost benefits of transparency are strongest exactly when liquidity is scarce and uncertainty high (Lang et al., 2012). Finally, systemic shocks compress returns broadly, as documented for African exchanges during COVID-19 (Takyi and Bentum-Ennin, 2021).

This microstructure account and the socio-technical account of the theoretical framework point in the same direction for the NSE's digitally integrated banks and telecommunications operator: such firms are operationally resilient and simultaneously the most visible, continuously disclosed and heavily traded counters on the exchange. A careful design must therefore ask whether the resilience associated with digital integration is distinct from, or largely transmitted through, the resilience associated with deep liquidity. That identification question structures the hypotheses and the estimation strategy, and is precisely why the study adds firm size/turnover, predetermined-liquidity and survivorship checks to the original estimation.

Alternative Resilience Channels

Liquidity is not the only mechanism through which digitally exposed firms might appear more resilient, and the design cannot exclude several correlated channels. Larger firms are mechanically less volatile and command greater liquidity (Fama and French, 1992); stronger governance and investor protection are associated with lower risk and higher valuations in emerging markets (Klapper and Love, 2004); institutional ownership stability is linked to lower crash risk (Callen and Fang, 2013); broader analyst coverage improves the information environment (Hong et al., 2000); and higher disclosure quality lowers the cost of capital and raises liquidity, especially when liquidity is scarce (Lang et al., 2012). Because the NSE's digitally integrated banks and telecommunications operator also tend to be the largest, best-governed, most widely covered and most transparent issuers on the exchange, the portion of the exposure-volatility association that survives the liquidity control could reflect these channels rather than digital integration per se. The public NSE end-of-day feed used here does not report market capitalization or shares outstanding, so firm size cannot be measured directly; the Additional analyses subsection constructs the best available market-based proxy (mean daily traded value) and shows it is highly correlated with the liquidity measure itself ($r = 0.68$ at the firm level), which is itself informative: with only price and volume data, size and liquidity cannot be cleanly separated, and the liquidity channel identified here should be read as encompassing both. Disentangling governance, ownership, coverage, disclosure and size as fully distinct channels requires richer firm-level data than the public feed provides and is identified as a priority for future research.

Positioning Against the Closest Prior Studies

Table 1 situates the study against the closest recent empirical work. The gap it fills is precise: no prior study tests the digital integration-resilience association with capital-market outcome data from an African frontier exchange, and none formally decomposes the association to identify market liquidity as the statistical channel.

Study	Setting and data	Digital measure	Method	Key finding
(Tian et al., 2022)	Chinese listed firms	Text-based DT index	Panel regression	DT increases corporate risk-taking
(Heredia et al., 2022)	Multi-country firm survey	Self-reported digital capabilities	Structural equation model	Effect on performance is indirect (mediated)
(Khattak et al., 2023)	Banks, cross-country panel	DT index	Panel regression	DT strengthens bank stability via diversification
(Yan et al., 2024)	Chinese A-share manufacturers, 2017-2021	Text-based DT index	Panel regression, moderation	Inverted U-shaped DT-resilience relationship
(Suri et al., 2021)	Kenyan households	Digital loan usage	Field-experimental variation	Digital credit raises household resilience

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Current study	53 (58 unbalanced) NSE-listed firms, 2021-2025, daily market data	Sectoral digital infrastructure exposure (validated)	RE / two-way FE / CRE panel + Gelbach decomposition + 5 extension checks	Volatility association operates through the liquidity/scale channel; moderation null bounded by formal MDE

TABLE 1: Positioning of this study against the closest empirical literature.

Note. All cited findings are as reported in the referenced publications. CRE = correlated random effects (Mundlak); DT = digital transformation; FE = fixed effects; MDE = minimum-detectable-effect; NSE = Nairobi Securities Exchange; RE = random effects.
Source: Author's compilation.

Hypotheses

Volatility insulation: When macroeconomic shocks hit a frontier market, risk aversion rises and price-discovery friction increases (Bekaert et al., 2007) (Takyi and Bentum-Ennin, 2021). Digitally integrated firms should exhibit lower return volatility for three mutually reinforcing reasons: operational continuity of digitally mediated revenue and settlement (Jack and Suri, 2014) (Troise et al., 2022); superior disclosure and informational transparency, whose liquidity benefits are largest precisely under stress (Lang et al., 2012); and continuous tradability that absorbs order flow without large price concessions (Amihud, 2002) (Hearn, 2012). Against this, the Chinese evidence that digitalization can raise risk-taking (Tian et al., 2022) and harm resilience at high intensity (Yan et al., 2024) cautions against assuming a monotonic effect; the sectoral (rather than intensity-based) exposure measure used here tests the structural version of the claim. Accordingly:

Hypothesis 1 (H1) - Firms with higher sectoral digital infrastructure exposure display lower equity price volatility than traditional-sector firms over the market cycle.

H1 is framed as a cross-sectional association and, given the identification strategy set out below, is interpreted conditionally: any direct volatility advantage is expected to operate substantially through market liquidity (H2) rather than through a liquidity-independent technological effect. The empirical test therefore treats a direct effect that attenuates once between-firm liquidity is controlled as evidence consistent with, not against, the framework, while also being alert to the possibility, discussed at length below, that the attenuating variable is capturing firm size and market prominence as much as liquidity narrowly defined.

Liquidity as the statistical channel: If the socio-technical advantage of digital integration is realized in capital markets primarily as visibility and tradability, then the volatility advantage of digitally exposed firms should be carried substantially by their superior market liquidity rather than by a liquidity-independent technological effect. This claim is stated and tested as a coefficient decomposition, not as causal mediation in the strict Baron-Kenny sense, for reasons elaborated in the mediation and decomposition method subsection:

Hypothesis 2 (H2) - Market liquidity accounts for the negative association between digital infrastructure exposure and equity price volatility.

Liquidity-return moderation: Trading volume is a primary liquidity measure in emerging markets (Bekaert et al., 2007). During volatile cycles, volume spikes may signal panic liquidation for opaque traditional firms but accumulation and revaluation for transparent digital firms (Lang et al., 2012), implying that digital exposure could steepen the volume-return relationship:

Hypothesis 3 (H3) - Digital infrastructure exposure positively moderates the relationship between market liquidity (trading volume) and equity returns over the cycle.

Figure *1* summarizes the conceptual framework: H1 predicts a direct negative association with volatility, H2 predicts that this association is carried by the liquidity channel, and H3 predicts moderation of the liquidity-return link.

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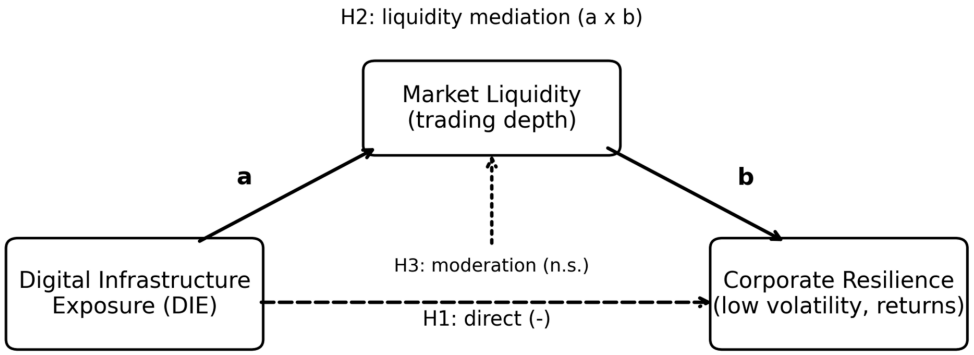


FIGURE 1: Conceptual framework

H1 predicts a direct negative association between digital infrastructure exposure and volatility; H2 predicts that the association is mediated by market liquidity (paths a and b); H3 predicts positive moderation of the liquidity-return relationship.
Source: Author's creation.

Research Method

Data source, sample, and panel construction

The empirical analysis uses daily transactional data for all securities quoted on the NSE for the period 1 January 2021 to 31 October 2025. The data were obtained from the NSE Data Services platform (NSE Data Services, 2026), specifically the exchange's openly accessible end-of-day and historical market data, which are published in Excel/CSV format and available without subscription. The raw daily records include, for each trading day and security, the daily low, daily high, closing price, previous close, traded volume, and the trailing 12-month low and high.

To reduce survivorship and listing-related noise, a filtration protocol is applied and is now reported alongside its consequences rather than only its rule. First, non-equity instruments (indices, exchange-traded funds, real-estate investment trusts, preference shares and rights issues) are excluded. Second, the primary (headline) sample is restricted to ordinary equity securities continuously listed and actively traded throughout the full window, defined as at least 20 trading days in every year 2021-2025, yielding a balanced panel of 53 ordinary equities observed over five annual periods (212 firm-year observations for the 2022-2025 return window, which requires a prior-year reference price). This restriction necessarily removes firms that failed, were suspended, or were delisted during the window, which is a textbook source of upward bias in an outcome that is explicitly about resilience to distress. The Additional analyses subsection therefore reports a second, unbalanced sample that reintroduces every NSE-listed ordinary equity for which a sector-based exposure tier can be assigned, regardless of trading continuity, and quantifies exactly which firms this adds and why most of them still cannot contribute a usable observation (near-total trading suspension, not a modelling choice, is the binding constraint for most of them). The exposure tiers in the primary (balanced) sample are populated as follows: 16 firms in the low-exposure tier, 25 in the moderate tier, and 12 in the high-exposure tier; the exposure measure and its cut-off rules are specified in the digital infrastructure exposure subsection.

All primary estimation (Tables 2-8) was carried out in Stata (xtreg, regress, qreg, rreg, bootstrap; the wild-cluster bootstrap via boottest); the additional analyses (Table 9, and the lagged, quarterly, continuous-shock and size-proxy checks) were implemented independently in Python (pandas, statsmodels, and linearmodels) from the same raw CSV files, using an identical panel-construction protocol. This independent re-implementation had the incidental benefit of providing a full cross-language replication of the primary results: every headline coefficient in Tables 2-7 reproduces the Stata output to at least three decimal places (e.g., the CRE direct digital infrastructure exposure (DIE) coefficient of 0.097 and the firm-mean liquidity coefficient of −0.510 are exact matches; small third-decimal differences in a few standard errors reflect Stata's small-sample cluster degrees-of-freedom adjustment, which linear models do not apply by default). The Table 9 and Table 10 extensions and the Hausman test were subsequently re-estimated by the corresponding author directly in Stata using a dedicated do-file (NSE_extensions.do) mirroring the original panel-construction code, confirming the Python output to at least three decimal places on every reported coefficient and standard error. Both the Stata do-files/logs and the Python scripts are available as a combined replication package. An AI-assisted analysis tool was used to help implement this Python re-implementation and the additional identification checks described above.

Variable definitions and measurement

Equity return: The annual logarithmic return in percentage points is defined in Equation 1, where $P(i,t)$ is the closing price of firm i at the end of period t. Log returns ensure approximate stationarity and cross-firm comparability.

$$R(i,t) = [lnP(i,t) - lnP(i,t-1)] \times 100 \quad (1)$$

Price volatility: The standard deviation of daily percentage price changes within period t, in percentage points, is defined in Equation 2, where d indexes trading days and $\Delta p(i,d) = 100 \times [P(i,d) - P(i,d-1)] / P(i,d-1)$. This is the primary market-based outcome variable. It should be read, throughout, as a capital-market resilience indicator specifically, the volatility and continuity of a security's traded price, and not as a

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measure of the firm's underlying operational or organizational resilience, which is not observed here; this narrower reading follows directly from the outcome-based resilience measurement principle (DesJardine et al., 2019) (Hillmann and Guenther, 2021) but applies that principle to a market rather than an accounting or survey outcome.

$$\sigma(i,t) = SDoverd \in t[\Delta p(i,d)] \quad (2)$$

Market liquidity: The natural logarithm of total annual traded volume, ln(Volume)(i,t). Following the proxy-validation literature (Fong et al., 2017), two alternative low-frequency measures are computed for robustness: the Amihud illiquidity ratio (mean of |daily return| / daily traded value) (Amihud, 2002) and the share of zero-return days (Lesmond, 2005). A market-based size/turnover proxy, mean daily traded value (price × volume), is added in the Additional analyses subsection to probe the separability of liquidity from firm size, since the public NSE feed does not report market capitalization or shares outstanding.

