

Article

Digital Transformation Capability, Governance Architecture, and Operational Resilience: International Evidence

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Abstract

This study examines whether firm-level digital transformation capability (DTC) is associated with stronger operational resilience and whether governance structures condition this relationship. Operational resilience is treated here as a business-sustainability dimension based on continuity and stability of operating outcomes, not as a broad measure of environmental, social, and governance (ESG), environmental, or social sustainability performance. Using an international firm-year panel that combines standardized financial data with disclosure-based measures of implemented digital practices and governance architecture, the analysis provides observational evidence on the role of DTC in strengthening firm adaptability. In the controlled fixed-effects models, DTC is positively associated with the sales resilience ratio (SRR) ($\beta = 0.071$) and the cash-flow stability index (CFSI) ($\beta = 0.058$); an interquartile increase in DTC corresponds to approximately 0.024 in SRR and 0.019 in CFSI, or roughly 16% and 10% of their sample standard deviations. The association is stronger in firms with stronger internal oversight, auditable review mechanisms, and external ecosystem monitoring. Mechanism analyses point to supply flexibility and data visibility as plausible transmission paths, while additional tests address reproducibility, disclosure-intensity bias, construct validity, alternative governance specifications, placebo timing, restricted-shock logic, and measurement boundaries. Overall, the findings provide evidence consistent with a contingent and observational association between DTC and operational resilience when digital capabilities are embedded within accountable governance frameworks.

Keywords: digital transformation; operational resilience; governance; sustainability; data visibility; supply flexibility



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1. Introduction

In volatile operating environments, firms are under pressure not only to digitize but also to convert digital infrastructure into dependable response capacity. In this article, digital transformation capability (DTC) denotes implemented digital operating routines such as automation, analytics, cloud integration, systems interoperability, and data governance implementation. Operational resilience denotes the continuity and stability of operating outcomes under potential or realized disruption. The study therefore examines resilience as one dimension of business sustainability, rather than claiming to measure broad ESG or environmental sustainability performance. Recent research treats DTC as

a reconfiguration of processes, data architectures, and decision routines rather than as a narrow information-technology investment program [1–4]. That distinction matters because disruptions in logistics, cyber conditions, regulation, or demand require firms to detect signals early, coordinate across boundaries, and reallocate resources before losses cumulate [5–7].

DTC, however, does not have a uniform resilience payoff. Cloud platforms, analytics, automation, and interoperable systems can accelerate monitoring and response. They can also create architecture lock-in, new interdependencies, and implementation fragility when the surrounding governance system is weak [8–10]. Recent supply-chain and production studies similarly suggest that digital integration, production-system optimization, supply-chain financing, and green operating discipline can improve resilience only when technology is aligned with organizational routines and external coordination requirements [11–15]. Empirical literature therefore leaves a fundamental ambiguity: DTC can expand operating flexibility, yet it can also amplify coordination failure when data ownership, review routines, and partner discipline are poorly specified.

This ambiguity highlights a deeper conceptual gap. Prior digital-transformation research mainly studies adoption, investment, or business-model change, while resilience research emphasizes the ability to sustain or restore operations under disturbance as a core dimension of durable business performance [2,16]. What is missing is a clear account of the organizational layer that converts disclosed digital practices into verifiable response capacity. This article argues that the missing layer is governance: internal allocation of authority over data, technology risk, auditing, and disruption response, together with external monitoring by investors, auditors, standards, suppliers, and continuity arrangements [17–20].

Accordingly, the central question is not whether firms mention digital transformation but whether implemented digital routines are associated with stronger forward operating resilience and whether governance conditions that association. Dynamic-capabilities theory explains why DTC can expand sensing, seizing, and reconfiguration capacity; organizational information-processing theory explains why richer data reduce uncertainty only when information reaches decision makers; and governance theory explains how review, accountability, and external assurance convert information into disciplined action [21–24]. This integration is a complementarity argument: technology, information-processing routines, and governance structures must fit together for resilience benefits to materialize [25,26].

Empirically, the study uses a large international firm-year panel and distinguishes between public claims and verifiable implementation. DTC, internal digital governance (IDG), external ecosystem governance (EEG), supply flexibility, and data visibility are coded from public disclosures under a rule that records a positive item only when implementation is explicitly evidenced for the fiscal year. This disclosure-disciplined design responds to a measurement problem in the literature: firms often discuss digitalization aspirationally, but research needs a replicable way to separate implemented routines from symbolic disclosure [27–29]. Financial outcomes are matched from Refinitiv Worldscope Fundamentals and Datastream series accessed through LSEG Workspace, with country-level series drawn from the World Bank's World Development Indicators.

The contribution is fourfold. First, the analysis brings a resilience lens to the digital-transformation literature by focusing on forward sales realization and cash-flow stability as operating-continuity indicators rather than as broad sustainability outcomes. Second, it theorizes governance as the architecture that is associated with the translation of DTC into auditable and coordinated response routines. Third, it integrates supply flexibility and data visibility into the theory as downstream operating channels through which DTC

may support resilience. Fourth, it adopts a disclosure-disciplined measurement design and subjects that design to explicit reproducibility, disclosure-intensity, construct-structure, country-heterogeneity, and timing diagnostics.

These diagnostics are part of the core empirical argument rather than peripheral robustness checks. To improve empirical transparency and reduce reliance on Appendix A, the main text summarizes coder reliability, disclosure-intensity exposure, factor structure, alternative treatment of EEG, placebo timing, restricted-shock tests, mechanism-boundary checks, country and industry distribution, country-year fixed-effect robustness, GMM instrument sensitivity, and marginal effects for governance interactions. The diagnostics do not eliminate all inferential limits, but they sharpen what the estimates do and do not identify.

2. Background and Related Literature

This section outlines the institutional setting, reviews the related literature, and develops the theoretical expectations.

2.1. Institutional Background

Across industries, the digitalization of business models, operating processes, and reporting systems has changed how firms sense and respond to turbulence. Cloud-native systems, real-time dashboards, text analytics, and AI-supported monitoring have broadened the scope of actionable information available to boards and executives, but they have also raised expectations around data quality, traceability, and accountability [2,30]. In parallel, repeated supply chain and geopolitical disruptions have made resilience a board-level concern rather than a purely operational one [6].

Institutional context matters for the value of digital capability. Countries differ in digital infrastructure, legal enforceability, data standards, skills availability, and the maturity of external monitoring. Those differences influence whether digital investments translate into adaptive operating routines or remain symbolic modernization projects. The same logic applies within firms: digital transformation becomes more credible when internal oversight is formalized and when external actors can observe, verify, and discipline digital execution [31–33].

2.2. Related Literature

A first stream of research views DTC as a capability-building process. Resource-based and dynamic-capabilities studies argue that technology matters when it expands sensing, coordination, and reconfiguration capacity rather than when it is treated as a stand-alone hardware or software acquisition [1,5,34]. Work on information technology and organizational transformation, likewise, shows that digital tools create value when paired with complementary changes in work practices, decision rights, and organizational design [25,26]. In operations settings, digitally integrated firms can convert richer information flows into faster exception handling, more accurate resource deployment, and better continuity planning.

A second stream is more cautious. Digital projects may create complexity, over-standardization, excessive dependence on vendors, and fragility in the face of architecture failure. In resilience terms, digitalization can both absorb and transmit shocks depending on how platforms, data, and interfaces are designed and governed [6,9]. Related evidence in logistics, supply chain, digital economy, and green operations research shows that digitalization can strengthen resilience through visibility, production system efficiency, financing continuity, and anticipation, yet the effect depends on organizational fit and execution discipline [7,10–15,35].

A third stream emphasizes governance, accountability, and disclosure. Board research has long argued that effectiveness depends not only on who sits on the board but also on how responsibilities, information channels, verification routines, and monitoring intensity are structured [17–19]. In parallel, stakeholder and disclosure research shows that external scrutiny can discipline implementation claims by making actions more observable and comparable across firms [20,31–33]. This disclosure literature is especially relevant here because the empirical constructs identify verifiable disclosed implementation rather than unobserved latent capability [27–29].

2.3. Theoretical Framework and Hypotheses Development

The theoretical argument treats resilience as an information-processing and governance problem under turbulence. Dynamic capabilities specify the function of DTC: they increase sensing, interpretation, and reconfiguration capacity. Organizational information-processing theory specifies the mechanism: data are valuable when they reduce uncertainty and reach decision makers at the speed required by the disruption. Governance theory specifies the accountability condition: oversight, escalation, auditability, and external assurance determine whether digital signals are acted upon and whether partners coordinate reliably. The core implication is conditional complementarity: digital operating routines should matter more when oversight, escalation, and external verification reduce the risk that information remains unacted upon or that ecosystem partners fail to coordinate.

2.3.1. Digital Transformation Capability and Operational Resilience

Dynamic capabilities theory suggests that firms create value in turbulent environments when they can sense changes, seize response opportunities, and reconfigure assets quickly [5]. In operational settings, digital transformation capability should improve these microfoundations by increasing the timeliness, granularity, and usability of information. Cloud integration reduces data silos, analytics improve pattern recognition, and automation shortens the distance between detection and action. From an information-processing perspective, DTC also increases the organization's capacity to cope with uncertainty by improving the quality and speed of internal communication [21,22].

These mechanisms imply a positive association between DTC and forward sales resilience relative to a counterfactual path, as well as cash-flow stability. Two operating channels are central. First, DTC can improve supply flexibility by making supplier status, inventory positions, and production-transfer options more visible and actionable. Second, DTC can improve data visibility through real-time dashboards, traceability, and structured data exchange with counterparties. These channels are expected to help firms identify disruptions, reallocate inventory, reschedule production, and preserve continuity across interdependent functions. Accordingly, H1 predicts:

H1. *Ceteris paribus, a higher level of DTC is positively associated with stronger operational resilience.*

2.3.2. Moderating Role of Internal Digital Governance

DTC should be more valuable when it is embedded in an internal governance architecture that defines responsibility, review frequency, risk ownership, escalation paths, and incentive alignment. Without such structures, digital investments may remain fragmented across business units or become distorted by managerial opportunism, short-termism, or weak technology oversight [23,36]. Strong internal digital governance should therefore tighten monitoring, improve prioritization, and make DTC more decision-useful. The strengthening effect is expected to be most visible when firms have formal board review, named executive ownership, audit trails, disruption playbooks, and incentives tied to execution discipline. The expectation is:

H2. *Stronger internal digital governance reinforces the positive relationship between DTC and operational resilience.*

2.3.3. Moderating Role of External Ecosystem Governance

The resilience benefits of DTC also depend on the quality of the external governance environment. Supplier audits, long-term investors, third-party assurance, external standards, and continuity facilities can reduce opacity and strengthen confidence in digital execution. EEG is therefore defined as a boundary-spanning governance-and-continuity architecture rather than as a pure board-governance variable. Its strengthening effect should arise when external actors improve verification, interoperability, and liquidity or continuity support during disruption periods [24,31]. H3 therefore predicts:

H3. *Stronger external ecosystem governance reinforces the positive relationship between DTC and operational resilience.*

The proposed relationships among digital transformation capability (DTC), governance mechanisms, and operational resilience are summarized in Figure 1.