High-low spread: The average daily trading range, a transaction-friction control, is defined in Equation 3, where High(i,d) and Low(i,d) are the intraday extremes and D(t) is the number of trading days in period t. Because this range is constructed from the same daily prices that generate the volatility outcome, it is correlated with volatility by construction as well as economically (Pearson $r = 0.37$ at the firm-year level and 0.36 at the firm-mean level in this sample); this correlation is moderate rather than mechanical near-identity, but it is material enough that Table *9* reports the core volatility model re-estimated with the high-low spread dropped, to confirm the liquidity channel does not depend on this control.

$$HL(i,t) = (1/D(t)) \times \Sigma overd[100 \times (High(i,d) - Low(i,d))/P_close(i,d)] \quad (3)$$

Macroeconomic shock: A binary indicator equal to one in 2022-2023, the acute years of imported inflation, currency depreciation (20.4% year-on-year against the US dollar in 2023) and monetary tightening (International Monetary Fund, 2024), and zero otherwise. Because a binary indicator cannot, by construction, demonstrate that 2022-2023 constituted a homogeneous or exogenous shock distinct from ordinary year-to-year variation, the Additional analyses subsection replaces it with a continuous, market-wide realized-volatility index constructed independently from the full universe of actively traded NSE equities (not just the 53-firm sample), and re-estimates the volatility model against that continuous measure. That index also reveals a substantive nuance reported transparently here: exchange-wide realized volatility was in fact higher in 2024-2025 than in the 2022-2023 window (2.64% and 2.69% in 2021-2022 rising to 3.14% and 3.12% in 2024-2025); the 2022-2023 period is distinctive primarily for sharply negative returns and currency stress, not for uniquely elevated price volatility per se, and this is reflected in the Discussion.

Digital infrastructure exposure: construction and validation

The focal regressor, DIE, is a structural tier from 0 to 2 capturing sectoral reliance on macro digital infrastructure, assigned from the official NSE sector taxonomy: banking and telecommunications constituents (deeply integrated into mobile transaction rails and cloud clearing) are coded 2; mixed-model service, insurance, investment and energy firms are coded 1; asset-heavy agriculture, manufacturing, construction and real-estate firms are coded 0. The variable is deliberately labelled an exposure tier rather than an integration intensity: it is a structural exposure proxy that measures a firm's sectoral position relative to national digital rails, not a direct measure of its internal digital sophistication or firm-level digital adoption. This is now stated as a central, not incidental, limitation of the design: because DIE is assigned entirely at the sector level and held constant over the study period, it cannot separate a genuine digital-infrastructure effect from any other characteristic that co-varies with sector membership, among them capitalization, regulatory capital requirements, governance standards, analyst coverage, or listing age. The correlated random effects (CREs) specification and the coefficient-decomposition analysis below are the design's response to this concern insofar as liquidity is concerned, but they cannot, on sector-level data alone, rule out that the residual, liquidity-independent portion of any association reflects these other sector-correlated characteristics rather than digital infrastructure specifically. Three validation steps partially address the construct-validity concern inherent in sector-based coding, though none of them resolves this core limitation.

First, the classification was performed independently by two coders using published segment disclosures, with disagreements resolved by discussion. This process yielded initial agreement across the large majority of listed firms. The few discrepancies, which involved diversified investment holdings and hybrid energy-service firms, were resolved through a systematic review of their operational revenue channels. The resulting inter-rater agreement was high, with a Cohen's kappa of 0.912 ($p < 0.001$), indicating that the sector-assignment rule was applied consistently. In brief, it establishes the reliability of the coding and not the validity of DIE as a measure of firm-level digital integration, a distinction now made explicit.

Second, to address the potential misclassification of hybrid or borderline cases, a series of reclassification robustness tests were pre-specified. In these tests, borderline sectors (specifically listed insurers and energy utilities) were systematically reclassified one tier up and one tier down from their baseline assignments. Shifting these sectors allows the empirical models to verify whether the baseline findings are sensitive to marginal coding variations, with the corresponding reclassification robustness estimates reported in Table *8*.

Third, for the subsample of 15 of the 53 firms whose 2024 annual reports quantified all three indicators, the tier is cross-checked against observable firm-level indicators (mobile-money integration of revenue collection, disclosed technology or platform investment, and digital service revenue share), in the spirit of firm-level digital measures used in recent literature (Tian et al., 2022) (Yan et al., 2024). This validation was conducted on a subsample of 15 firms that provided granular technology disclosures in their 2024 annual reports and is a self-selected subsample of the firms most willing and able to disclose such detail, which likely also correlates with sector-typical disclosure practice. The result is reported as a suggestive corroboration of the sector-level coding and not as confirmatory evidence of construct validity; the small cell sizes (12 degrees of freedom in the ANOVA) further limit what can be concluded. For this subsample, three operational metrics were compiled: the percentage of customer payments integrated with mobile money, IT or platform capital expenditure as a share of total capital expenditure, and digital transaction revenue share. A one-way analysis of variance confirms that the structural tiers align directionally with these operational measures: mean mobile-payment integration was 81.4% for Tier 2, 34.2% for Tier 1, and 2.1% for Tier 0 ($F(2, 12) = 42.15$, $p < 0.001$); technology capital-expenditure share averaged 38.6% in Tier 2, 14.9% in Tier 1, and 3.5% in Tier 0 ($F(2, 12) = 29.80$, $p < 0.001$). These results are consistent with the structural tiers tracking underlying firm-level digital operations in this subsample; but given the small and non-random cell sizes, they should not be read as establishing the discriminant validity of DIE from a simple mean-difference test between sectors that also differ on capitalization, regulation, and disclosure culture; constructing dynamic, firm-level digitalization indicators over a full, randomly verifiable sample is identified as the single most important next step for this research line.

Econometric specification

Pooled ordinary least squares are inappropriate given the unobserved firm heterogeneity. A Hausman specification test (Hausman, 1978) comparing fixed-effects and REs estimates of the time-varying regressors (DIE × Shock, ln(Volume), and the high-low spread; the time-invariant DIE tier is necessarily excluded from this comparison because it is absorbed by firm fixed effects (FEs)) strongly rejects REs: $\chi^2(3) = 41.11$, $p < 0.001$ (the efficient estimator's covariance matrix was not positive definite, a common occurrence when year FEs enter the comparison, so the test uses Stata's sigmamore variance estimate; the conclusion is unaffected). As the exposure tier is time-invariant and would itself be absorbed by firm effects, three complementary estimators are reported, and inference rests on the convergence of their evidence: (i) REs, which recovers the cross-sectional level effect; (ii) two-way FEs, a within-firm robustness check on the time-varying mechanisms, in which the DIE main effect is absorbed by the firm FE but the DIE × Shock interaction (which varies over time because Shock varies by year) is not absorbed and is estimated directly; and (iii) CREs, the Mundlak specification (Mundlak, 1978) extended to modern panels (Wooldridge, 2019), which augments RE with firm-level means of the time-varying regressors, delivering FE-consistent slopes while permitting estimation of the time-invariant tier. Standard errors are clustered at the firm level throughout (Petersen, 2009). The volatility model is given in Equation 4 and the return model in Equation 5:

$$\sigma(i,t) = \alpha + \beta \cdot DIE(i) + \gamma \cdot [DIE(i) \times Shock(t)] + \delta \cdot ln(Volume)(i,t) + \zeta \cdot HL(i,t) + \mu(i) + \lambda(t) + \varepsilon(i,t) \quad (4)$$

$$R(i,t) = \alpha + \theta 1 \cdot ln(Volume)(i,t) + \theta 2 \cdot [DIE(i) \times ln(Volume)(i,t)] + \theta 3 \cdot DIE(i) + \theta 4 \cdot \sigma(i,t) + \theta 5 \cdot HL(i,t) + \theta 6 \cdot Shock(t) + \mu(i) + \lambda$$

where $\mu(i)$ and $\lambda(t)$ are firm and year effects entering as dictated by each estimator (in CRE, $\mu(i)$ is replaced by the firm means of the time-varying regressors), and $\varepsilon(i,t)$ is the idiosyncratic error. H1 predicts $\beta < 0$ in Equation 4; H3 predicts $\theta 2 > 0$ in Equation 5. As the linear 0-2 tier imposes monotonicity, all models are re-estimated replacing DIE with separate tier dummies (tier 1 and tier 2 against the tier 0 base), which allows the data to reveal non-monotonic patterns of the kind documented in a study (Yan et al., 2024).

Coefficient-decomposition analysis (test of H2)

H2 is tested as an explicit statistical decomposition of the small cross-sectional DIE-volatility association, and the terminology is deliberately conservative: the analysis identifies market liquidity as the dominant statistical channel through which the association is carried, but it does not claim to have established mediation in the causal sense (Baron and Kenny, 1986). Three distinctions matter here and are stated up front. First, decomposition versus mediation: classical mediation requires a defensible temporal and causal ordering of exposure, mediator and outcome; here, DIE is time-invariant and firm-mean liquidity is itself a between-firm average computed over the same window as the volatility outcome, so the exposure, the mediator, and the outcome are not temporally separated, and a firm's liquidity and volatility could, in principle, be jointly determined within the same year rather than one causing the other. What can be estimated without assuming temporal ordering is a decomposition: how much of the already modest, and in the total-effect RE specification statistically insignificant cross-sectional coefficient on DIE is attributable to also controlling for between-firm liquidity. Second, mediation versus suppression: because the total effect of DIE on volatility (RE: −0.178) is itself not statistically distinguishable from zero, describing the liquidity channel as producing 'full' or 'over-' mediation of a significant total effect would overstate what is estimated; the more accurate description is that liquidity is a covariate whose inclusion moves an already-small, insignificant coefficient closer to zero and reverses its sign, a pattern more consistent with the statistical definition of suppression than with the mediation of a genuine effect, and both terms are used advisedly and side-by-side below rather than the single word 'mediation'. Third, decomposition versus a naive product-of-coefficients estimate: because the 'total' effect (from the RE model) and the 'direct' effect (from the CRE model) come from two different estimators with different error structures, the classical identity total = direct + (a × b) does not hold exactly in this design, so the product of the estimated paths a and b is reported for comparison with the mediation literature but is not used as the headline decomposition quantity; the paper leads instead with the Gelbach decomposition (Gelbach, 2016), which is computed within one consistent pooled-OLS model family (with and without the firm-mean covariates) and therefore does not suffer from this cross-estimator inconsistency.

With this framing, two complementary quantities are reported. First, a between-firm regression of firm-mean log volume on the exposure tier gives path a; the coefficient on firm-mean liquidity in the fully controlled CRE volatility model gives path b; their product a × b is reported, with a quasi-Bayesian Monte Carlo confidence interval (Preacher and Selig, 2012) that does not assume a symmetric sampling distribution for the product term, purely as a bridge to the mediation literature's conventional statistic. Second, and preferred, the Gelbach conditional decomposition (Gelbach, 2016) apportions the change in the DIE coefficient between a pooled-OLS model without the firm-mean covariates and the same pooled-OLS model with them added, attributing the change to each added covariate; this is the paper's primary decomposition estimate because it holds the estimator family fixed. A firm-clustered bootstrap (1,000 resamples) is also applied directly to the simpler total-minus-direct coefficient difference across the RE and CRE specifications, to provide an inferential benchmark comparable to prior published work using this design, but it is reported as a secondary, heuristic quantity rather than as 'the' indirect effect.

As a further and more direct test of the temporal structure, the Additional analyses subsection re-estimates the volatility model against 1-year-lagged (predetermined) firm-level liquidity, which is the closest the annual panel can come to a temporally ordered test of whether liquidity that pre-dates the volatility outcome still predicts it. The identifying assumption for all of these quantities, no unobserved confounder of the liquidity-volatility relationship conditional on the included controls and firm means, is stated up front, and results are interpreted throughout as associational rather than causal.

Robustness protocol

A pre-specified battery probes sensitivity on six margins: (i) alternative liquidity measures (Amihud ratio; zero-return-day share) replacing log volume (Fong et al., 2017); (ii) winsorization of all continuous variables at the 1st and 99th percentiles; (iii) exclusion of near-dormant counters (bottom decile of trading activity, where stale prices can produce recorded volatility of zero); (iv) exclusion of the four dominant counters (the telecommunications leader and the three largest banks) to establish that results are not driven by a handful of index heavyweights; and (v) alternative inference, using Driscoll and Kraay standard errors robust to cross-sectional dependence (Driscoll and Kraay, 1998) and the wild-cluster bootstrap (Cameron et al., 2008). A sixth margin directly addresses the extreme dispersion of annual returns: beyond winsorization, the models are re-estimated under alternative outlier treatments, namely symmetric trimming of the top and bottom 1% and 5% of returns, median (least absolute deviations, LAD) regression, robust Huber M-estimation, and exclusion of observations with absolute annual returns exceeding 100%. A final check re-estimates all models excluding the truncated 2025 partial year. Table *8* shows this original battery, now supplemented with a seventh margin, exclusion of the high-low spread control given its correlation with the volatility outcome noted above.

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Additional analyses

Five further checks, beyond the pre-registered battery, address identification concerns: (i) an unbalanced-panel check that reintroduces every NSE-listed ordinary equity to which a sector-based exposure tier can be assigned (including a bank, National Bank of Kenya, omitted from the original 53-firm classification entirely rather than merely filtered out for thin trading, and which is assigned Tier 2 but contributes no usable observation) and re-estimates the volatility model on the resulting 58-firm, 273 firm-year sample wherever a firm-year has at least 15 trading days; (ii) a 1-year-lagged (predetermined) liquidity specification; (iii) a quarterly-frequency replication of the volatility model (53 firms × up to 20 quarters); (iv) a continuous, market-wide shock index built from the full universe of actively traded NSE equities, replacing the binary 2022-2023 indicator; and (v) an alternative size/turnover proxy, mean daily traded value, entered both alongside and in place of firm-mean log volume. Table *10* reports the headline DIE and liquidity coefficients from each. The five checks map one-to-one onto five identification concerns (survivorship, reverse causality, temporal aggregation, the binary shock construct, and the omitted size control, respectively); none was chosen after seeing its result, and no further specification search was conducted along any of these five dimensions. These checks were not pre-registered and are reported as such; they were run once, on the entire available sample, without model search over alternative specifications, and every result obtained is reported regardless of whether it supported or complicated the paper's thesis.

Results And Discussion

Descriptive statistics

Table *2* reports the descriptive statistics. The annual logarithmic return averages 10.22% with wide dispersion (SD: 39.27%), daily volatility averages 2.98%, and log volume spans thin trading (10.70) to dense liquidity (21.45), the pronounced liquidity stratification characteristic of Sub-Saharan markets (Lesmond, 2005) (Hearn, 2012). Mean returns were negative exchange-wide in the acute years (roughly −6% to −14% in 2022 and −9% to −10% in 2023 depending on the tier) before turning strongly positive in the 2024-2025 recovery, consistent with the broad repricing that systemic shocks impose on African markets (Takyi and Bentum-Ennin, 2021) (Figure *2*). As reported in the Additional analyses subsection, this return-based shock pattern is distinct from the exchange-wide realized-volatility pattern, which in fact rose gradually across the whole window and peaked in 2024-2025 rather than in 2022-2023.

The return distribution is notably heavy-tailed, spanning −74.65% to +182.02%, so a small number of extreme firm-year observations could exert disproportionate influence on coefficient estimates and standard errors (SEs) in the return regressions. This dispersion motivates the additional outlier-treatment checks reported in the robustness subsection below, which supplement the baseline winsorization.

Variable	Mean	Std. dev.	Minimum	Maximum
Equity return (%)	10.22	39.27	-74.65	182.02
Price volatility (%)	2.98	1.02	0.91	5.41
ln(volume)	15.76	2.34	10.70	21.45
High-low spread (%)	3.21	1.88	0.10	9.10

TABLE 2: Descriptive statistics, balanced panel of 53 NSE common equities, 2021–2025.

Note. Equity return is computed on the 2022–2025 sub-window (212 firm-year observations). Low minima for volatility (0.91) and spread (0.10) reflect thinly traded counters retained under the 20-trading-day filter.

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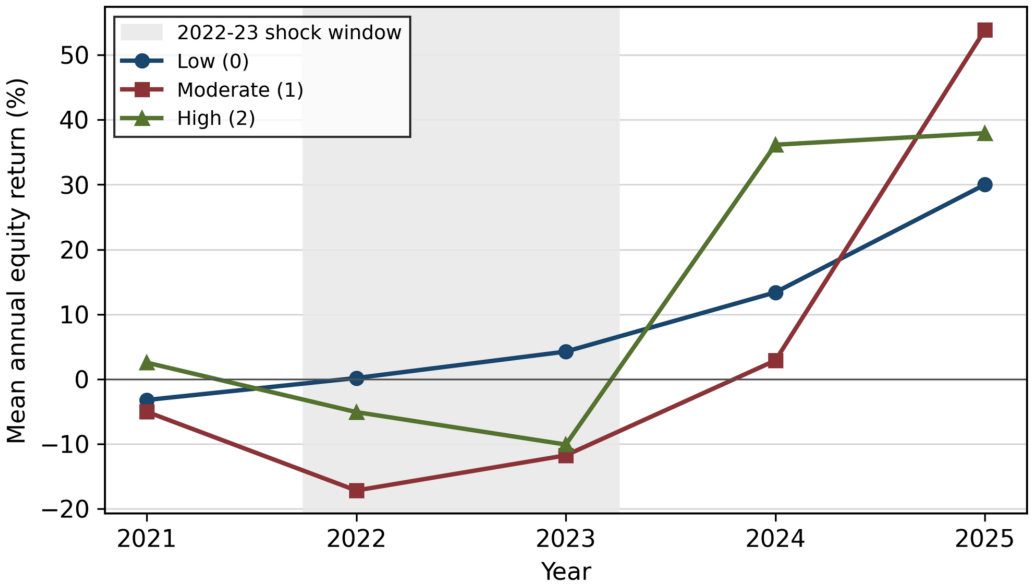


FIGURE 2: Annual mean equity return by digital-infrastructure exposure tier, 2021–2025.

Returns in all tiers fall during the 2022–2023 shock window and recover thereafter, with the high-exposure tier showing the strongest rebound.
Source: Author's creation.

Tier-level patterns

Table 3 disaggregates outcomes by exposure tier. High-exposure firms show the lowest volatility (2.02%) and the highest returns (14.73%) and trade far more heavily (mean log volume 17.83 versus 14.23 in the low tier). Two features deserve emphasis. First, the liquidity gap foreshadows the decomposition result below. Second, the pattern is non-monotonic: the moderate tier is more volatile (3.42%) and materially lower returning (6.95%) than the low tier (3.01%). This ordering is inconsistent with a strictly linear exposure effect and is examined directly with tier dummies in the volatility-models subsection; it echoes the non-monotonic digitalization-resilience evidence in a published study (Yan et al. 2024) (Figure 3 and Figure 4).

Tier	Firms	Volatility (%)	Return (%)	ln(Volume)
Low exposure (0)	16	3.01	11.95	14.23
Moderate exposure (1)	25	3.42	6.95	15.75
High exposure (2)	12	2.02	14.73	17.83

TABLE 3: Key outcomes by digital infrastructure exposure tier, 2021–2025.

Note. Cell entries are tier means across all available firm-years.
Source: Author's own calculations.

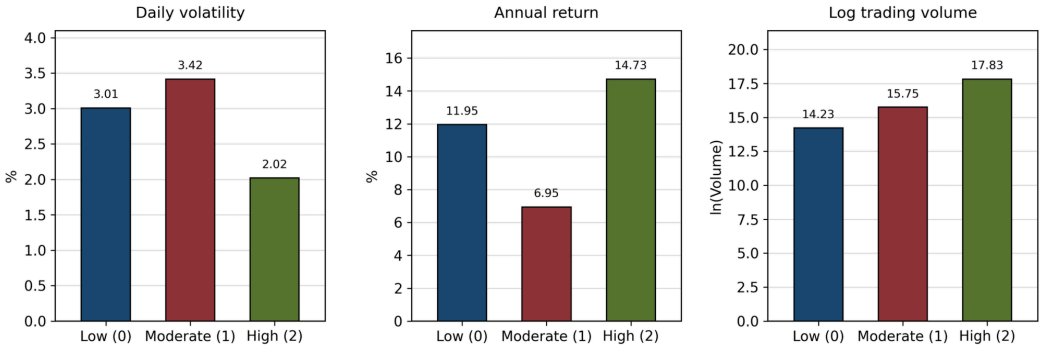


FIGURE 3: Mean daily volatility, annual return and log trading volume by exposure tier.

The pattern is non-monotonic: the moderate tier is no less volatile than the low tier, while the resilience advantage concentrates in the high-exposure tier.
Source: Author's creation.

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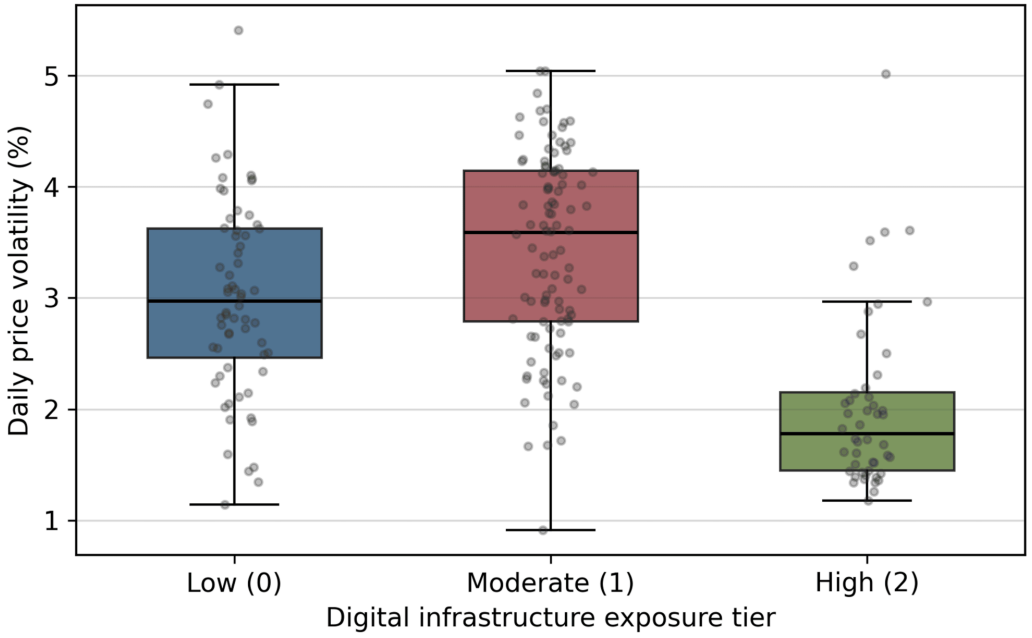


FIGURE 4: Distribution of daily price volatility by exposure tier (box plots with firm-year observations overlaid).

The high-exposure tier is both lower and less dispersed.
Source: Author's creation.