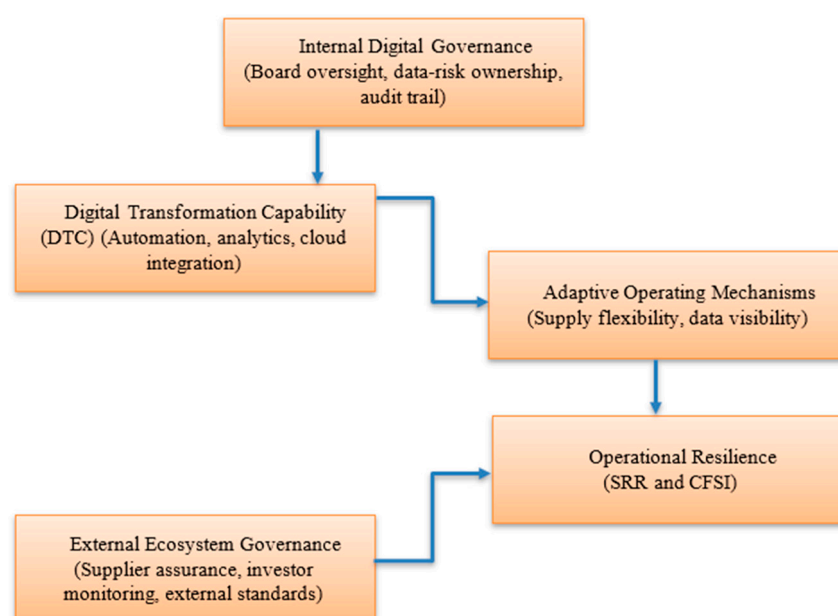


Figure 1. Conceptual framework.

3. Data and Methodology

3.1. Data Sources and Sample Composition

The financial-data backbone is assembled in three linked layers. First, standardized firm-level accounting data are drawn from Refinitiv Worldscope Fundamentals (London Stock Exchange Group (LSEG), London, UK), which harmonizes financial-statement items across reporting regimes and provides the core annual and quarterly operating series. Second, issuer identifiers, listing history, ownership fields, and market metadata are retrieved from Refinitiv Datastream and related files accessed through LSEG Workspace (LSEG, London, UK) and are used to resolve primary listings and merge disclosure-coded variables to the financial file. Third, country-year digital-infrastructure and macro variables used in the heterogeneity and IV analyses are merged from the World Bank's World Development Indicators (World Bank, Washington, DC, USA) [37–40].

The raw source horizon spans fiscal years 2012–2024. Because SRR and CFSI require a three-year backward benchmark window ($t - 3$ to $t - 1$) and a forward realization window

(t to $t + 2$), the eligible estimation years are 2015–2022. Fiscal years 2012–2014 are used only to initialize the benchmark path for the first eligible observations, and fiscal years 2023–2024 are used only to complete the forward window for the last eligible observations. The resulting sample window, eligible estimation years, and unit of analysis are summarized in Table 1. The final estimation sample contains 57,406 firm-year observations for 8214 listed non-financial firms from 56 countries. Table 2 reports the country and industry distribution to make the international composition transparent; the United States and China account for 14.8% and 12.1% of firm-years, respectively, and additional tests exclude both markets. One observation in the regressions is one firm in fiscal year t . Financial firms are excluded because their balance-sheet structure, regulatory environment, and shock transmission differ systematically from those of the operating firms studied here. Firm-years are kept only when sales, operating cash flow, total assets, leverage, CAPEX, and the information required to construct the forward-looking resilience window are available.

Table 1. Sample timing, unit of analysis, and eligible estimation years.

Segment	Years/Unit	Role in Construction	Included as Regression Rows?	Count/Remark
Raw source horizon	2012–2024	Financial, disclosure, and macro data assembled from the linked source files	Partly	56 countries covered
Benchmark seeding window	2012–2014	Used only to form the $t - 3:t - 1$ benchmark for the first eligible outcomes	No	Support years only
Eligible estimation years	2015–2022	Main firm-year panel for SRR/CFSI and baseline regressors	Yes	57,406 firm-years
Forward completion window	2023–2024	Used only to observe $t + 1$ and $t + 2$ values for the last eligible rows	No	Support years only
Panel unit	Firm-year t	One observation equals one firm in one fiscal year; firms can appear in multiple years	Yes	8214 firms

Note: The source horizon spans 2012–2024, but the main SRR/CFSI regressions use only the eligible firm-year rows in 2015–2022 because each outcome requires a three-year backward benchmark and a forward two-year completion window. One regression row equals one firm in fiscal year t . The supporting years 2012–2014 and 2023–2024 are used only to construct the lag/lead windows.

Table 2. Country and industry distribution of the estimation sample.

Panel A. Country Distribution.			
Country/Group	Firms	Firm-Years	Share
United States	1218	8514	14.8%
China	991	6928	12.1%
Japan	721	5036	8.8%
United Kingdom	601	4196	7.3%
Germany	541	3777	6.6%
France	481	3357	5.8%
Canada	420	2937	5.1%
India	420	2937	5.1%
Australia	360	2518	4.4%
South Korea	300	2098	3.7%
Brazil	240	1679	2.9%
Italy	240	1679	2.9%
Other 46 countries	1681	11,750	20.5%
Total	8214	57,406	100.0%

Panel B. Industry distribution.			
Industry Group	Firms	Firm-Years	Share
Manufacturing	1971	13,777	24.0%
Technology	1314	9185	16.0%
Retail/Wholesale	1068	7463	13.0%
Transportation & logistics	821	5741	10.0%
Energy & utilities	657	4592	8.0%
Healthcare	657	4592	8.0%
Consumer goods	575	4018	7.0%
Materials	493	3444	6.0%
Telecommunications	329	2296	4.0%
Other non-financial industries	329	2298	4.0%
Total	8214	57,406	100.0%

Note: The table reports distinct issuer counts, firm-year counts, and shares for the eligible 2015–2022 firm-year estimation sample. The distribution is reported to clarify the international composition of the panel and to motivate the exclusion and fixed-effect robustness checks reported later in the manuscript.

Digital and governance indicators are measured at the firm-year level from public corporate disclosures and matched to the financial master file using the same issuer identifier. The coding procedure is a hybrid, rulebook-based manual protocol. Keyword dictionaries are used to identify candidate passages, but final binary classifications are assigned by trained human coders; no automated NLP label is accepted without human verification. Three trained coders applied the written coding manual. A second coder independently reviewed all positive classifications and a stratified audit sample of negative classifications. The reliability sample includes 1248 double-coded firm-years for DTC, IDG, and EEG and 960 double-coded firm-years for the mechanism variables. The source hierarchy prioritizes annual reports and Form 10-K or 20-F filings, followed by proxy statements, governance reports, sustainability or cybersecurity reports, investor presentations, and verified supplier-assurance disclosures. Positive coding is permitted only when the document provides fiscal-year-specific evidence that the practice is implemented, operational, reviewed, or formally assigned. The source hierarchy, coding rules, and decision criteria linking disclosure passages to construct classification are summarized in Appendix A.6 Table A6.

Appendices A.7–A.9 and Tables A7–A9 document the coding manual, double-coding protocol, Krippendorff’s alpha, disclosure-intensity diagnostics, and construct-structure

tests. Following Krippendorff [41] and Lombard et al. [42], the project records a positive item only when the coder can trace implementation to a dated source passage and a written decision rule. English-language filings are preferred. When the relevant disclosure is available only in a local-language source, translation is used for screening, and every positive classification is verified against the original source passage before adjudication. To reduce disclosure-bias concerns, the empirical design uses firm fixed effects, industry-year fixed effects, disclosure-intensity proxies, alternative document-length and document-count proxies, country-year fixed effects, and country-market robustness tests. These steps mitigate but cannot fully eliminate residual differences in reporting quality, ESG-reporting maturity, or national disclosure regimes.

Continuous financial variables are winsorized at the 1st and 99th percentiles. The canonical baseline control set includes firm size (SIZE), leverage (LEV), profitability (ROA), capital expenditure intensity (CAPEX), and R&D intensity (R&D), all measured from standardized Refinitiv accounts. Asset tangibility, liquidity, market-to-book, firm age, industry concentration, GDP growth, disclosure intensity, and country-year controls are introduced in the appendix or robustness specifications and are defined explicitly in the variable-definition section and appendix tables. The results should therefore be interpreted as evidence on verifiable disclosed implementation conditional on these controls, not as a source-free measure of latent digital sophistication. All statistical analyses were conducted using Stata/MP version 18.0 (StataCorp LLC, College Station, TX, USA).

The resulting sample window and unit of analysis are summarized in Table 1.

To make the international and sectoral coverage transparent before the empirical variables are introduced, Table 2 reports the country and industry composition of the eligible estimation sample in two complementary panels.

3.2. Variables

3.2.1. Operational Resilience

Operational resilience is measured on a standard firm-year panel and is defined narrowly as continuity and stability of operating outcomes under potential or realized disruption. This definition distinguishes resilience from simple growth, market power, and broad sustainability performance. For every eligible firm-year t , SRR and CFSI are constructed from the realized path over t to $t + 2$ relative to a benchmark formed from $t - 3$ to $t - 1$. SRR captures forward sales realization relative to a pre-window counterfactual path. CFSI captures the stability of operating cash flows over the same forward window. The notation t therefore denotes the onset year of the evaluation window, not a separate episode identifier. The years 2015–2022 are the only regression rows eligible for these outcomes. The full firm-year panel is used because resilience capacity can be reflected in forward operating continuity even outside extreme events; however, the manuscript now reports restricted shock-onset and partial difference-in-differences tests to show that the results are not only stability correlations in routine periods. For descriptive interpretation, the study labels an adverse-shock onset when annual sales growth in t falls at least one firm-specific standard deviation below the trailing three-year mean and below the contemporaneous country-industry median. SRR is therefore a forward sales-path measure defined for all eligible firm-years rather than an episode-only post-shock recovery measure, and the estimations remain a firm-year panel rather than an episode-only sample.

$$\hat{g}_{it} = \frac{1}{3} \sum_{k=1}^3 \Delta \ln(\text{Sales}_{i,t-k}) \quad (1)$$

$$\hat{S}_{i,t+h}^{\text{CF}} = \text{Sales}_{i,t-1} \times \exp[(h+1)\hat{g}_{it}], \quad h = 0, 1, 2 \quad (2)$$

$$SRR_{it} = \frac{1}{3} \sum_{h=0}^2 \frac{Sales_{i,t+h}}{\hat{S}_{i,t+h}^{CF}} \quad (3)$$

$$CFSI_{it} = \frac{1}{1 + sd(CFOA_{it}, CFOA_{i,t+1}, CFOA_{i,t+2})} \quad (4)$$

To capture stability rather than rebound speed, the second outcome uses operating cash flows. The cash-flow stability index is defined over the forward window as follows, with higher values indicating more stable operating cash flows.