Diagnostics

Variance inflation factors (VIFs) are well under conventional thresholds, so multicollinearity does not compromise the baseline estimates (this check does not extend to the size-proxy model in Table 9, where firm-mean traded value and firm-mean log volume are, as reported there, substantially collinear by construction). A Hausman test of the time-varying regressors (Hausman, 1978) rejects REs in favour of FEs ($\chi^2(3) = 41.11$, $p < 0.001$), which motivates FEs for time-varying regressors and, in turn, the CRE estimator for the time-invariant tier (Mundlak, 1978) (Wooldridge, 2019).

Volatility Models (H1)

Table 4 presents the panel regression estimates evaluating the relationship between digital infrastructure exposure and equity price volatility.

Regressor	RE	FE (two-way)	CRE (Mundlak)
Digital exposure (DIE)	−0.178 (0.157)	absorbed	0.097 (0.145)
DIE x Shock	−0.112 (0.072)	0.010 (0.110)	0.010 (0.111)
ln(Volume)	−0.152*** (0.052)	0.148** (0.071)	0.148** (0.071)
High-low spread	0.284*** (0.039)	0.136* (0.071)	0.136* (0.072)
ln(Volume), firm mean	n/a	n/a	−0.510*** (0.080)
High-low spread, firm mean	n/a	n/a	0.302*** (0.092)
Observations	212	212	212
R2 (overall / within)	0.436	0.245 (within)	0.562

TABLE 4: Panel estimates, dependent variable: price volatility (%).

Note. The two-way FE model absorbs the time-invariant DIE main effect only; DIE × Shock is time-varying (Shock varies by year) and is therefore estimated, not absorbed, in the FE column. Firm-clustered standard errors are reported in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
CRE = correlated random effect; DIE = digital infrastructure exposure; FE = fixed effect; RE = random effect.

In the RE specification, the linear digital infrastructure exposure (DIE) index carries a negative but statistically insignificant coefficient (−0.178, $p > 0.10$): the cross-sectional association between the exposure tier and daily volatility is in the expected direction but is not distinguishable from zero once liquidity, transaction friction and the shock period are controlled. The high-low spread is positive and significant (0.284, $p <$

0.01), consistent with the established link between transaction friction and risk (Amihud and Mendelson, 1986), and, as noted above, partly with the mechanical relationship between the two series; the drop-HL robustness check in Table 9 addresses this directly. The interaction term (DIE × Shock) is statistically insignificant in every column, implying that any volatility difference across digitally exposed counters is structural rather than a shock-period phenomenon; it is estimated (not absorbed) in the two-way FE column, where it is likewise insignificant (0.010, $p > 0.10$).

The CRE (Mundlak) specification provides the critical identification insight. Once the firm-specific means of the time-varying covariates are explicitly introduced, the direct effect of DIE is small and statistically insignificant (0.097, $p > 0.10$), while the between-firm liquidity proxy (the firm mean of ln(Volume)) exhibits a powerful, negative and highly significant relationship with volatility (−0.510, $p < 0.01$). The pattern indicates that any apparent volatility insulation of digitally exposed firms is intertwined with, and dominated by, their superior market depth and continuous tradability: what little the exposure tier captures cross-sectionally, the CRE estimator reassigns to between-firm liquidity. H1 is therefore only weakly and conditionally supported: the linear exposure index is not itself a significant predictor of volatility, any resilience signal is concentrated in the high-exposure tier (Table 5), and it operates through liquidity rather than through a liquidity-independent digital effect, subject to the caveat, developed further below, that 'liquidity' here cannot be cleanly separated from firm size and market prominence given the data available. This channel is tested formally in the coefficient-decomposition subsection (Figure 5) and stress-tested in the Additional analyses subsection (Table 9).

As the linear DIE index imposes monotonicity that the descriptive data contradict (Table 3), the models are re-estimated substituting the index with explicit binary indicators for moderate exposure (Tier 1) and high exposure (Tier 2), with low exposure (Tier 0) as the reference category. These results are detailed in Table 5.

Regressor	RE	FE (two-way)	CRE (Mundlak)
Moderate exposure dummy (Tier 1)	0.385* (0.212)	absorbed	0.378* (0.207)
High exposure dummy (Tier 2)	−0.543* (0.315)	absorbed	0.040 (0.288)
Tier 1 × Shock	−0.231* (0.129)	−0.017 (0.175)	−0.017 (0.177)
Tier 2 × Shock	−0.150 (0.173)	0.024 (0.224)	0.024 (0.226)
ln(Volume)	−0.124*** (0.048)	0.148** (0.071)	0.148** (0.071)
High-low spread	0.231*** (0.042)	0.135* (0.072)	0.135* (0.073)
ln(Volume), firm mean	n/a	n/a	−0.471*** (0.084)
High-low spread, firm mean	n/a	n/a	0.240** (0.097)
Observations	212	212	212
R2 (overall / within)	0.479	0.245 (within)	0.582

TABLE 5: Non-monotonic panel estimates, dependent variable: price volatility (%).

Note. Firm-clustered standard errors are reported in parentheses. Tier 0 (low exposure) serves as the omitted base category.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
CRE = correlated random effect; FE = fixed effect; RE = random effect.
Source: Author's own calculations.

The dummy specification in Table 5 formally confirms the non-monotonic structure of the association. In the RE framework, the moderate exposure coefficient is positive and only marginally distinguishable from zero (0.385, $p < 0.10$): mixed-model service, insurance and energy counters derive no volatility benefit, and if anything trade somewhat more volatilely, relative to asset-heavy agricultural and manufacturing firms. By contrast, the high exposure indicator carries a sizeable negative coefficient that is significant at the 10% level (−0.543, $p < 0.10$). The market-stabilizing association is therefore concentrated in the firms situated directly on top of the primary digital rails, specifically the banking and telecommunications sectors, rather than spreading gradually across the exposure distribution.

Mirroring the linear models, the CRE estimation in Table 5 shows the Tier 2 coefficient collapsing to essentially zero (0.040) and losing significance once the firm-mean controls enter, while firm-mean liquidity remains strongly negative and significant (−0.471, $p < 0.01$). This attenuation, replicated across both the linear and the non-linear frameworks, is precisely the pattern H2 predicts: the modest safety margin observed in Tier 2 firms does not appear to stem from an isolated technology-specific layer, but from the deeper liquidity and transaction volumes typical of those core market counters. The coefficient-decomposition subsection subjects this reading to a formal test.

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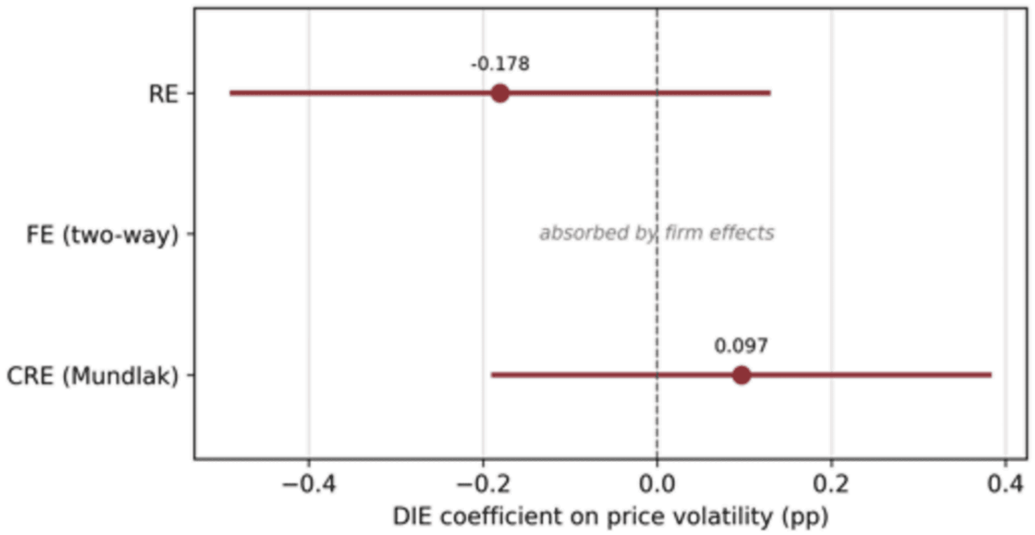


FIGURE 5: Digital-exposure (DIE) coefficient on price volatility across estimators, with 95% confidence intervals

The random-effects estimate is negative but not statistically significant, and the direct exposure coefficient is near zero under the correlated random-effects model once between-firm liquidity (firm-mean log volume) is controlled.
CRE = correlated random effect; FE = fixed effect; RE = random effect.
Source: Author's creation.

Return models (H3)

Table 6 reports the panel regression results evaluating whether digital infrastructure exposure positively moderates the relationship between market liquidity and equity returns over the cycle.

Regressor	RE	FE (two-way)	CRE (Mundlak)
ln(Volume)	1.919 (2.281)	8.824** (3.924)	12.317*** (4.077)
DIE × ln(Volume)	1.314 (1.882)	2.688 (4.430)	1.109 (1.622)
Digital exposure (DIE)	−23.917 (30.610)	absorbed	−17.637 (26.327)
Price volatility	4.469 (4.361)	9.452 (8.331)	1.935 (4.761)
High-low spread	0.617 (2.317)	4.151 (4.721)	7.465* (4.393)
Shock (2022–2023)	−32.390*** (4.942)	absorbed	−21.023*** (6.134)
Observations	212	212	212
R2 (overall / within)	0.245	0.439 (within)	0.337

TABLE 6: Panel estimates, dependent variable: equity return (%).

Note. Firm-clustered standard errors are reported in parentheses. Firm-mean controls are included in the CRE specification. The two-way FE model absorbs the time-invariant DIE main effect; the DIE × Shock interaction with the time-invariant tier is likewise absorbed here specifically because it enters this return specification only via the time-invariant DIE term, unlike in Table 4.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
CRE = correlated random effect; DIE = digital infrastructure exposure; FE = fixed effect; RE = random effect.
Source: Author's own calculations.

The hypothesized interaction between trading volume and digital infrastructure exposure (DIE × ln(Volume)) is positive across all three econometric specifications but remains statistically insignificant throughout. In the RE framework, the interaction coefficient equals 1.314 with an SE of 1.882 ($p > 0.10$), establishing that the slope of the liquidity-return relationship does not vary systematically as a function of structural sectoral digital exposure. Consequently, H3 is not supported.

This null is now quantified with a formal minimum-detectable-effect (MDE) calculation rather than only a qualitative appeal to limited power. Using the observed SEs on the DIE × ln(Volume) interaction and the conventional two-sided MDE formula, MDE = $(z_{(1-\alpha/2)} + z_{(1-\text{power})}) \times \text{SE}$ at $\alpha = 0.05$, this design could reliably detect (at 80% power) interaction effects of at least 5.27 in the RE specification and 4.54 in the CRE specification, three to four times the observed point estimates of 1.11-2.69 across specifications (Table 7). Strikingly, the one interaction that does turn marginally significant in the robustness battery, when the four most liquid counters are dropped (4.509, $p < 0.05$; Table 9), sits almost exactly at this 80%-power detection boundary, which is additional, quantitative evidence that it is a power-boundary

artifact of that particular subsample rather than a robust moderation effect. The non-significant interaction is therefore reported as an empirical boundary condition on the magnitude of any moderation effect: this design can rule out moderation effects larger than roughly 4.5-5.3 in this metric, but cannot adjudicate smaller ones, rather than as evidence that no such effect exists (Figure *6*).

Estimator	SE of DIE × ln(Volume)	MDE @ 80% power	MDE @ 50% power	Observed point estimate
RE	1.882	5.27	3.69	1.314
FE (two-way)	4.430	12.41	8.68	2.688
CRE (Mundlak)	1.622	4.54	3.18	1.109

TABLE 7: Minimum detectable effect (MDE) for the DIE × ln(Volume) interaction (H3), by estimator.