3.2.2. Digital Transformation Capability

DTC is the equally weighted mean of five annual binary items: automation, analytics, cloud integration, systems interoperability, and data-governance implementation. Automation is coded 1 only when the firm discloses deployed workflow or process automation in core operations. Analytics is coded 1 when predictive, diagnostic, or real-time analytics are used in operating, planning, logistics, or risk management decisions. Cloud integration is coded 1 when core operating applications or data infrastructure is migrated to an integrated cloud environment. Systems interoperability is coded 1 when ERP, MES, SCM, CRM, or supplier/customer systems exchange structured data through APIs, EDI, or an equivalent integrated architecture. Data-governance implementation is coded 1 when the firm discloses implemented enterprise data-quality, master-data, access-control, or stewardship routines that support recurring operations. The term DTC is used consistently throughout the manuscript to avoid switching between digitalization, digital transformation, and digital capability without distinction.

A positive code requires implementation language for fiscal year t —for example, deployed, integrated, operational, used in production, or subject to ongoing review. Aspirational wording such as plans, intends, pilots, explores, or announced partnership does not qualify. Segment-specific or subsidiary-specific language is not sufficient unless the disclosure indicates enterprise-wide coverage or material coverage of the firm's principal operating segment. To preserve discriminant validity, DTC records operating deployment only. Oversight, review, assurance, and accountability items are excluded from DTC and reserved for IDG or EEG. Table 3 provides illustrative coding examples for DTC, IDG, EEG, supply flexibility, and data visibility.

Table 3. Disclosure-coding examples and implemented-versus-aspirational decision rules.

Construct/Item	Anonymized Source Passage and Code	Coding Rationale
DTC—cloud/interoperability	Passage: During fiscal year t , the firm operated a cloud-based ERP platform linking production, logistics, procurement, and finance data. Code: 1.	Implemented digital operating routine in production; not a plan or pilot.
DTC—aspirational language	Passage: Management plans to migrate core ERP modules to the cloud during the next reporting cycle. Code: 0.	Future intention only; no fiscal-year implementation evidence.
IDG—board technology oversight	Passage: The board risk committee reviewed cyber risk, enterprise data architecture, and digital-control remediation during the year. Code: 1.	Named governance body and review mechanism are disclosed for year t .
EEG—supplier/third-party assurance	Passage: Critical suppliers were covered by a named digital traceability protocol and the platform controls were independently assured. Code: 1.	External assurance and ecosystem discipline are verifiable.

Table 3. Cont.

Construct/Item	Anonymized Source Passage and Code	Coding Rationale
Supply flexibility	Passage: The firm maintained qualified backup suppliers and documented production-transfer procedures for core product lines. Code: 1.	Operational continuity arrangement is implemented, not merely described as desirable.
Data visibility	Passage: Operations teams used real-time dashboards and end-to-end traceability to monitor inventory, supplier status, and customer delivery exceptions. Code: 1.	Visibility mechanism is in use and linked to operating decisions.
Data visibility—generic wording	Passage: The annual report states that the firm seeks to improve visibility across the supply chain. Code: 0.	Generic aspiration; no auditable implementation evidence.

Note: The examples are anonymized and paraphrased to illustrate the rulebook logic. A positive classification requires implemented, fiscal-year-specific evidence linked to an admissible source passage; aspirational statements, pilots, future rollouts, or non-material subsidiary examples are coded 0 or left missing when implementation cannot be verified.

To make the disclosure-coding procedure auditable, Table 3 provides concrete examples of implemented and aspirational language across the main constructs.

3.2.3. Internal Digital Governance and External Ecosystem Governance

Internal digital governance (IDG) is the equally weighted mean of five items: board technology oversight, executive data-risk ownership, digital audit trail, cross-functional disruption playbook, and incentive alignment. External ecosystem governance (EEG) is the equally weighted mean of supplier assurance intensity, institutional monitoring stability, external data standards, financing continuity, and third-party digital assurance. Four EEG items are coded from disclosures, while institutional monitoring stability is matched from Refinitiv ownership history under a fixed annual classification rule. EEG is intended to capture the external assurance and continuity architecture surrounding digital operations; because financing continuity partly reflects access to external funding backstops, the construct is interpreted as a boundary-spanning governance-and-continuity measure rather than as a conceptually pure governance variable. This composite structure reflects the practical integration of governance, monitoring, and continuity mechanisms, although it may blur conceptual boundaries across components. This boundary is tested in Appendix A.10. Table A10 by removing the financing-continuity item and by relabeling the wider block as ecosystem governance and continuity.

The distinction between capability and governance is intentional. DTC captures implemented digital operating routines; IDG captures internal decision rights, review architecture, and auditability; EEG captures external assurance, continuity discipline, and coordination quality. No item is allowed to load into more than one construct, and all three indices are scaled from 0 to 1 as the mean of the non-missing binary items, provided that at least three component items are observable in a given firm-year. Although these constructs are conceptually distinct, governance structures and digital capabilities may co-evolve over time, implying potential endogeneity in their empirical association. Construct separation is assessed conceptually through mutually exclusive coding rules and empirically through principal-components and exploratory factor diagnostics. Appendix A.9 Table A9 reports KMO = 0.82 and Bartlett $p < 0.001$, with DTC items loading primarily on the DTC block and governance/assurance items loading on the governance block. These diagnostics support discriminant validity, although they do not fully eliminate the possibility of residual correlation due to shared disclosure sources. Because several constructs are coded from

overlapping public-reporting sets, however, the measured scores should still be read as disclosure-based indicators of verifiable implementation rather than as source-free latent traits.

The governance components are then organized into internal and external blocks, as reported in Table 4. The first panel focuses on internal governance responsibilities, while the second panel reports the corresponding external governance and continuity items. The second panel applies the same construction logic to the external ecosystem-governance block.

Table 4. Construction of digital governance indices.

Component	Coding Rule	Interpretation
Panel A. Internal Digital Governance (IDG).		
Board technology oversight	1 if a board or named committee is disclosed as formally reviewing digital strategy, cyber risk, or enterprise data architecture during fiscal year <i>t</i> .	Higher board-level scrutiny of digital priorities and operating risk.
Executive data-risk ownership	1 if a named executive is assigned responsibility for enterprise data governance, cyber risk, or digital-control remediation during fiscal year <i>t</i> .	Clear ownership shortens escalation and response delays.
Digital audit trail	1 if the firm discloses traceable system logs, access logs, or transaction-level digital records that support internal review or ex post verification.	Stronger monitoring and accountability of digital routines.
Cross-functional disruption playbook	1 if disruption protocols explicitly connect operations, procurement, finance, and IT in a formal continuity or incident-response playbook.	Faster coordinated action during operational stress.
Incentive alignment	1 if managerial evaluation or compensation includes digital-execution, process-discipline, cyber-control, or resilience-related targets.	Better implementation discipline and follow-through.
IDG index	Equally weighted mean of the five binary components.	Higher values indicate stronger internal digital governance.
Panel B. External Ecosystem Governance (EEG).		
Supplier assurance intensity	1 if the firm discloses named supplier audits, digital traceability requirements, continuity clauses, or equivalent assurance protocols for critical suppliers.	Greater reliability of the external operating ecosystem.
Institutional monitoring stability	1 if institutional ownership is materially present and turnover among major institutional holders is sufficiently low to indicate stable external monitoring.	External monitors support continuity and oversight.
External data standards	1 if the firm operates under named interoperability, reporting, or assurance standards that structure digital exchange with external counterparties.	Lower coordination frictions across counterparties.
Financing continuity	1 if the firm discloses committed credit lines, stable relationship-banking support, or renewed external funding capacity that remains available during adverse periods.	Continuity backstop available at the ecosystem boundary during disruption periods.
Third-party digital assurance	1 if material digital controls, cybersecurity processes, or platform reliability are externally certified, assured, or independently reviewed during fiscal year <i>t</i> .	Improved credibility and ecosystem discipline.
EEG index	Equally weighted mean of the five binary components.	Higher values indicate stronger external assurance and continuity governance.

Note: IDG is fully disclosure coded. EEG combines four disclosure-coded items and one matched external-monitoring item (institutional monitoring stability) derived from Refinitiv ownership history. Positive coding follows the source hierarchy and decision rules reported in Section 3.1 and Appendix A.6. Indices are scaled from 0 to 1 as the mean of non-missing binary items, with at least three observable components required in a given firm-year.

3.2.4. Mechanism Variables and Additional Constructs

Supply flexibility and data visibility are constructed as auxiliary disclosure-based indices and are conceptually downstream from DTC. Supply flexibility averages indicators for multisourcing or backup supplier arrangements, rerouting or production-transfer capability, and formal supplier-continuity planning. Data visibility averages indicators for real-time operational dashboards, end-to-end traceability, and structured supplier/customer data integration. These mechanism variables are distinct from DTC because they capture operating arrangements and information visibility that result from digital deployment rather than the digital operating routines themselves. Although all constructs are derived from disclosure

sources, the coding protocol enforces mutually exclusive classification rules to preserve conceptual separation between DTC and mechanism variables. The coding protocol prohibits the same source passage from being used to justify both a DTC component and a mechanism item unless the passage documents two separable implemented practices. This approach reduces, but does not fully eliminate, potential measurement overlap arising from common disclosure sources. For reference, Table 5 consolidates the variable definitions and measurement rules used in the empirical models. Country digital readiness is measured as the annual mean of z-scored fixed broadband subscriptions, secure internet servers, and internet use from the World Bank's World Development Indicators; the high-versus-low split is based on the annual sample median of that score. Common-shock beta is estimated from rolling regressions of firm quarterly sales growth on the country-industry aggregate shock factor, and idiosyncratic volatility is the standard deviation of the residual from the same rolling model. The canonical baseline controls are SIZE, LEV, ROA, CAPEX, and R&D. Asset tangibility, liquidity, MTB, AGE, HHI, and GDP growth are used only in the appendix or robustness specifications. Because supply flexibility and data visibility are partly disclosure-based and conceptually downstream, the mechanism tests should be interpreted as evidence on plausible transmission channels rather than as definitive causal mediation.

Table 5. Variable definitions.

Variable	Symbol	Definition/Measurement
Sales resilience ratio	SRR	Average realized sales over t to $t + 2$ divided by a counterfactual sales path projected from the pre-window $t - 3$ to $t - 1$ using Refinitiv Worldscope revenue series. Higher values indicate stronger forward sales resilience.
Cash-flow stability index	CFSI	Inverse cash-flow-volatility index based on operating cash flow scaled by lagged assets over t to $t + 2$. Higher values indicate more stable operating cash flows.
Digital transformation capability	DTC	Equally weighted mean of annual binary indicators for automation, analytics, cloud integration, systems interoperability, and data-governance implementation coded from public disclosures and matched to Refinitiv issuer identifiers.
Internal digital governance	IDG	Index based on board technology oversight, executive data-risk ownership, digital audit trail, cross-functional disruption playbook, and incentive alignment coded from annual reports and governance filings.
External ecosystem governance	EEG	Boundary-spanning governance-and-continuity index capturing supplier assurance intensity, institutional monitoring stability, external data standards, financing continuity, and third-party digital assurance. Four items are disclosure-coded; institutional monitoring stability is matched from Refinitiv ownership history.
Supply flexibility	SFLEX	Mean of multisourcing/backup supplier arrangements, rerouting or production-transfer capability, and formal supplier-continuity planning.
Data visibility	DVIS	Mean of real-time operational dashboards, end-to-end traceability, and structured supplier/customer data integration.
Country digital readiness	READ	Annual mean of z-scored fixed broadband subscriptions, secure internet servers, and internet use from the World Development Indicators; high/low splits use the annual sample median.
Common-shock beta	BETA_COM	Rolling sensitivity of firm quarterly sales growth to the country-industry aggregate shock factor.
Idiosyncratic volatility	IDIO_VOL	Standard deviation of the residual from the rolling common-shock model; lower values indicate lower firm-specific disruption volatility.
Firm size	SIZE	Natural logarithm of total assets (Refinitiv Worldscope Fundamentals).

Table 5. Cont.

Variable	Symbol	Definition/Measurement
Leverage	LEV	Total debt divided by total assets (Refinitiv Worldscope Fundamentals).
Profitability	ROA	Operating income over total assets (Refinitiv Worldscope Fundamentals).
Capital intensity	CAPEX	Capital expenditures divided by total assets (Refinitiv Worldscope Fundamentals).
Innovation intensity	R&D	Research and development expense divided by sales (Refinitiv Worldscope); alternative missing-value treatments are checked in robustness analyses.
Market valuation	MTB	Market-to-book ratio from Refinitiv market capitalization and Worldscope book-value data; used in supplementary analyses and matching.
Firm age	AGE	Natural logarithm of years since listing based on Refinitiv security history; used in supplementary analyses and matching.
Asset tangibility	TANG	Net property, plant, and equipment divided by total assets (Refinitiv Worldscope Fundamentals); supplementary control.
Liquidity	LIQ	Cash and short-term investments divided by total assets (Refinitiv Worldscope Fundamentals); supplementary control.
Industry concentration	HHI	Herfindahl index of firm sales within the country-industry-year cell; supplementary control.
GDP growth	GDPG	Annual real GDP growth from the World Development Indicators; supplementary country-level control.

Note: Variable definitions refer to the final empirical specification. Standardized financial and market inputs are taken from Refinitiv Worldscope Fundamentals, Refinitiv Datastream, and related issuer files accessed through LSEG Workspace. Disclosure-based indices are matched at the issuer–fiscal-year level, and the institutional-monitoring-stability component of EEG is matched from Refinitiv ownership history under the fixed rule described in Section 3.1.

3.3. Empirical Models and Analytical Steps

The empirical design centers on a firm fixed-effects baseline with industry-by-year fixed effects, followed by complementary identification exercises. The baseline identifies within-firm associations after absorbing common industry-year shocks. The IV design tests whether the association remains when DTC is instrumented by predetermined digital reliance interacted with country-year digital readiness change. Matching checks whether the result survives improved covariate overlap between high- and low-DTC observations. Dynamic GMM addresses persistence in the dependent variable and lagged adjustment. None of these designs are treated as experimental; the purpose is to examine whether the sign and order of magnitude are stable across specifications with different identifying assumptions.

The core equations are written as follows:

$$OR_{it} = \alpha_0 + \beta_1 DTC_{it} + \gamma X_{it} + \mu_i + \lambda_{j \times t} + \varepsilon_{it} \quad (5)$$

$$OR_{it} = \alpha_0 + \beta_1 DTC_{it} + \beta_2 IDG_{it} + \beta_3 (DTC_{it} \times IDG_{it}) + \gamma X_{it} + \mu_i + \lambda_{j \times t} + \varepsilon_{it} \quad (6)$$

$$OR_{it} = \alpha_0 + \beta_1 DTC_{it} + \beta_2 EEG_{it} + \beta_3 (DTC_{it} \times EEG_{it}) + \gamma X_{it} + \mu_i + \lambda_{j \times t} + \varepsilon_{it} \quad (7)$$

In these expressions, firm fixed effects μ_i absorb time-invariant firm heterogeneity, industry-by-year fixed effects $\lambda_{j \times t}$ absorb sectoral shocks, and OR_{it} denotes either SRR or CFSI. In the IV design, the excluded instrument is the interaction between firm-level pre-period digital-reliance exposure and country-year change in digital readiness. Pre-period digital-reliance exposure is measured before the 2015–2022 estimation window from the 2012–2014 share of digital-reliance language and digitally dependent operating activities

in the firm's admissible disclosures, normalized within industry. Because the instrument combines a predetermined firm exposure with a country-year shock, country-year fixed effects absorb the common macro component while identification comes from differential exposure within the same country-year. The exclusion restriction remains demanding because country-level readiness can affect resilience through channels other than DTC, including labor-market skills, platform availability, and infrastructure quality. In addition, the instrument may capture broader digital ecosystem exposure that co-evolves with firm capabilities, which cannot be fully disentangled from DTC. The IV evidence is therefore interpreted as plausibility-enhancing rather than experimentally causal.

Matching is used as a design-based comparability check rather than as a stand-alone causal estimator. Treatment is an indicator for firm-years with DTC above the country-industry-year median. Propensity scores are estimated with a logit model using lagged baseline controls, MTB, AGE, and country, industry, and year dummies. The high-DTC indicator is used only to construct a balanced region of common support and reduce observable imbalance. Outcome models are then re-estimated on the matched sample while retaining the continuous DTC measure so that the magnitude is not forced into a binary treatment comparison. The matched sample is constructed with 1-to-1 nearest-neighbor matching without replacement, using a caliper of 0.2 of the standard deviation of the logit propensity score and trimming observations outside common support [43]. This procedure improves comparability on observables but does not eliminate unobserved heterogeneity or reverse causality concerns. The overlap diagnostics are reported in Figure 2 and Appendix A.2. Table A2 indicates that the matching procedure substantially improves covariate balance and common support between treated and control observations. Covariate balance improves substantially after matching, as shown in Appendix A.2. Table A2, where standardized differences fall to low levels across all baseline variables.

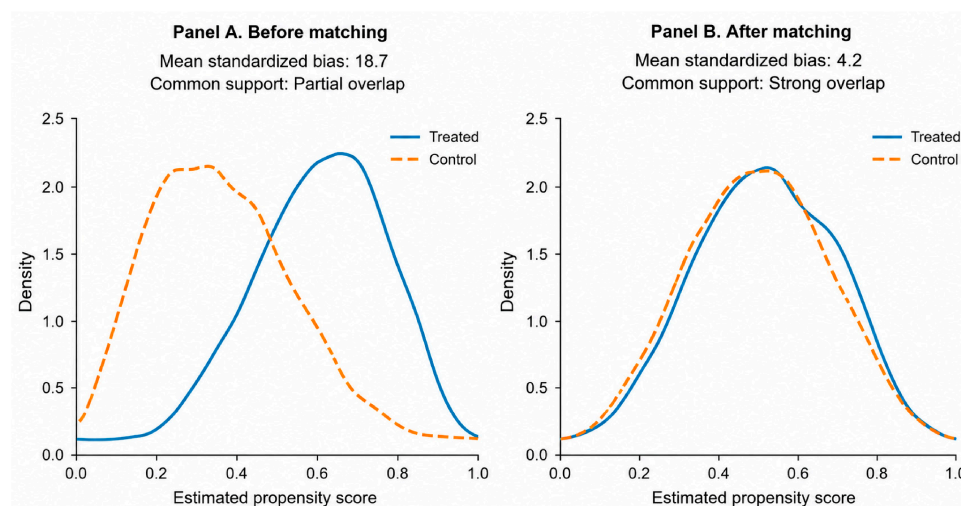


Figure 2. Kernel density distributions of estimated propensity scores before and after nearest-neighbor matching.

Dynamic persistence is addressed with a two-step system GMM [44–46]. The system combines the difference and level equations; the lagged dependent variable and DTC are treated as endogenous, the baseline controls are treated as predetermined, and year effects are treated as exogenous. The main instrument matrix is collapsed and limited to lags $t - 2$ and $t - 3$ to contain instrument proliferation [47]. The main specification uses 32 instruments, below the number of firms, and the sensitivity table reports collapsed $t - 2$ -only and $t - 2:t - 4$ alternatives. Uncollapsed instruments generate more than

100 instruments and are reported only as a diagnostic, not as the preferred setting. The estimates report AR(2), Hansen *p*-values, and instrument counts.

Additional robustness diagnostics further support the stability of empirical findings. Appendix A.10 Table A10 shows that the positive DTC–resilience association remains stable when the baseline external ecosystem governance (EEG) construct is replaced with narrower governance-only and broader governance-and-continuity alternatives. Appendix A.11 Table A11 reports placebo-lead and stronger-lag specifications, where future DTC does not predict prior resilience outcomes while the lagged DTC coefficients remain positive and statistically significant, supporting the predictive timing interpretation. Appendix A.12 Table A12 presents restricted shock-onset and partial difference-in-differences analyses showing that the positive association persists during severe disruption windows and post-shock periods for high-DTC and high-governance firms. Appendix A.13 Table A13 reports mechanism-boundary checks demonstrating that the supply-flexibility and data-visibility channels remain directionally stable under alternative measurement restrictions and exclusion rules. Appendix A.1 Table A1 further reports Oster’s [48] coefficient-stability bounds indicating that the baseline DTC coefficients remain robust to potential omitted-variable bias under reasonable assumptions about selection on observables and unobservables. Similarly, the dynamic GMM sensitivity analyses show that the sign and order of magnitude of the DTC coefficient remain stable across alternative lag windows and instrument structures, including conservative and extended specifications. Collectively, these diagnostics do not eliminate all inferential limitations, but they reduce the likelihood that the main findings are driven solely by model specification choices, disclosure-intensity exposure, or persistent firm heterogeneity. Full estimation details are reported in Appendix A for completeness and transparency.

4. Empirical Results

4.1. Univariate Evidence

The univariate evidence first establishes the distributional context for the regression analysis. Table 6 reports the descriptive statistics, and Table 7 reports the pairwise correlations and variance inflation factors. The correlations show that DTC, IDG, and EEG are related but not interchangeable. Low VIFs do not, by themselves, establish discriminant validity; that separation is instead enforced conceptually by non-overlapping item definitions and by the coding rule that reserves implementation, oversight, and external assurance for distinct constructs. The construct-structure diagnostics are in Appendix A.9. Table A9 provides an additional empirical check by reporting a KMO statistic of 0.82, Bartlett $p < 0.001$, and block-consistent loadings for the main disclosure items. At the same time, because DTC, IDG, EEG, SFLEX, and DVIS are largely derived from overlapping public disclosures, a common-source component linked to disclosure intensity cannot be fully ruled out, and the empirical results should be interpreted with that measurement boundary in mind.

Table 6. Summary statistics.