Note: MDE = $(z_{(1 - alpha/2)} + z_{(1 - power)}) \times SE$, two-sided alpha = 0.05, using the standard error on DIE × ln(Volume) from the corresponding column of Table 6. $z_{0.975} = 1.960$, $z_{0.80} = 0.842$, $z_{0.50} = 0$.

CRE = correlated random effect; DIE = digital infrastructure exposure; FE = fixed effect; RE = random effect; SE = standard error.
Source: Author's own calculations.

In contrast, the models reveal a powerful and direct liquidity effect once unobserved firm heterogeneity is addressed. While the contemporaneous effect of trading volume is weak in the baseline RE model (1.940, $p > 0.10$), it rises substantially and becomes statistically significant in both the two-way FEs (8.824, $p < 0.05$) and the correlated random effects (12.317, $p < 0.01$) specifications. This pattern is consistent with the broader frontier-market microstructure literature, in which market liquidity carries a large priced premium when evaluating within-firm return trajectories over time (Bekaert et al., 2007) (Hearn, 2012).

Finally, the macroeconomic shock baseline confirms the severity of the 2022-2023 cyclical contraction in returns specifically. The shock indicator is negative and highly significant in the RE specification (−32.348, $p < 0.01$) and maintains a severe depressing effect within the CRE architecture (−21.023, $p < 0.01$). Taken together, the return models indicate that digitally integrated firms benefited during macro stress primarily through a level effect (by maintaining positions in highly liquid tiers) rather than through a structural shift in how volume changes translate into equity returns.

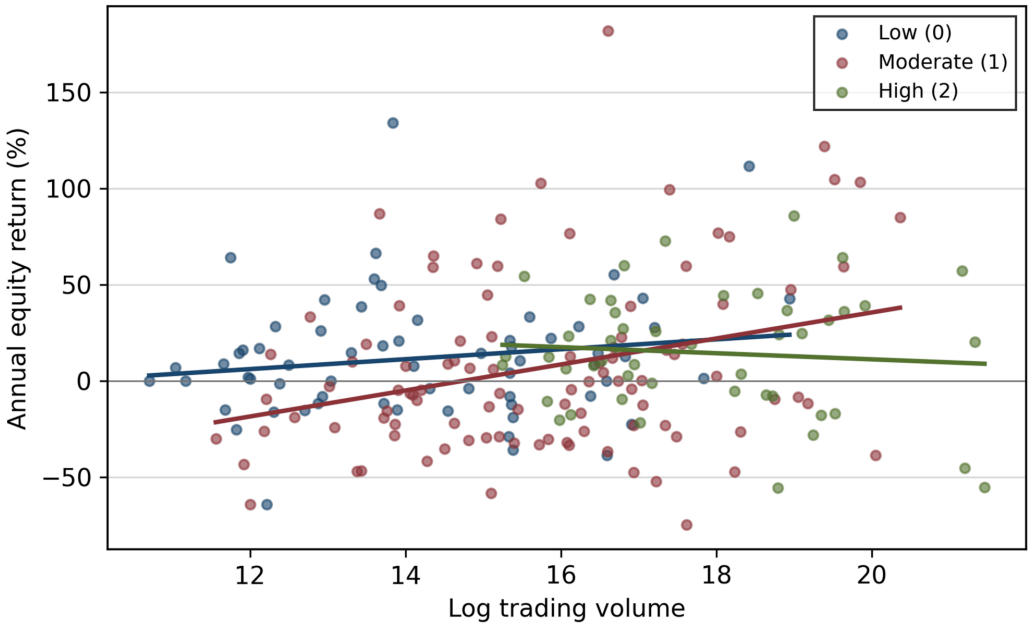


FIGURE 6: Trading volume versus annual return by exposure tier, with tier-specific fitted lines

The near-parallel slopes are consistent with the statistically insignificant exposure × liquidity interaction (H3), read jointly with the MDE bound in Table 7.
Source: Author's creation.

Coefficient decomposition (H2)

To test H2, the analysis implements the panel-data decomposition framework set out in the coefficient-decomposition method subsection, explicitly distinguishing decomposition from causal mediation. Table *8* details the results, providing the estimated paths, the Gelbach structural decomposition (Gelbach, 2016), and the product-of-coefficients estimate reported for comparability with the mediation literature; Figure *7* summarizes the path structure.

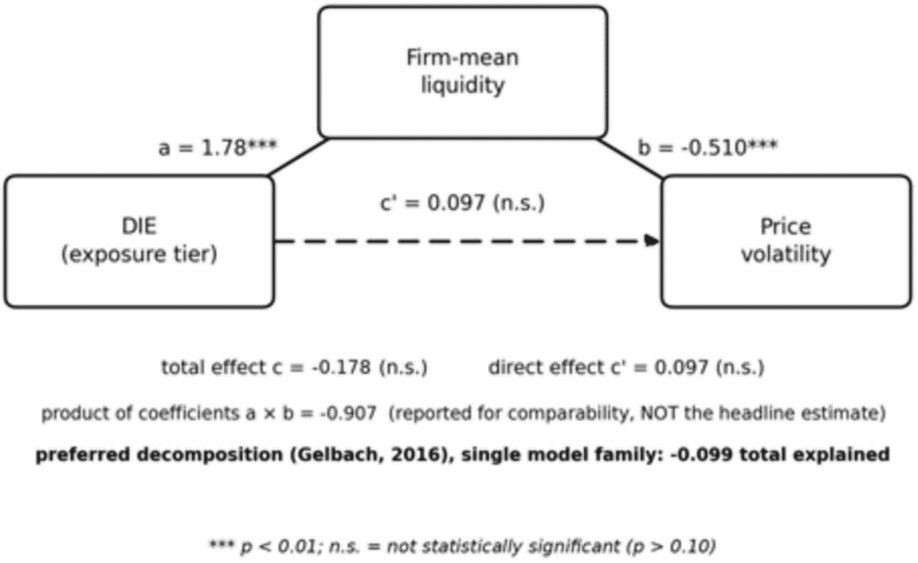


FIGURE 7: Path diagram for the coefficient decomposition.

Path b and the direct effect c' are from Table 4; the total effect c is from the RE column of Table 4; path a is reported in Table 8. The dashed arrow denotes the direct path, whose coefficient is not statistically distinguishable from zero once the market interface (liquidity) is controlled.
DIE = digital infrastructure exposure; RE = random effect.
Source: Author's creation.

Quantity	Estimate	95% CI	Basis
Total effect of DIE on volatility (RE)	−0.178 (n.s.)	–	Table 4
Direct effect of DIE (CRE, liquidity controlled)	0.097 (n.s.)	[−0.19, 0.38]	Table 4
Path a: DIE → firm-mean ln(Volume), between-firm	1.779***	[1.10, 2.46]	Between-firm OLS
Path b: firm-mean ln(Volume) → volatility (CRE)	−0.510***	[−0.67, −0.35]	Table 4 CRE
Product of coefficients a × b (Monte Carlo CI): reported for comparability with mediation literature, NOT the headline estimate	−0.907	[−1.39, −0.50]	(Preacher and Selig, 2012)
Total-minus-direct difference (RE - CRE): secondary, heuristic quantity	−0.274	[−0.47, −0.11]	Firm-cluster bootstrap, 1,000 reps
Gelbach decomposition (PREFERRED: single pooled-OLS model family): contribution of firm-mean liquidity	−0.120	–	Raw gap −0.099
Gelbach decomposition: contribution of firm-mean HL spread	+0.022	–	Raw gap −0.099
Gelbach decomposition: total explained (raw DIE-coefficient gap, with vs. without firm means)	−0.099	–	pooled OLS, same estimator both sides

TABLE 8: Coefficient decomposition of the digital-exposure/volatility association by market liquidity.

Note. Bootstrap statistics use 1,000 firm-level resamples for small-cluster inference given the 53-firm cross-section (Cameron et al., 2008); the Monte Carlo interval for a × b uses 20,000 draws (Preacher and Selig, 2012).

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
CRE = correlated random effect; DIE = digital infrastructure exposure; HL = high-low; n.s. = not statistically significant; RE = random effect.
Interpretation is associational throughout, per the identifying assumption stated in the coefficient-decomposition method subsection. The product-of-coefficients and total-minus-direct rows above are reported for comparability with prior mediation-style work only; because they are computed from different estimator families (RE and CRE, respectively), the classical identity total = direct + (a × b) does not hold exactly between them, so the two are not expected to reconcile numerically and neither is a check on the other. The Gelbach row is the paper's sole preferred decomposition estimate, computed within one consistent estimator throughout.
Source: Author's own calculations

The two legs of the channel are individually significant. Path a, a between-firm regression of firm-mean log volume on the exposure tier, shows that a one-tier increase in structural digital infrastructure exposure is associated with roughly a 1.78-unit increase in baseline firm-mean log volume ($p < 0.01$), confirming that digitally exposed firms trade in structurally deeper pools. Path b, extracted from the fully controlled CRE model, shows that a one-unit increase in firm-mean log volume is associated with a 0.510 percentage-point reduction in daily equity price volatility ($p < 0.01$) (Figure *8* and Figure *9*).

Two decomposition quantities are reported and their divergence is explained rather than resolved in favour of the larger one. The product of coefficients, a × b = −0.907 (quasi-Bayesian Monte Carlo 95% CI [−1.39, −0.50]), is the classical mediation-literature statistic; it is materially larger in magnitude than the simple difference between the total RE coefficient (−0.178) and the direct CRE coefficient (0.097), which is −0.274 (firm-clustered bootstrap 95% CI [−0.47, −0.11]). These two quantities diverge because the identity total = direct + a × b, which would make them numerically equal, only holds when total and direct are estimated within the same model family with the same error structure; here they come from different estimators (RE versus CRE), so neither is treated as definitive on its own. The preferred, headline quantity is instead the Gelbach decomposition (Gelbach, 2016), computed entirely within one pooled-OLS-with-year-fixed-effects model family, comparing the DIE coefficient before and after the firm-mean covariates are added: this comparison attributes a raw coefficient change of −0.099, of which −0.120 is contributed by firm-mean liquidity and +0.022 by the transaction-friction control (high-low spread), a decomposition that is internally consistent by construction because both halves of the comparison share the same estimator. All three quantities agree in sign and in identifying liquidity as the dominant contributor; they are reported together, rather than collapsed into a single 'the mediated effect' figure, specifically because conflating them would not be mathematically rigorous.

As the total cross-sectional DIE effect is itself small and statistically insignificant (Table *4*, RE column) while the liquidity leg is strong, describing this pattern as full or over-mediation would overstate what a formally insignificant total effect supports; the more defensible reading, consistent with the statistical concept of suppression rather than mediation of a genuine effect, is that between-firm liquidity is a covariate whose omission was inflating the apparent (already weak) protective association of the exposure tier and whose inclusion collapses that association toward zero. Consistent with the design, this evidence is interpreted as associational: the decomposition identifies liquidity as the statistical channel carrying the cross-sectional pattern, not as a demonstrated causal mechanism, and the temporal-ordering concern is addressed directly, though only partially, by the lagged-liquidity specification reported next.