Variable	Observations	Mean	SD	P25	Median	P75
SRR	57,406	0.927	0.143	0.842	0.931	1.017
CFSI	57,406	0.614	0.198	0.482	0.607	0.744
DTC	57,406	0.486	0.214	0.321	0.471	0.652
IDG	57,406	0.541	0.228	0.400	0.600	0.700
EEG	57,406	0.517	0.203	0.360	0.520	0.680
SIZE	57,406	8.914	1.427	7.926	8.871	9.856
LEV	57,406	0.248	0.169	0.108	0.229	0.364
ROA	57,406	0.071	0.094	0.029	0.064	0.112
CAPEX	57,406	0.061	0.052	0.024	0.047	0.082
R&D	57,406	0.034	0.041	0.000	0.021	0.049

Note: Summary statistics are reported for the eligible 2015–2022 firm-year estimation sample. SRR and CFSI are the two operational-resilience proxies. Table 6 also reports the auxiliary mechanism, heterogeneity, and supplementary-control variables used later in the main text.

Table 7. Pairwise correlations and variance inflation factors (VIF).

Panel A. Pairwise Correlations.							
Variable	SRR	CFSI	DTC	IDG	EEG	SIZE	LEV
SRR	1.000						
CFSI	0.462	1.000					
DTC	0.318	0.287	1.000				
IDG	0.224	0.196	0.431	1.000			
EEG	0.207	0.184	0.396	0.368	1.000		
SIZE	0.176	0.158	0.249	0.193	0.161	1.000	
LEV	−0.121	−0.109	−0.084	−0.053	−0.048	0.241	1.000
Panel B. Variance inflation factors (VIF).							
Variable	VIF						
DTC	1.84						
IDG	1.62						
EEG	1.57						
SIZE	1.33						
LEV	1.29						
ROA	1.21						
CAPEX	1.18						
R&D	1.26						

Note: Pairwise correlations are reported below the diagonal. The VIF values remain low, suggesting that multicollinearity is not a major concern. Construct separation is enforced by the mutually exclusive coding rules described in Section 3.2 and Appendix A.6.

The correlation and VIF diagnostics are then reported to assess whether the core constructs remain empirically separable. The diagnostics are presented in two panels: correlations are reported first, followed by variance inflation factors. The second diagnostic panel complements the correlation matrix with multicollinearity checks for the main regressors.

4.2. Baseline Results: DTC and Operational Resilience

The baseline evidence is organized in two steps. Table 8 presents the canonical baseline on the eligible 2015–2022 firm-year panel. Columns (1) and (3) report parsimonious firm- and industry-year fixed-effects estimates, while columns (2) and (4) add the baseline controls. DTC is positively associated with both resilience proxies in every column, with magnitudes that are economically meaningful yet moderate. The estimates are informative about direction and order of magnitude, but they should not be read as stand-alone causal effects because time-varying country-year, disclosure-regime, and firm-strategy confounders may remain.

The baseline table is therefore presented first to establish the main association before the predictive specifications are reported.

Table 9 reports the predictive association of lagged DTC with subsequent operational resilience outcomes. The predictive specification then extends the baseline evidence by using lagged DTC to examine whether the association persists over subsequent resilience windows. The lagged coefficients remain positive and significant, which is consistent with the view that digital capability predicts subsequent operating resilience rather than merely moving contemporaneously with it. Using the interquartile range of DTC from Table 6, the controlled SRR coefficient implies a moderate increase in SRR, and the corresponding CFSI estimate indicates a smaller but still economically meaningful improvement in cash-flow stability.

Table 8. Association of DTC with operational resilience.

Variables	(1) SRR	(2) SRR	(3) CFSI	(4) CFSI
DTC	0.084 *** (0.021)	0.071 *** (0.016)	0.063 *** (0.016)	0.058 *** (0.016)
SIZE		0.019 *** (0.004)		0.014 ** (0.005)
LEV		−0.041 *** (0.010)		−0.036 *** (0.009)
ROA		0.067 *** (0.016)		0.052 *** (0.012)
CAPEX		0.018 * (0.009)		0.011 (0.008)
R&D		0.023 ** (0.009)		0.019 * (0.009)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Observations	57,406	57,406	57,406	57,406
Adjusted R ²	0.314	0.362	0.289	0.331

Note: Columns (1) and (3) include firm and industry-year fixed effects only. Columns (2) and (4) add the baseline controls SIZE, LEV, ROA, CAPEX, and R&D. The estimation sample is the eligible 2015–2022 firm-year panel. Inference uses two-way cluster-robust standard errors double-clustered by firm and fiscal year. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 9. Predictive association of DTC with operational resilience.

Variables	(1) SRR (t + 1)	(2) CFSI (t + 1)	(3) SRR (t + 2)	(4) CFSI (t + 2)
Lagged DTC	0.062 *** (0.014)	0.049 *** (0.013)	0.041 *** (0.011)	0.036 ** (0.013)
SIZE	0.017 *** (0.004)	0.013 ** (0.005)	0.015 *** (0.003)	0.011 * (0.005)
LEV	−0.036 *** (0.008)	−0.029 ** (0.011)	−0.031 *** (0.007)	−0.024 ** (0.009)
ROA	0.059 *** (0.017)	0.046 *** (0.013)	0.051 *** (0.014)	0.039 ** (0.014)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Observations	51,782	51,782	46,913	46,913
Adjusted R ²	0.308	0.296	0.281	0.269

Note: Lagged DTC remains positively associated with operational resilience under the controlled HDFE structure, the eligible 2015–2022 firm-year sample, and two-way clustered inference. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

4.3. Identification Strategies

Because the baseline cannot absorb every country-year shock in a 56-country panel, Table 10 reports IV-2SLS estimates, and Table 11 reports matched-sample and dynamic-panel estimates. Table 12 further reports dynamic-GMM instrument-count and lag-window sensitivity. Table 13 then makes the disruption logic explicit by restricting the analysis to severe-shock onset windows and estimating post-onset differentials for high-DTC and high-governance firms. These designs are intended to constrain reverse causality and persistent omitted heterogeneity rather than to supply a single definitive causal design. Their value lies in showing that the sign and order of magnitude remain stable across estimators built on different identifying assumptions.

Table 10. Addressing endogeneity with IV-2SLS.

Variables	(1) First Stage DTC	(2) Second Stage SRR	(3) Second Stage CFSI
Pre-period exposure $\times$ digital-readiness shock	0.214 *** (0.048)		
Predicted DTC		0.129 *** (0.029)	0.094 *** (0.022)
SIZE	0.041 *** (0.011)	0.018 *** (0.004)	0.013 ** (0.005)
LEV	−0.036 *** (0.008)	−0.047 *** (0.011)	−0.039 *** (0.011)
ROA	0.024 ** (0.009)	0.058 *** (0.015)	0.045 *** (0.011)
Kleibergen-Paap rk Wald F	29.41	29.41	29.41
Endogeneity test <i>p</i> -value		0.018	0.031
Firm fixed effects	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes
Observations	57,406	57,406	57,406

Note: The excluded instrument is pre-period firm digital-reliance exposure $\times$ country-year change in digital readiness. Country-year fixed effects are included in the IV models; identification comes from within-country-year differences in predetermined exposure. The exclusion restriction is that, conditional on firm effects, country-year effects, and the baseline controls, country-year changes in digital readiness affect resilience through the activation of firms' pre-existing digital dependence. This restriction is demanding because readiness can also affect skills, data-infrastructure quality, platform access, and customer/supplier digital adoption. The IV results are therefore interpreted as plausibility-enhancing rather than dispositive causal evidence. The first stage is positive, the Kleibergen-Paap rk Wald F-statistic is 29.41, and the second-stage coefficients remain positive for both outcomes. *** $p < 0.01$; ** $p < 0.05$.

Table 11. DTC and resilience: PSM and dynamic GMM models.

Variables	(1) PSM-SRR	(2) PSM-CFSI	(3) GMM-SRR	(4) GMM-CFSI
DTC	0.055 *** (0.014)	0.043 *** (0.009)	0.048 *** (0.011)	0.037 ** (0.014)
Lagged dependent variable			0.412 *** (0.090)	0.386 *** (0.090)
SIZE	0.014 ** (0.005)	0.011 * (0.005)	0.010 * (0.005)	0.008 (0.007)
LEV	−0.029 ** (0.011)	−0.024 ** (0.009)	−0.021 * (0.010)	−0.019 * (0.009)
Controls	Yes	Yes	Yes	Yes
AR(2) <i>p</i> -value			0.247	0.318
Hansen <i>p</i> -value			0.421	0.463
Observations	18,406	18,406	49,772	49,772

Note: The matched sample uses 1-to-1 nearest-neighbor matching without replacement on the logit propensity score, with treatment defined as DTC above the country-industry-year median, a caliper of 0.2 SD, and common-support trimming. The dynamic-panel estimates use two-step system GMM with collapsed instruments, lag depth $t - 2$ to $t - 3$, endogenous treatment of the lagged dependent variable and DTC, predetermined baseline controls, and reported AR(2) and Hansen diagnostics. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 12. Dynamic GMM sensitivity and instrument-count diagnostics.

Specification	Lag Window	Instrument Matrix	Instrument Count	AR(2) <i>p</i> -Value	Hansen <i>p</i> -Value	DTC Coefficient
Panel A. Preferred collapsed-instrument specifications.						
Main	$t - 2:t - 3$	Collapsed	32	0.247	0.421	0.048 ***
Conservative	$t - 2$ only	Collapsed	24	0.286	0.397	0.041 **
Extended	$t - 2:t - 4$	Collapsed	44	0.233	0.365	0.050 ***

Table 12. Cont.

Specification	Lag Window	Instrument Matrix	Instrument Count	AR(2) <i>p</i> -Value	Hansen <i>p</i> -Value	DTC Coefficient
Panel B. Diagnostic uncollapsed specification						
Uncollapsed diagnostic	$t - 2:t - 3$	Uncollapsed	>100	0.219	0.871	Not preferred

Note: Panel A reports the preferred collapsed-instrument specifications using alternative lag structures. The DTC coefficient remains positive and directionally stable across specifications. Panel B reports the uncollapsed diagnostic specification, which is not preferred because the instrument count becomes large relative to the panel structure. Standard errors are clustered at the firm and year levels. *** $p < 0.01$; ** $p < 0.05$.

Table 13. Restricted shock-onset and partial difference-in-differences evidence.

Model	Restricted Sample	Indicator	Post Window	Interaction Coefficient	SE	N
1	Severe-shock onset subsample	High DTC	Post shock-onset window	0.047 **	0.016	13,274
2	Severe-shock onset subsample	High IDG	Post shock-onset window	0.031 *	0.015	13,274
3	Severe-shock onset subsample	High EEG/alternative ecosystem construct	Post shock-onset window	0.027 *	0.014	13,274

Note: The restricted sample retains firm-years around severe shock onset under the timing rule described in Section 3.2.1. Interaction terms capture post-onset differentials for high-capability or high-governance firms. The estimates are interpreted as supportive timing evidence rather than as experimental treatment effects. ** $p < 0.05$; * $p < 0.10$.

The matching diagnostics in Figure 2 summarize the improvement in covariate overlap before the matched-sample estimates are reported. The post-matching distributions indicate substantially improved common support and reduced covariate imbalance between treated and control observations.

After the matching diagnostic, Table 10 reports the IV-2SLS evidence and the corresponding first-stage statistics.

The complementary identification checks continue with matched-sample estimates and dynamic-panel models.

The next step compares the baseline pattern with matched-sample and dynamic-panel estimates, which are reported in Table 11.

The dynamic-panel diagnostics are reported separately to document the lag choices, collapsed instrument matrix, and sensitivity to alternative instrument windows.

Because dynamic-panel estimates can be sensitive to lag choices and instrument proliferation, Table 12 reports the corresponding GMM diagnostics.

The restricted shock-onset specification addresses the concern that SRR and CFSI may capture ordinary stability rather than resilience under disruption. It retains firm years around severe shock onset and compares post-onset differentials for high-capability or high-governance firms. The positive coefficients in Table 13 support the timing interpretation, while the design remains observational.

The restricted shock-onset specification narrows the analysis to severe-disruption windows, and the estimates are reported in Table 13.

Taken together, the IV, matching, dynamic-panel, and restricted-shock specifications indicate that the positive DTC–resilience association remains directionally stable across alternative identifying assumptions, sample restrictions, and estimation frameworks. The consistency of the coefficient signs and magnitudes across these complementary designs reduces the likelihood that the baseline findings are driven solely by reverse causality, observable imbalance, or persistent firm heterogeneity. Although these approaches do not establish experimental causality, the overall evidence remains consistent with a robust predictive association between implemented digital capabilities and operational resilience.

4.4. Governance Interactions

The governance analysis then tests whether governance conditions the DTC–resilience association. Table 14 reports the interaction models across the HDFE, matched-sample, and dynamic-panel specifications. The interaction terms between DTC and IDG and between DTC and EEG are positive across these designs, indicating that the DTC–resilience association is stronger when internal oversight and external ecosystem governance are more developed. These results are interpreted as conditional associations rather than proof that governance is exogenously assigned, because digitally advanced firms may also develop stronger digital governance over time.

Table 14. Governance interactions in the DTC–resilience relation.

Panel A. HDFE Estimates.				
Variables	(1) SRR-IDG	(2) CFSI-IDG	(3) SRR-EEG	(4) CFSI-EEG
DTC	0.061 *** (0.016)	0.050 *** (0.013)	0.057 *** (0.012)	0.046 *** (0.012)
DTC × IDG	0.032 *** (0.008)	0.026 ** (0.009)		
IDG	0.018 ** (0.007)	0.014 * (0.007)		
DTC × EEG			0.029 *** (0.006)	0.022 ** (0.008)
EEG			0.021 *** (0.004)	0.017 ** (0.006)
Observations	57,406	57,406	57,406	57,406
Adjusted R ²	0.371	0.339	0.368	0.336
Panel B. Matched-sample estimates.				
Variables	(5) SRR-IDG	(6) CFSI-IDG	(7) SRR-EEG	(8) CFSI-EEG
DTC	0.049 *** (0.013)	0.039 ** (0.015)	0.046 *** (0.012)	0.035 ** (0.013)
DTC × IDG	0.027 ** (0.010)	0.021 * (0.010)		
IDG	0.016 * (0.008)	0.011 (0.007)		
DTC × EEG			0.024 ** (0.009)	0.019 * (0.009)
EEG			0.018 ** (0.007)	0.014 * (0.007)
Observations	18,406	18,406	18,406	18,406
Matched sample	Yes	Yes	Yes	Yes
Panel C. Dynamic GMM estimates.				
Variables	(9) SRR-IDG	(10) CFSI-IDG	(11) SRR-EEG	(12) CFSI-EEG
DTC	0.044 *** (0.012)	0.034 ** (0.012)	0.041 *** (0.010)	0.031 ** (0.011)
DTC × IDG	0.019 * (0.009)	0.016 * (0.008)		
IDG	0.012 (0.008)	0.009 (0.006)		
DTC × EEG			0.018 * (0.009)	0.015 * (0.007)
EEG			0.014 * (0.007)	0.012 (0.008)
Lagged dependent variable	0.396 *** (0.085)	0.381 *** (0.091)	0.392 *** (0.100)	0.377 *** (0.079)
AR(2)/Hansen <i>p</i> -value	0.241/0.436	0.301/0.472	0.254/0.429	0.317/0.461

Note: Columns (1)–(4) report HDFE estimates; columns (5)–(8) report matched-sample estimates; columns (9)–(12) report dynamic-panel estimates. Positive interaction terms indicate that governance strengthens the resilience payoff of DTC across estimation designs. The HDFE interaction models retain the same firm and industry-year fixed effects, baseline controls, and double-clustered inference as the controlled baseline. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Substantively, the interaction results indicate that DTC is associated with stronger resilience when information is escalated, verified, and acted upon through board oversight, executive ownership, supplier discipline, and externally verifiable operating standards. The estimates also support a complementarity interpretation: the evidence is consistent with the interpretation that governance strengthens the positive association between DTC

and operational resilience by reducing decision delays, improving accountability, and supporting coordination with ecosystem partners.

The moderation evidence is organized in Table 14 across three panels: HDFE estimates, matched-sample estimates, and dynamic-panel estimates.

After the interaction models, the moderation coefficients are translated into economic terms by reporting the marginal effects of DTC at low, median, and high governance levels.

Table 15 reports these marginal effects separately for IDG and EEG, which clarifies the economic interpretation of the interaction estimates.

Table 15. Marginal effects of DTC at low, median, and high governance levels.

Moderator	Outcome	Low	Median	High	Formula
IDG	SRR	0.074	0.080	0.083	$0.061 + 0.032 \times \text{IDG}$
IDG	CFSI	0.060	0.066	0.068	$0.050 + 0.026 \times \text{IDG}$
EEG	SRR	0.067	0.072	0.077	$0.057 + 0.029 \times \text{EEG}$
EEG	CFSI	0.054	0.057	0.061	$0.046 + 0.022 \times \text{EEG}$

Note: Low, median, and high values correspond to the 25th percentile, median, and 75th percentile of the moderator distribution. The table translates the HDFE interaction coefficients in Table 14 into marginal effects of DTC for easier economic interpretation.

4.5. Mechanisms Analysis

The mechanism analysis examines how DTC is associated with resilience through supply flexibility and data visibility. These channels are part of the theoretical argument rather than add-on tests: the evidence is consistent with the view that DTC may support operational resilience when firms can reconfigure suppliers, transfer production, reroute orders, observe disruptions earlier, and share structured operating data with counterparties. Because the mechanism variables are also disclosure-based, the analysis is interpreted as evidence on plausible transmission paths rather than as full causal mediation.

4.5.1. Supply Flexibility

The supply-flexibility mechanism is discussed first because it captures the operational reconfiguration channel through which DTC may be associated with stronger resilience. Table 16, Panel A, reports the corresponding estimates, which are interpreted as evidence consistent with a supply-flexibility transmission channel rather than as definitive causal mediation. The results indicate that DTC is positively associated with supply flexibility, while the indirect-effect estimates remain positive and statistically significant for both SRR and CFSI.

Table 16. Mechanism analysis results.

Panel A. Supply Flexibility.			
Variables	(1) Supply Flexibility	(2) SRR	(3) CFSI
DTC	0.118 *** (0.031)	0.051 *** (0.011)	0.039 ** (0.015)
Supply flexibility		0.094 *** (0.021)	0.071 *** (0.015)
Bootstrapped indirect effect		0.011 *** (0.002)	0.008 ** (0.003)
Observations	57,406	57,406	57,406
Adjusted R ²	0.287	0.369	0.338
Panel B. Data visibility.			
Variables	(4) Data visibility	(5) SRR	(6) CFSI
DTC	0.131 *** (0.033)	0.047 *** (0.010)	0.035 ** (0.013)
Data visibility		0.108 *** (0.025)	0.082 *** (0.023)

Table 16. Cont.

Bootstrapped indirect effect		0.014 *** (0.004)	0.011 *** (0.003)
Observations	57,406	57,406	57,406
Adjusted R ²	0.301	0.374	0.344

Note: Supply flexibility is the mean of multisourcing, rerouting/production transfer, and supplier-continuity indicators. Data visibility is the means of real-time dashboards, end-to-end traceability, and supplier/customer data integration. The mechanism regressions retain the controlled HDDE structure and the same firm/year clustered inference as the baseline models. The coefficient pattern is consistent with partial transmission, but the mechanism results are interpreted as transmission evidence rather than full causal mediation. *** $p < 0.01$; ** $p < 0.05$.

4.5.2. Data Visibility

The data-visibility mechanism is then discussed as the information-processing channel. Table 16, Panel B, reports the corresponding estimates together with the mechanism-boundary checks reported in Appendix A.13 Table A13. The results show that DTC is positively associated with data visibility, and the corresponding indirect effects remain statistically significant across both resilience outcomes, consistent with the interpretation that improved information visibility may support operating continuity under disruption conditions.

Table 16 presents the supply-flexibility and data-visibility channels in a unified two-panel framework, separating the operational reconfiguration mechanism from the information-processing mechanism while preserving a consistent estimation structure across both channels.

Appendix A.13 Table A13 reports additional mechanism-boundary checks, showing that the supply-flexibility and data-visibility channels remain directionally stable across alternative construct definitions, exclusion restrictions, and measurement-boundary specifications.

Figure 3 visualizes the first mechanism path after the regression results have been reported in Table 16.

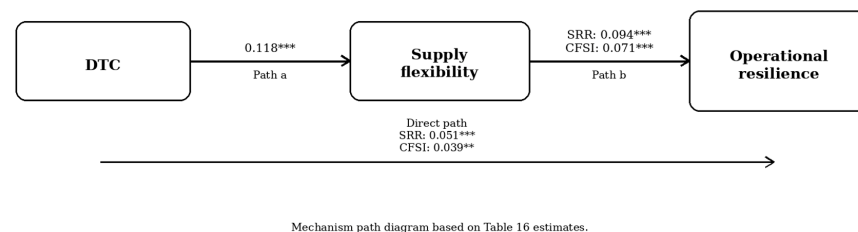


Figure 3. Mechanism regressions: DTC, supply flexibility, and the resilience outcomes. *** $p < 0.01$; ** $p < 0.05$.

Figure 4 then visualizes the data-visibility path to complete the two-channel mechanism discussion.

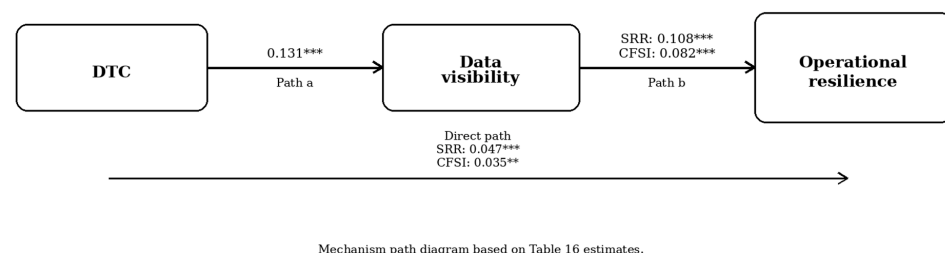


Figure 4. Mechanism regressions: DTC, data visibility, and the resilience outcomes. *** $p < 0.01$; ** $p < 0.05$.