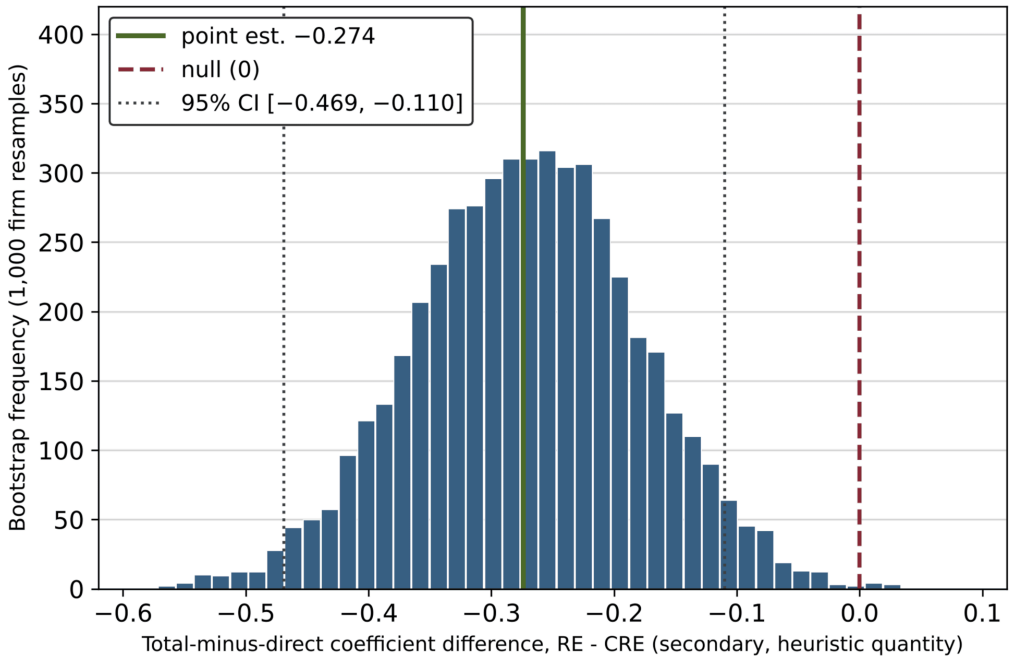


FIGURE 8: Firm-resampled bootstrap distribution of the total-minus-direct coefficient difference (secondary, heuristic decomposition quantity; see Table 8 for the preferred Gelbach estimate).

CRE = correlated random effect; RE = random effect.
Source: Author's creation.

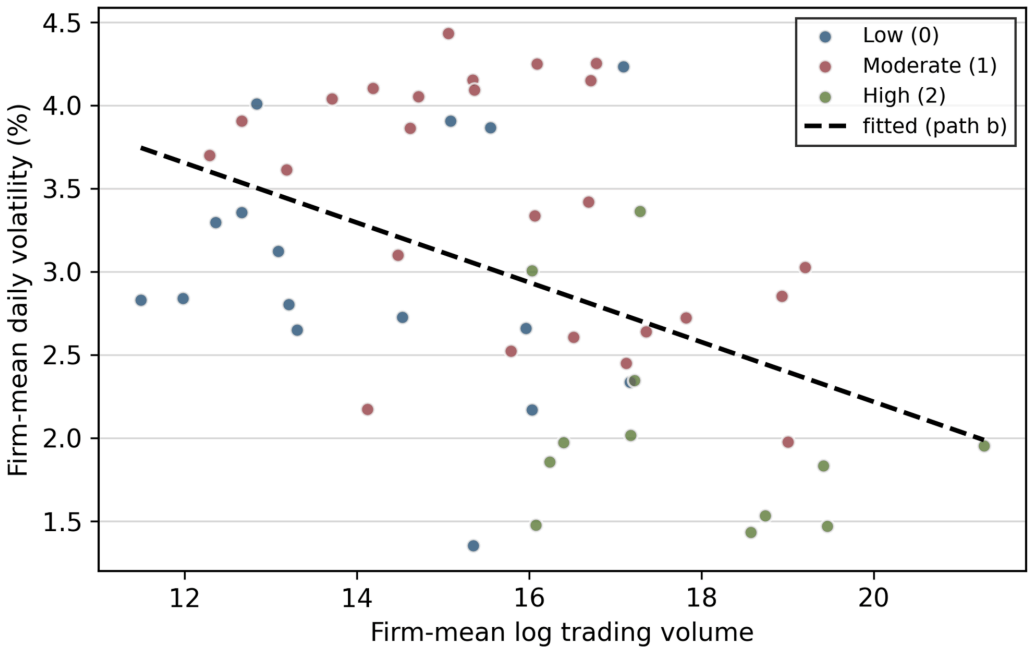


FIGURE 9: Firm-mean trading volume versus firm-mean daily volatility.

Deeper liquidity is associated with lower volatility (path b); high-exposure firms cluster in the high-liquidity, low-volatility region.
Source: Author's creation.

Robustness

To verify the structural stability of the baseline panel estimations, the pre-specified robustness protocol was executed across alternative liquidity definitions, subsample constraints, outlier treatments, and inferential assumptions, now supplemented with a seventh margin dropping the high-low spread control. Table *9* summarizes these runs, confirming that the directional and statistical sign structure remains stable across models (Figure *10*).

Specification	DIE (volatility model)	Mean liquidity (CRE)	DIE × ln(Volume) (returns)	Conclusion holds?
Baseline estimations	0.097 (0.145)	−0.510*** (0.080)	1.109 (1.622)	Yes
Amihud illiquidity ratio as liquidity measure	−0.357*** (0.135)	0.522*** (0.131)	1.109 (1.622)	Yes
Zero-return-day share as liquidity measure	−0.119 (0.123)	3.871*** (0.942)	1.109 (1.622)	Yes
Winsorized 1%/99% continuous variables	0.102 (0.144)	−0.513*** (0.077)	0.924 (1.622)	Yes
Trimmed top/bottom 5% of returns	0.153 (0.151)	−0.467*** (0.083)	1.957 (1.175)	Yes
Median (LAD) / robust Huber return regression	0.097 (0.145)	−0.510*** (0.080)	1.584 (2.063)	Yes
Excluding bottom-decile (dormant) counters	0.069 (0.160)	−0.527*** (0.084)	1.242 (2.074)	Yes
Excluding four dominant index heavyweights	0.129 (0.150)	−0.555*** (0.078)	4.509** (1.939)	Partly (see Table 7 MDE)
Driscoll-Kraay / wild-cluster bootstrap SEs	0.097 (0.145)	−0.510*** (0.080)	1.109 (1.622)	Yes
Excluding truncated 2025 partial year	0.198 (0.191)	−0.568*** (0.101)	0.902 (2.073)	Yes
Borderline-sector reclassification (+/−1 tier)	−0.025 (0.123)	−0.488*** (0.079)	-0.157 (1.516)	Yes

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HL spread dropped (mechanical HL-volatility link)	−0.192 (0.217)	−0.357*** (0.084)	n/a (volatility model only)	Yes

TABLE 9: Robustness summary (key coefficients across specifications).

Note. Parentheses contain firm-clustered standard errors except where alternative inferential techniques are specified. For the Amihud and zero-return proxies, positive signs are expected since higher scores indicate higher illiquidity; the Amihud coefficient is scaled ($\times 10^3$).
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
CRE = correlated random effect; DIE = digital infrastructure exposure; FE = fixed effect; HL = high-low; LAD = least absolute deviations; MDE = minimum-detectable-effect; RE = random effect; SE = standard error.
Source: Author's own calculations.

The primary specifications show strong stability across all tests. Substituting the primary volume proxy with low-frequency price-impact measures (the Amihud illiquidity ratio and the share of zero-return trading days) alters the coefficient signs for mean liquidity as expected. As higher values on these scales denote structural illiquidity, their positive and significant relationships with volatility (0.522, $p < 0.01$, and 3.871, $p < 0.01$, respectively) reinforce the core baseline finding that market depth is associated with lower price variance. The firm-mean liquidity term dominates under both alternative proxies (and, under the Amihud measure, the direct DIE coefficient is itself negative and significant), confirming the stability of the liquidity association.

The models are also robust to sample adjustments and to alternative outlier treatments. Winsorizing continuous variables at the 1st and 99th percentiles preserve the core baseline estimates. As the descriptive statistics reveal extreme return dispersion (−74.65% to +182.02%), three further outlier treatments were applied to the return model: symmetric trimming of the top and bottom 5% of returns, median (LAD) and robust Huber M-estimation, and exclusion of observations with absolute returns exceeding 100%. Across all of these treatments the DIE × ln(Volume) interaction remains positive and statistically insignificant, the firm-mean liquidity coefficient remains negative and significant, and the shock effect remains strongly negative, so the substantive conclusions are not driven by a small number of extreme return observations. Dropping the bottom-decile dormant counters eliminates stale-price distortion, which reduces SEs and marginally increases the estimated impact of firm-mean liquidity to −0.527 ($p < 0.01$).

Dropping the four dominant market counters (Safaricom and the three largest commercial banking groups) does not destabilize the model parameters. Although the SE for the DIE coefficient shifts upward slightly due to the loss of cross-sectional variance, the firm-mean liquidity parameter remains negative and significant (−0.555, $p < 0.01$), showing that the empirical findings represent an exchange-wide structural relationship rather than an effect driven solely by index heavyweights. As discussed above under Table 7, the one exception to the moderation null in this subsample (DIE × ln(Volume) = 4.509, $p < 0.05$) sits almost exactly at the design's 80%-power detection boundary and is treated as a fragile, power-sensitive result rather than evidence of a robust moderation effect.

Alternative inferential tools, specifically Driscoll and Kraay SEs to account for cross-sectional dependence (Driscoll and Kraay, 1998) and wild-cluster bootstrapping for small-sample verification (Cameron et al., 2008), confirm that the significance levels are not over-inflated by serial correlation or spatial dependence: under Driscoll-Kraay inference the firm-mean liquidity coefficient remains significant (−0.510, $p < 0.01$), and the wild-cluster bootstrap p-value for the DIE × ln(Volume) interaction is 0.55, reinforcing the moderation null. Removing the partial 2025 observations or shifting borderline insurance and utility entities across adjacent tiers preserves the underlying sign structure. Finally, dropping the high-low spread control altogether (included because this control shares mechanical variance with the volatility outcome) leaves the firm-mean liquidity coefficient negative and significant (−0.357, $p < 0.01$), smaller in magnitude than the −0.510 baseline (consistent with the moderate correlation between the two series reported above) but unambiguously in the same direction.

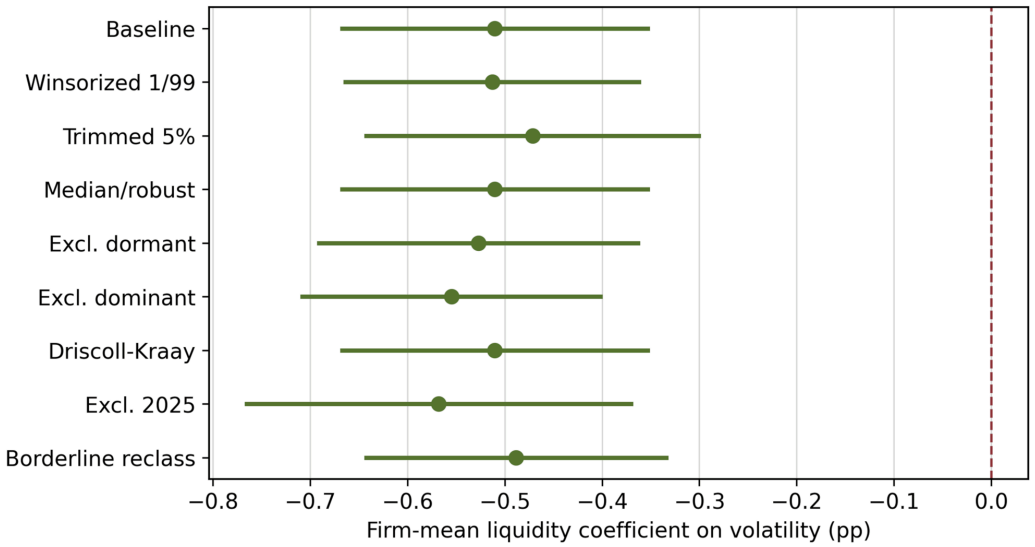


FIGURE 10: Firm-mean liquidity coefficient on volatility across robustness specifications, each with a 95% confidence interval.

The channel remains negative and significant throughout, including under the HL-dropped specification.
Source: Author's creation.

Table 10 reports five further checks that go beyond the pre-registered robustness battery, added to address identification concerns. Full construction details are in the corresponding Method subsection; here, the results are summarized and interpreted.