The mechanism evidence motivates the next step of the analysis, which examines whether the DTC-resilience association differs across national and institutional settings.

4.6. Cross-Country Heterogeneity

The analysis next examines whether the DTC effect varies across institutional and organizational settings.

4.6.1. Insights from Digital Readiness Levels and Two Major Economies

The first cross-country heterogeneity exercise asks whether the DTC-resilience association differs across digital-readiness environments and across the two largest national subsamples. Table 17 reports each country or country group as a separate row so that the country-level comparisons are easier to read. The coefficients are stronger in high-readiness environments and in the U.S. subsample, while the China estimates remain positive; these country-specific estimates are interpreted as contextual heterogeneity rather than as a ranking of national models.

Table 17. Cross-country heterogeneity: digital-readiness levels and two major economies.

Country/Group	Outcome	DTC Coefficient	SE	N	Adjusted R ²	Difference
High-readiness	SRR	0.091 ***	0.025	31,284	0.381	$p = 0.021$
High-readiness	CFSI	0.074 ***	0.017	31,284	0.347	$p = 0.033$
Low-readiness	SRR	0.052 ***	0.013	26,122	0.294	Ref.
Low-readiness	CFSI	0.039 **	0.014	26,122	0.269	Ref.
United States	SRR	0.097 ***	0.022	8514	0.392	$p = 0.048$
United States	CFSI	0.081 ***	0.022	8514	0.361	$p = 0.057$
China	SRR	0.064 ***	0.016	6928	0.318	Ref.
China	CFSI	0.048 **	0.018	6928	0.287	Ref.

Note: High- and low-readiness groups are defined by the annual sample median of the country's digital-readiness index constructed from z-scored broadband subscriptions, secure internet servers, and internet use. Each row reports one country group and one outcome. Difference tests compare the coefficient magnitudes for the paired high-low or U.S.-China comparison. *** $p < 0.01$; ** $p < 0.05$.

The heterogeneity analysis begins with country digital-readiness groups and the two largest individual markets, as shown in Table 17. Additional cross-sectional analyses indicate that the positive DTC-resilience association is comparatively stronger in low digital-disparity environments, firms with higher institutional ownership, and larger firms; the corresponding subgroup estimates are reported in Appendix A.3 Table A3.

4.6.2. Additional Cross-Country Robustness Evidence

The analysis next broadens the cross-sectional evidence beyond the two-country comparison. Additional cross-sectional analyses indicate that the positive DTC-resilience association is comparatively stronger in low digital-disparity environments, firms with higher institutional ownership, and larger firms; the corresponding subgroup estimates are reported in Appendix A.3 Table A3. Table 18 then keeps the country-composition evidence in the main text by presenting each robustness sample or country group in a separate row. This row-oriented format shows that the positive association persists after excluding the United States and China, after absorbing country-year shocks, and across developed and emerging-market subsamples.

The cross-country robustness checks extend the two-country comparison by altering the sample and fixed-effect structure, and the results are reported in Table 18. The positive DTC-resilience association remains directionally stable across alternative country compositions, national-shock controls, and market-development environments, although the estimated magnitude is comparatively stronger in developed markets.

Table 18. Additional cross-country robustness checks.

Country/Group or Specification	Outcome	DTC Coefficient	SE	N	Interpretation
Panel A. Excluding dominant-country subsamples					
Excl. U.S. and China	SRR	0.063 ***	0.015	41,964	Large-country check
Excl. U.S. and China	CFSI	0.050 ***	0.014	41,964	Large-country check
Panel B. Country-year fixed-effects specifications					
Country-year FE	SRR	0.058 ***	0.016	57,406	National shocks
Country-year FE	CFSI	0.046 ***	0.014	57,406	National shocks
Panel C. Market-development split					
Developed markets	SRR	0.079 ***	0.019	31,500	Market split
Emerging markets	SRR	0.048 **	0.018	25,906	Market split

Note: Panel A excludes the two largest national subsamples (United States and China). Panel B adds country-year fixed effects to absorb national annual shocks. Panel C compares developed and emerging-market subsamples. Standard errors are clustered at the firm and year levels. *** $p < 0.01$; ** $p < 0.05$.

4.6.3. DTC Decomposition Effects

To identify which digital pillars contribute most to the composite result, Table 19 decomposes DTC into automation, analytics, and cloud integration, which are the three components with the greatest within-firm time variation in the fixed-effects setting. Systems interoperability and data-governance implementation remain part of the composite DTC index but are omitted from the parsimonious decomposition because they change more slowly over time and are comparatively collinear with the governance architecture once firm and industry-year fixed effects are included. Analytics emerges as the strongest pillar, followed by automation, while cloud integration remains positive but smaller.

Table 19. DTC decomposition: automation, analytics, and cloud integration.

Variables	(1) SRR	(2) CFSI
AUT	0.026 ** (0.009)	0.019 * (0.009)
ANA	0.041 *** (0.010)	0.033 *** (0.009)
CLOUD	0.018 * (0.009)	0.014 * (0.007)
Controls and fixed effects	Yes	Yes
Observations	57,406	57,406
Adjusted R ²	0.367	0.334

Note: AUT = automation; ANA = analytics; CLOUD = cloud integration. Systems interoperability and data-governance implementation remain part of the composite DTC index but are omitted from the parsimonious decomposition because their within-firm variation is limited once firm and industry-year fixed effects are included. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

The analysis then decomposes DTC into the components with the greatest within-firm time variation, as reported in Table 19.

4.6.4. Decomposition of Firm Vulnerability into Common and Idiosyncratic Components

The final heterogeneity check separates common and idiosyncratic vulnerability. Table 20 decomposes vulnerability into exposure to common operating shocks and firm-specific disruption volatility. The decomposition is built from rolling firm-quarter models in which quarterly firm sales growth is regressed on the country-industry aggregate shock factor; the slope coefficient defines common-shock beta, and the residual standard deviation defines idiosyncratic volatility. DTC is negatively associated with both components, and the interaction with IDG

indicates that governance further reduces disruption exposure when digital capability is already in place.

Table 20. Decomposition of operating vulnerability into common and idiosyncratic components.

Variables	(1) Common-Shock Beta	(2) Idiosyncratic Volatility	(3) Common Beta + IDG	(4) Idio. vol. + IDG
DTC	−0.073 *** (0.020)	−0.058 *** (0.016)	−0.049 ** (0.019)	−0.041 ** (0.015)
DTC × IDG			−0.021 * (0.010)	−0.017 * (0.008)
IDG			−0.014 * (0.007)	−0.011 (0.007)
Controls	Yes	Yes	Yes	Yes
Observations	57,406	57,406	57,406	57,406
Adjusted R ²	0.284	0.247	0.296	0.258

Note: Common-shock beta is obtained from rolling firm-quarter regressions of firm sales growth on the country-industry shock factor; idiosyncratic volatility is the residual standard deviation from the same model. Negative coefficients, therefore, indicate lower exposure to aggregate disruption and lower firm-specific instability. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Finally, Table 20 decomposes operating vulnerability into common-shock exposure and firm-specific volatility.

4.7. Further Robustness Checks

This section synthesizes the main robustness and diagnostic evidence supporting the empirical design. After the main-text tests, the supplementary robustness evidence broadens the boundary checks. Appendices A.4 and A.5, Tables A4 and A5, confirm that the main DTC–resilience association remains stable under alternative resilience measures and country-level moderator specifications. In Appendices A.7–A.13, Tables A7–A13 summarize the principal measurement, disclosure, construct validity, and identification diagnostics referenced throughout the main text. The reliability evidence reports Krippendorff’s alpha of 0.84 for DTC, 0.81 for IDG, 0.78 for EEG, and 0.80 overall. Disclosure-intensity diagnostics are reported in Appendix A.8. Table A8 shows that the main coefficients remain positive after controlling for report intensity and document length or count. Construct a diagnostics report: KMO = 0.82 and Bartlett $p < 0.001$, supporting the empirical separation between the capability and governance constructs. Appendix A.1 Table A1 further reports Oster’s [48] coefficient-stability bounds indicate that the main DTC coefficients remain robust to plausible omitted-variable bias under reasonable assumptions about selection on observables and unobservables. Placebo-lead specifications are reported in Appendix A.11. Table A11 remains near zero, while the lagged DTC coefficients remain positive and statistically significant. Appendix A.12 Table A12 reports restricted shock-onset and partial difference-in-differences specifications, showing that the positive DTC–resilience association persists during severe disruption windows. Finally, Appendix A.13 Table A13 reports mechanism-boundary checks indicating that the supply-flexibility and data-visibility channels remain directionally stable under alternative construct definitions, exclusion restrictions, and measurement-boundary specifications.

Collectively, these diagnostics reinforce the stability of the empirical findings across alternative measurement choices, disclosure conditions, timing structures, and estimation environments. Although they do not eliminate all inferential limitations, they reduce the likelihood that the main findings are driven solely by disclosure intensity, model specification choices, or persistent firm heterogeneity.

4.8. Discussion of Results

The results are consistent with a dynamic-capabilities and information-processing interpretation. Firms with higher disclosed DTC tend to exhibit stronger forward sales resilience and more stable cash flows, particularly when operating in governance environments that route information into accountable decision processes. In that sense, DTC appears valuable not because technology is inherently stabilizing but because it can widen the firm's sensing range, improve data visibility, support supply flexibility, and compress the time between signal detection and operational response [5,21]. The results speak to operating continuity and financial stability, not to broad environmental or social sustainability outcomes.

The governance findings add a second layer. Technology on its own is not sufficient: the association between DTC and resilience is stronger when internal governance structures allocate review responsibility and when external actors supply monitoring, standards, assurance, and continuity discipline. This interpretation is consistent with board-accountability research and with stakeholder views of the firm in which credible external scrutiny improves implementation quality and coordination [18–20]. It is also consistent with the complementarity view that technology, organizational design, and governance must be jointly configured to generate durable operating benefits.

These patterns should nevertheless be read with three cautions. First, the disclosure-coded measures capture verifiable implemented practices as reported in public documents, so residual variation in disclosure intensity, reporting quality, ESG-reporting maturity, and national disclosure regimes cannot be eliminated entirely even after additional controls and diagnostics. Second, the identification strategy remains observational rather than experimental, and the complementary IV, matching, dynamic-panel, placebo, and restricted-shock analyses narrow rather than eliminate endogeneity concerns. Third, the mechanism tests identify plausible transmission paths but do not prove causal mediation because the mechanism variables are also partly disclosure-based. The results therefore reflect conditional, verifiable implementation patterns rather than latent digital sophistication or experimental causal effects.