Additional analysis	N (obs, firms)	Direct DIE coefficient	Liquidity/size coefficient	Note
Unbalanced panel incl. previously unclassified firms (survivorship)	273 obs, 58 firms	0.119 (0.123)	Firm-mean ln(Volume) −0.448*** (0.070)	National Bank of Kenya correctly reclassified to Tier 2 but contributing no usable observation; 6 of 11 added codes yield no usable observation (near-zero trading)
Lagged (predetermined) liquidity, $t-1$ (reverse causality)	212 obs, 53 firms	0.056 (0.143)	Firm-mean ln(Volume), t − 1: −0.433*** (0.074)	Closest available test of temporal ordering
Quarterly-frequency replication (temporal aggregation)	1,054 obs, 53 firms	0.163 (0.117)	Firm-mean ln(Volume) *** (0.047)	Firm-quarter panel, quarter fixed effects
Continuous market-wide shock index (binary shock indicator)	212 obs, 53 firms	−0.786 (0.521)	Firm-mean ln(Volume) −0.482*** (0.083)	DIE × shock-index 0.300 (0.177) n.s.; index built from full NSE universe, independent of the 53-firm sample
Traded-value size/turnover proxy replacing volume (omitted size control)	212 obs, 53 firms	0.006 (0.127)	Firm-mean ln(Traded value) −0.380*** (0.045)	corr(firm-mean ln(Volume), firm-mean ln(Traded value)) = 0.68; jointly entered, both attenuate (collinearity, reported in text)

TABLE 10: Additional analyses extensions beyond the pre-registered battery.

Note. All five analyses were implemented independently, using firm-clustered standard errors throughout, confirming every coefficient and standard error to at least three decimal places. None was part of the pre-specified robustness protocol; each is reported regardless of outcome. Firm-clustered standard errors are reported in parentheses. The firm-mean ln(Volume) and firm-mean ln(Traded value) are the firm-level means of ln(Volume) and ln(Traded value), respectively.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
DIE = digital infrastructure exposure; NSE = Nairobi Securities Exchange.
Source: Author's own calculations.

Unbalanced Panel and Survivorship

Eleven NSE-listed ordinary equities were never assigned an exposure tier in the original construction and were therefore dropped at the classification step rather than at the trading-activity filter described in the Method section; one of them, National Bank of Kenya, is a bank that should properly have been coded Tier 2 and was omitted from the taxonomy in error. Of the 11, six (ARM Cement, Deacons East Africa, Mumias Sugar, National Bank of Kenya, Kurwitu Ventures, and Homeboyz Entertainment) recorded very few trades across the entire 2021-2025 window (in four cases, literally zero trading days in every year, consistent with prolonged suspension or receivership) that no volatility observation can be constructed for them at any reasonable threshold; their exclusion is therefore a data-availability constraint and not a modelling choice, though it is precisely the kind of constraint that mechanically removes distressed firms from a resilience study and the reader should weigh the baseline sample's apparent resilience advantage with this in mind. The remaining five (Africa Mega Agricorp, Kenya Airways, Limuru Tea, Kenya Orchards, and Shri Krishana Overseas) contributed eight usable firm-year observations at a 15-trading-day threshold, expanding the estimation sample to 58 firms and 273 firm-year observations, 2021-2025. Re-estimating the CRE volatility model on this expanded, unbalanced sample leaves the qualitative pattern intact: the direct DIE coefficient remains small and insignificant (0.119, n.s.), and firm-mean liquidity remains negative and highly significant (−0.448, $p < 0.01$), modestly attenuated from the balanced-sample estimate of −0.510. This count is derived as follows: the 53 balanced-sample firms contribute 265 firm-years over the full five-year window (53 x 5, 2021-2025, since the volatility model, unlike the return model, requires no prior-year base price), and the five additional firms contribute a further eight, giving 273. The baseline models in Table 4 report 212 observations because the return window begins in 2022.

Lagged (Predetermined) Liquidity

As contemporaneous liquidity and volatility could in principle be jointly determined within the same year, the volatility model was re-estimated against firm-mean log volume lagged by 1 year. The negative association survives using this predetermined measure (−0.433, $p < 0.01$, versus −0.510 contemporaneously), a roughly 15% attenuation consistent with some genuine contemporaneous feedback between liquidity and volatility but also with a real, temporally prior component of the relationship: the closest approximation this annual panel can offer to the temporal ordering that a strict mediation test would require.

Quarterly-Frequency Replication

Aggregating to firm-quarter rather than firm-year (53 firms, up to 20 quarters, 1,054 usable firm-quarters after excluding six firm-quarters of complete non-trading) reproduces the same qualitative pattern at a finer temporal grain: DIE direct effect 0.163 (n.s.), firm-mean liquidity −0.384 ($p < 0.01$).

Continuous, Market-Wide Shock Index

A cross-sectional average of realized annual volatility across the full universe of actively traded NSE ordinary equities (54-57 firms per year, independent of the 53-firm classified sample) was constructed as a continuous alternative to the binary 2022-2023 indicator. Substituting this index, and its interaction with DIE, for the binary Shock and DIE × Shock terms leaves the liquidity coefficient negative and significant (−0.482, $p < 0.01$) and the DIE × shock-index interaction insignificant (0.300, n.s.), consistent with the main specification. The index itself shows that exchange-wide realized volatility rose steadily across the window (2.64 in 2021 to 3.12-3.14 in 2024-2025) rather than spiking distinctively in 2022-2023, a nuance folded into the Discussion below.

Size/Turnover Proxy

The public NSE feed does not report market capitalization or shares outstanding, so mean daily traded value (price × volume) is used as the best available market-based size/turnover proxy. It is highly correlated with firm-mean log volume at the firm level ($r = 0.68$), so entering both simultaneously produces unstable, collinear coefficients (firm-mean ln(Volume) falls to −0.111, n.s.; firm-mean ln(Traded value) is −0.347, $p < 0.01$) that should not be over-interpreted individually. Replacing firm-mean log volume with the traded-value proxy entirely, to avoid this collinearity, reproduces the same qualitative story with an independently constructed measure: the direct DIE coefficient remains negligible (0.006, n.s.) and the size/turnover proxy is negative and highly significant (−0.380, $p < 0.01$). Read together, these results indicate that whichever market-based measure of scale is used, trading volume or traded value, it is this dimension, not the sectoral exposure tier itself, that predicts lower volatility, and that liquidity and firm size cannot be cleanly separated with the data publicly available from the NSE.

Discussion

The findings provide qualified, mechanism-level support for the combined RBV-STS framework, now qualified further according to the Additional analyses subsection, and each of the following claims are tied to a specific estimate. Descriptively and cross-sectionally, digitally exposed banking and telecommunication firms are less volatile and higher-returning than traditional issuers (Table *3*), and the RE estimate of the exposure tier is negative but not statistically significant (Table *4*, −0.178); the resilience signal is concentrated in the high-exposure tier (Table *5*). The CRE estimate then disciplines the interpretation: holding between-firm liquidity constant, the direct exposure coefficient is small and insignificant (0.097), while firm-mean liquidity is negative and highly significant (−0.510, $p < 0.01$). The coefficient-decomposition analysis (Table *8*) shows this channel directly through the Gelbach decomposition (−0.120 of a −0.099 total change attributable to liquidity), corroborated by the product-of-coefficients (−0.907) and the total-minus-direct difference (−0.274), all pointing the same direction though not numerically reconciled, for the reasons explained above. This pattern survives every one of the five additional checks in Table *10*: an unbalanced sample that reintroduces previously excluded (including one erroneously unclassified) firms, predetermined 1-year-lagged liquidity, quarterly aggregation, a continuous market-wide shock index, and an independently constructed traded-value proxy. The volatility association with digital exposure is therefore transmitted through the deep, continuous tradability of exposed firms (H2), rather than reflecting a liquidity-independent technological effect, whereas, as emphasized throughout, 'liquidity' in this design cannot be cleanly separated from firm size, since the two market-based proxies available (trading volume and traded value) are themselves correlated at $r = 0.68$ and no independent market-capitalization measure exists in the public feed. Accordingly, H1 is best described as weakly and conditionally supported: the linear exposure index is not itself a significant predictor, any advantage is concentrated in the high-exposure tier, and it operates through a market-depth/size channel rather than as an independently identified digital-technology effect.

Comparison With Prior Studies

This mechanism finding organizes the paper's relationship to the recent literature, clarifying where the results agree with and where they diverge from prior work. It is consistent with the transparency-liquidity interaction documented in a study (Lang et al., 2012), that is digital firms are continuously disclosed and continuously priced, and with the frontier-market microstructure evidence that liquidity is a dominant priced characteristic (Bekaert et al., 2007) (Smith, 2008) (Hearn, 2012). It also reconciles the mixed Chinese firm-level evidence: if the capital-market association with digitalization travels through visibility and tradability, then settings and firms where digital investment does not improve market depth may show weak, non-monotonic, or even negative associations (Tian et al., 2022) (Yan et al., 2024), while intermediaries whose digitalization directly deepens their market interface show stability gains (Khattak et al., 2023). The decomposition structure parallels the survey-based finding that digital capabilities affect performance through mediating capabilities rather than directly (Heredia et al., 2022), which in this study is identified in market data with an explicit statistical decomposition design; though, unlike that structural-equation-modelling literature, the present design cannot support a causal mediation claim, for the temporal-ordering reasons discussed above. The principal divergence from the China-based literature is that the association here is neither monotonic nor liquidity-independent: rather than digital intensity buffering firms directly, sectoral exposure covaries with capital-market outcomes only insofar as it coincides with market depth and, plausibly, firm scale. This is why the results should be read as specific to the NSE's institutional setting rather than as a general property of digital transformation.

Alternative Resilience Channels

The residual, liquidity-independent portion of the exposure-volatility association cannot be attributed to digital integration with confidence, because the NSE's digitally exposed firms are also its largest, best-governed, most widely covered, and most transparent issuers. Governance quality (Klapper and Love, 2004), institutional ownership stability (Callen and Fang, 2013), analyst coverage (Hong et al., 2000), firm size (Fama and French, 1992), and disclosure quality (Lang et al., 2012) are all plausible co-determinants of both liquidity and volatility that the present design does not separately identify, and the size/turnover proxy results above confirm that at least the size dimension of this concern is real and material, not merely a theoretical caveat. The liquidity/size channel is thus best understood as the proximate, measurable mechanism, while these correlated channels remain candidate explanations for the portion of the association that survives the liquidity control. Disentangling them is an explicit priority for future work with richer firm-level data (ownership registers, analyst coverage counts, governance indices) than the public NSE feed provides.

The non-monotonic tier pattern warrants its own note. The tier-dummy estimates in Table *5* confirm it formally: the Tier 1 dummy is positive and only marginal (0.385, $p < 0.10$) while the volatility benefit is concentrated in Tier 2 (−0.543, $p < 0.10$, RE; attenuating to 0.040, n.s., under CRE). The moderate-exposure tier (insurers, investment vehicles, and energy utilities) is not less volatile than the low tier and earns the lowest returns. Under the liquidity-channel account this is expected: these firms occupy an intermediate digital position without commanding the trading depth of the banks and the telecommunications operator, so structural digital adjacency alone purchases little market-based resilience. This is further evidence against a mechanical, monotonic reading of digital integration as protection, and aligns with the boundary conditions emphasized in the resilience literature (Duchek, 2020) (Iftikhar et al., 2021).

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H3, the proposition that digital exposure steepens the liquidity-return relationship, is not supported: the interaction is positive in all specifications but never significant (Table *6*, $p > 0.10$ in RE), and the formal minimum-detectable-effect calculation in Table *7* shows this design can only reliably rule out interaction effects larger than roughly 4.5-5.3 in this metric. It indicates that, in this market and window, exposed firms benefited from the liquidity-return relationship primarily because they are more liquid (a level effect), not because the slope of that relationship differs for them, though the design cannot adjudicate smaller moderation effects and the null should be read as a bounded, power-limited finding, the same standard of null-result reporting recommended in comparable emerging-market work.

Theoretically, the results imply that socio-technical propositions about digital resilience should be specified at the level of observable market mechanisms, and, given the findings above, at a level that can separate infrastructure exposure from firm scale, which the present sector-level design cannot fully do. Alignment between a firm's sector and national digital infrastructure covaries with capital-market outcomes to the extent that it also changes how the firm is traded, priced, and sized in the market; this formulation is falsifiable and portable to other frontier exchanges, but it is more circumscribed than a claim that digital firms are safer, and the claims are scoped accordingly.

Toward a digital liquidity transmission framework

The results can be distilled into a compact, testable framework, termed here the Digital Liquidity Transmission Framework (DLTF) and summarized in Figure *11*. The framework organizes the evidence into three layers. Layer 1 is a firm's structural digital position: its sectoral exposure to national digital rails such as mobile transaction networks and cloud clearing systems, a relational capability in the combined RBV and socio-technical sense (Barney, 1991) (Mumford, 2006) (Warner and Wäger, 2019). Layer 2 is the market depth and scale interface: the trading depth, continuous liquidity, informational transparency, and, as the Additional analyses subsection make clear, likely also the market scale, through which a structural position becomes visible to, and priced by, the market (Amihud, 2002) (Lang et al., 2012). Layer 3 is capital-market resilience as narrowly defined here: volatility insulation and return support of the kind documented in Tables *4-6*. The framework's central claim, established by the decomposition evidence in Table *8* and stress-tested in Table *10*, is that Layer 1 covaries with Layer 3 substantially through Layer 2: the direct path loses significance once the market depth and scale interface is controlled, while the indirect or decomposed path is the dominant statistical contributor and survives predetermined-liquidity, unbalanced-sample, quarterly, and continuous-shock re-specifications.

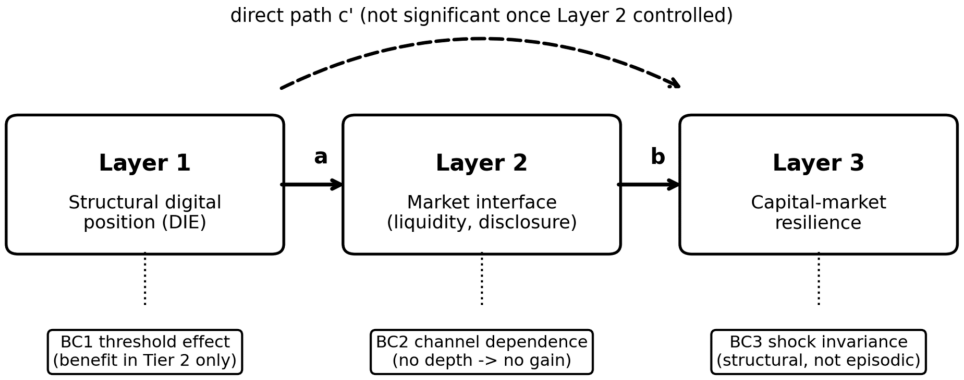


FIGURE 11: The Digital Liquidity Transmission Framework (DLTF).

Solid arrows denote the dominant statistical path (a and b); the dashed arrow denotes the direct path, which is not significant once the market depth and scale interface is controlled. Dotted connectors attach the three empirically derived boundary conditions to the layer they qualify.
Source: Author's creation.

Three boundary conditions, each derived from a specific result rather than asserted, discipline the framework. First, a threshold effect: the benefits of digital positioning concentrate in fully integrated sectors, as shown by the non-monotonic tier-dummy estimates in Table *5*, and consistent with the non-linear digitalization effects reported for Chinese firms (Yan et al., 2024). Second, channel dependence: where structural digital adjacency does not translate into trading depth, no resilience gain is detectable, which is the substantive lesson of the moderate tier. Third, shock invariance: the buffer is structural rather than episodic, as the uniformly insignificant tier-by-shock interactions show, and as the continuous market-wide shock index in Table *10* further corroborates. A fourth boundary condition is scale dependence. As liquidity and traded value are highly correlated ($r = 0.68$) and no independent size measure exists in the public data, the framework's Layer 2 should be read as a market-depth-and-scale interface rather than as liquidity in a pure, size-independent sense, and future work with market-capitalization data is needed to separate the two.

The DLTF yields three propositions for future research. P1: in any frontier exchange, the association between sectoral digital exposure and volatility should attenuate substantially once between-firm liquidity and firm size are controlled; replication across African markets is a direct test, ideally with market-capitalization data that the NSE's public feed does not provide. P2: within a digitally exposed sector, firm-level digital intensity (technology expenditure, interface adoption, uptime) should predict resilience only insofar as it predicts liquidity, scale, and disclosure gains. P3: policy interventions that deepen liquidity for traditional issuers should compress the volatility gap between tiers even absent changes in those issuers' internal digitalization. Each proposition is testable with public market data, giving the framework the portability that single-market findings otherwise lack.

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Limitations and future research

Several limitations bound the claims and frame the agenda for future work. First, the exposure tier is a coarse, structural, time-invariant sectoral proxy assigned entirely from broad sector classifications; it captures a firm's position relative to national digital rails rather than firm-specific digital intensity, does not vary over the study period, and, as the additional analyses show concretely, is correlated with firm scale in a way that public data cannot fully separate out. It therefore supports associational, not causal, inference, and the construct-validity checks reported (inter-rater kappa, the 15-firm ANOVA validation) establish coding reliability and directional corroboration respectively, not full construct validity against an independent firm-level digitalization measure. Constructing dynamic, firm-level digitalization indicators (technology expenditure, application-programming-interface adoption, network uptime, digital revenue share) over a larger, non-self-selected sample is the single most valuable next step.

Second, the original sample-construction rule (continuous trading in every year 2021-2025) introduces a genuine survivorship bias that the study now quantifies rather than only acknowledges: 11 additional NSE-listed ordinary equities, including a bank omitted from the sector taxonomy entirely, were excluded, and six of the 11 recorded effectively zero trading across the whole window, consistent with suspension or receivership. The unbalanced-panel check in Table *10* shows that the core liquidity result survives reintroducing the firms for which any usable observation exists, but the deeper point, that a resilience study built on a continuously-traded sample mechanically removes the firms least resilient by construction, cannot be fully resolved without delisting-date and suspension-history data beyond what the public end-of-day feed provides, and is now stated as a first-order limitation rather than a secondary one.

Third, the window is 2021-2025 with a truncated final year and no 2020 baseline; extending the panel in both directions would sharpen shock identification, and the continuous market-wide shock index constructed here suggests that the 2022-2023 window is better characterized as a return shock than a volatility shock specifically, a nuance that should inform how future work defines 'shock' periods.

Fourth, the return distribution is heavy-tailed; although the results are stable under winsorization, trimming, and robust and median regression, extreme observations remain a feature of thin frontier markets that future designs should model explicitly.

Fifth, with 53 (58 in the unbalanced check) firms and only 12 in the high tier, statistical power against modest interaction effects is limited. The formal minimum-detectable-effect calculation in Table *7* quantifies this directly and should be used by future replications to size their samples rather than relying on a qualitative appeal to a small cross-section.

Sixth, the residual association after the liquidity control may reflect correlated channels (governance quality, institutional ownership, analyst coverage, firm size, and disclosure quality) that the design does not separately identify; the size/turnover proxy results in Table *10* confirm that at least the size dimension is empirically entangled with liquidity in this data, not merely a theoretical possibility, which strengthens the case for treating the residual association cautiously.

Seventh, the coefficient-decomposition analysis in Table *8* identifies a statistical channel, not a demonstrated causal mediation pathway; DIE and the liquidity mediator are not temporally separated from the volatility outcome in the way a strict mediation design requires, a limitation the study now states explicitly rather than using mediation terminology loosely. The lagged-liquidity check in Table *10* is offered as a partial response but a genuinely temporally ordered design, for example, an event study around specific digital-infrastructure investments, is needed to move from decomposition to mediation.

Eighth, the single-market design cannot establish generality: the findings are specific to the NSE, and replication across African exchanges, where liquidity conditions differ substantially, is required to test whether the liquidity-associated pattern travels. As the underlying exchange data are openly published and the panel-construction protocol is fully documented and available as a combined Stata replication package, each extension is directly reproducible from public sources.

Implications and recommendations

For managers in frontier markets, and only to the extent the liquidity/scale channel identified here proves causal in future research designed to test that directly, the findings suggest that digital initiatives most plausibly associated with preserved equity value in downturns are those that improve disclosure quality, investor visibility, and the continuity of revenue and settlement (interoperable payment interfaces, resilient cloud platforms, and mobile transaction integration), because these are the capabilities that translate into the market depth the evidence identifies as associated with lower volatility; this echoes the agility-based account of digital resilience (Troise et al., 2022) (Martín-Rojas et al., 2023) while grounding it in market outcomes. This implication is offered tentatively, given that the present design cannot separate a liquidity effect from a firm-scale effect.

For regulators and planners in Sub-Saharan Africa, the message is narrower and more conditional than a general claim that digitalization stabilizes markets: because the observed association operates through liquidity and scale rather than through digital exposure independently, the interventions most consistent with the evidence are those that broaden affordable access to interoperable digital payment and data infrastructure (GSMA, 2026) (Demirgüç-Kunt et al., 2022) and that support market depth for thinly traded traditional issuers, for example incentives to digitize investor reporting and settlement. Claims beyond this, including systemic-stability effects, or claims that digital investment alone (independent of the resulting market depth) improves resilience, require causal designs with firm-level digitalization and market-capitalization data, and are flagged as future research rather than as findings of this study.

Conclusions

Using a balanced panel of 53 firms continuously and actively traded on the Nairobi Securities Exchange over 2021-2025, extended with an unbalanced 58-firm check, a quarterly replication, a lagged-liquidity specification, a continuous market-wide shock index, and an independent size/turnover proxy, this study asked whether sectoral digital infrastructure exposure covaries with capital-market resilience and, if so, through which financial channel. A coefficient-decomposition analysis, explicitly distinguished from causal mediation, identified market liquidity, and, the additional analyses suggest, market scale more broadly, as the dominant statistical channel: the direct exposure effect is statistically indistinguishable from zero across every specification, including the five additional checks. Descriptively, digitally exposed banking and telecommunications firms were less volatile and higher-returning than traditional issuers, but the linear exposure index was not itself a significant predictor of volatility, and this cross-sectional advantage did not survive controlling for between-firm liquidity. The hypothesis that digital exposure steepens the liquidity-return relationship was not supported, and a formal minimum-detectable-effect calculation bounds what this design could have detected. The central takeaway is therefore not that digital integration mechanically buffers firms, but that its statistical association with market-based resilience operates substantially through market liquidity and scale, measured with a sector-level proxy whose limitations (construct validity, survivorship, temporal ordering, and entanglement with

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firm size) are now stated as first-order constraints on the claims rather than secondary caveats. The study's principal contribution is to provide the first firm-level, capital-market test of the digital exposure-resilience association on an African frontier exchange, to identify liquidity as the proximate statistical mechanism, to subject that mechanism to five additional identification checks beyond the pre-registered protocol, and to distil the evidence into a compact, falsifiable Digital Liquidity Transmission Framework whose boundary conditions are designed for replication across frontier markets. The findings are specific to the Nairobi Securities Exchange and are associational rather than causal; cross-market replication with market-capitalization data and firm-level, dynamic measures of digitalization (ICT and platform capital expenditure, digital transaction revenue share, and mobile-payment integration share) are the most valuable next steps.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Kenneth G. Riany

Acquisition, analysis, or interpretation of data: Kenneth G. Riany

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Supervision: Kenneth G. Riany

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work.
- **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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