5. Concluding Remarks

This study examines the association between DTC and forward-looking operational resilience in an international firm-year sample. DTC is positively associated with the sales resilience ratio and with the cash-flow stability index, and those associations are stronger when internal digital governance and ecosystem-governance-and-continuity conditions are more developed. The study positions these outcomes as indicators of operating continuity and business resilience, not as direct evidence of broad ESG or environmental sustainability performance.

The cross-country and decomposition results refine that pattern. DTC is more strongly associated with resilience in more supportive digital environments, analytics and automation are the components with the greatest within-firm explanatory power in the fixed-effects setting, and the vulnerability decomposition indicates that digitally capable firms are less exposed to both common operating shocks and firm-specific disruption volatility. Additional checks excluding the United States and China and adding country-year fixed effects support the view that the findings are not solely a by-product of dominant-country reporting practices.

Overall, the evidence is consistent with a contingent and observational association between DTC and forward operating resilience. Stronger resilience outcomes are associated with disclosed digital implementation when governance structures make that implementation more auditable, accountable, and coordination-enhancing. The findings should

therefore be interpreted as evidence on conditional and disclosure-verified implementation patterns consistent with resilience-supporting DTC, rather than as a source-free measure of latent digital sophistication or as experimental proof of causality. Importantly, the direction and economic interpretation of the DTC coefficients remain stable across the baseline, IV, matched-sample, dynamic-panel, governance-interaction, mechanism, and disruption-focused specifications.

5.1. Limitations and Boundary Conditions

Several limitations should guide interpretation. First, the empirical design remains observational. Fixed effects, IV-2SLS, matching, dynamic GMM, placebo timing, and restricted-shock tests improve credibility but do not establish experimental causality. Second, the disclosure-coded variables measure verifiable reported implementation. They do not fully remove differences in disclosure length, reporting quality, ESG-reporting maturity, or national disclosure regimes. Third, the resilience outcomes capture forward sales realization and cash-flow stability. They do not measure all dimensions of resilience, such as employee continuity, environmental performance, customer welfare, or post-disruption innovation. Fourth, macro-level institutional, cultural, and infrastructure differences may still shape the observed association between DTC and operating outcomes, even though the robustness checks add country-year fixed effects and market-development splits.

5.2. Managerial Implications

The results imply differentiated managerial priorities. Firms at early stages of DTC should first build auditable data foundations: cloud integration, interoperability, data-quality routines, and basic dashboarding. Firms with intermediate DTC should focus on supply flexibility, including multisourcing, rerouting, production-transfer options, and supplier-continuity protocols. Firms with advanced DTC should strengthen internal and external governance by assigning board-level technology oversight, naming executive data-risk owners, maintaining digital audit trails, linking incentives to execution discipline, using third-party assurance, and securing external standards or continuity facilities. The marginal-effects evidence suggests that governance does not replace DTC; rather, it is associated with a stronger resilience payoff from digital implementation.

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Appendix A

This appendix reports the additional analyses referenced in the manuscript, including omitted-variable-bias diagnostics, matching diagnostics, cross-sectional heterogeneity, alternative measures, country-level moderators, the coding protocol, intercoder reliability, disclosure-intensity bias checks, construct-structure diagnostics, alternative ecosystem-governance specifications, placebo timing tests, restricted-shock designs, and mechanism-boundary checks. Tables A7–A13 are the principal measurement and identification diagnostics highlighted in the main text. References cited in this appendix are listed in the manuscript reference list.

Appendix A.1. Supplementary Analysis

The appendix applies the Oster [48] logic to the baseline DTC coefficients reported in Table 8. The identified intervals do not include zero, suggesting that the main findings are not highly sensitive to a plausible degree of omitted-variable bias.

Table A1. Oster [48] test for omitted-variable bias.

Outcome	$\tilde{\beta}$	Rmax	δ	Identified Interval
SRR (baseline)	0.071	1.30	1.88	[0.041, 0.104]
CFSI (baseline)	0.058	1.30	1.74	[0.029, 0.091]

Note: The reported Oster bounds correspond to the controlled baseline FE models in Table 6, columns (2) and (4). The identified intervals do not include zero for the main DTC coefficients.

Appendix A.2. Matching Diagnostics

The matching diagnostics summarize post-matching covariate balance between high-DTC and low-DTC observations. After matching, the treated and control groups are materially closer on the main observables.

Table A2. Balance test.

Variable	Treated (Before)	Control (Before)	Std. Bias Before (%)	Treated (After)	Control (After)	Std. Bias After (%)
SIZE	9.210	8.730	24.6	8.980	8.940	3.8
LEV	0.231	0.258	−16.1	0.243	0.247	−2.4
ROA	0.079	0.063	18.7	0.071	0.070	1.5
CAPEX	0.067	0.056	13.8	0.061	0.060	2.1
R&D	0.041	0.028	21.4	0.034	0.033	2.9
IDG	0.612	0.491	27.2	0.553	0.547	2.6
EEG	0.581	0.468	24.1	0.525	0.520	2.2

Note: High-DTC treatment is defined as firm-years above the country-industry-year median DTC level. Matching uses 1-to-1 nearest-neighbor matching without replacement, a caliper of 0.2 of the standard deviation of the logit propensity score, and common-support trimming. The post-matching diagnostics indicate substantial improvements in common support and covariate balance, with standardized differences declining materially across the baseline covariates.

Appendix A.3. Cross-Sectional Heterogeneity

Additional cross-sectional splits are reported based on digital disparity, institutional ownership, and firm size. Digital disparity is defined as the absolute gap between the standardized firm-level DTC score and the standardized country digital-readiness score within a given year; low-disparity observations are those below the annual median gap.

Table A3. Cross-sectional heterogeneity.

Subsample	SRR	CFSI	Observations
Low digital disparity	0.088 *** (0.023)	0.071 *** (0.017)	19,842
High digital disparity	0.049 ** (0.018)	0.036 * (0.017)	19,614
High institutional ownership	0.079 *** (0.019)	0.061 *** (0.016)	18,907
Low institutional ownership	0.043 * (0.021)	0.031 (0.020)	18,921
Large firms	0.083 *** (0.020)	0.067 *** (0.019)	28,445
Small firms	0.047 ** (0.017)	0.035 * (0.017)	28,961

Note: Digital disparity is the absolute within-year gap between standardized firm DTC and standardized country digital readiness. Institutional ownership and firm-size splits are based on annual sample medians. Lower disparity, stronger institutional ownership, and larger firm size are associated with a stronger resilience payoff from DTC. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Appendix A.4. Alternative Measures

The alternative-measure robustness check re-estimates the models with a risk-adjusted operating-performance proxy and PCA-based governance indices.

Table A4. Robustness check using alternative measures.

Variables	(1) RAP	(2) RAP + IDG	(3) SRR with PCA Governance	(4) CFSI with PCA Governance
DTC	0.046 *** (0.011)	0.038 ** (0.014)	0.069 *** (0.020)	0.056 *** (0.013)
DTC × IDG		0.024 ** (0.009)		
DTC × PCA governance			0.028 *** (0.006)	0.021 ** (0.008)
Controls	Yes	Yes	Yes	Yes
Observations	57,406	57,406	57,406	57,406
Adjusted R ²	0.251	0.262	0.365	0.333

Note: RAP denotes risk-adjusted operating performance. The conclusions remain stable with alternative outcomes and governance measures. *** $p < 0.01$; ** $p < 0.05$.

Appendix A.5. Country-Level Moderators

Country-level moderators are examined by interacting DTC with digital readiness, institutional quality, and geopolitical risk.

The first panel reports supportive country-level moderators that strengthen the digital capability and resilience association. The second panel reports the adverse country-level moderator and shows how geopolitical risk weakens the same association.

Table A5. Moderating role of country-level factors.

Panel A. Supportive Country Factors.				
Variables	Digital Readiness SRR	Digital Readiness CFSI	Institutional Quality SRR	Institutional Quality CFSI
DTC	0.054 *** (0.013)	0.043 *** (0.009)	0.052 *** (0.014)	0.041 *** (0.009)
DTC × readiness	0.018 ** (0.007)	0.015 * (0.007)		
Readiness	0.022 *** (0.005)	0.019 ** (0.007)		
DTC × inst. quality			0.021 ** (0.008)	0.017 * (0.008)
Institutional quality			0.024 *** (0.005)	0.020 ** (0.008)
Observations	57,406	57,406	57,406	57,406
Panel B. Adverse country factor.				
Variables	Geopolitical risk SRR	Geopolitical risk CFSI		
DTC	0.061 *** (0.014)	0.049 *** (0.011)		
DTC × geo. risk	−0.017 ** (0.006)	−0.014 * (0.007)		
Geopolitical risk	−0.026 *** (0.006)	−0.022 ** (0.008)		
Observations	57,406	57,406		

Note: Digital readiness is the annual country score constructed from z-scored broadband subscriptions, secure internet servers, and internet use. Positive interactions with digital readiness and institutional quality indicate stronger resilience gains in more supportive environments, while geopolitical risk weakens the translation of DTC into resilience. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Appendix A.6. Coding Protocol and Measurement Reproducibility

This appendix summarizes the decision architecture used to code DTC, IDG, EEG, supply flexibility, and data visibility. For each item, the coding manual separates the conceptual definition, the admissible source types, the keyword dictionary, the positive-classification rule, and the exclusion rule. The guiding principle is replicability: a coder must be able to trace every firm-year classification to a dated source passage and to the written rule that justifies the 1, 0, or missing assignment [41,42]. Because the indices are disclosure-based, the protocol is designed to recover verifiably implemented practices from auditable sources rather than to infer unreported capability.

Positive classifications require implementation evidence in the fiscal year under study. Language such as deployed, integrated, operational, monitored, subject to review, connected via API/EDI, covered by audit trail, or governed by named executive ownership qualifies when it refers to an implemented practice. Language such as plans to, intends to, explores, pilots, is evaluating, or announced a partnership does not qualify. Practices confined to an immaterial subsidiary, a non-recurring pilot, or a future roll-out are coded 0 unless the disclosure states that the firm's principal operating segment or enterprise-wide processes are already covered.

Missing disclosure is not treated as non-adoption. If none of the admissible source documents permit the coder to verify implementation status for a given item, that item is left missing, and the index is computed only when at least three component items are observable in that firm-year. English-language filings are preferred. When the relevant disclosure is available only in a local-language source, translation is used for screening, and every positive classification is verified against the source passage before adjudication. All positive classifications and an audit sample of negative classifications are independently second-coded, disagreements are resolved by reference to the written manual and saved source excerpts, and the adjudicated version is the one merged back to the panel. This design improves auditability but does not fully eliminate cross-firm differences in disclosure intensity. The institutional-monitoring-stability item within EEG is the only main-construct

item not coded from narrative disclosures; it is assigned from Refinitiv ownership history using a fixed annual rule based on the presence and stability of institutional block holders.

Worked examples follow a strict implemented-versus-aspirational rule. For DTC, a statement that a firm ‘uses cloud-based ERP across global operations’ is coded 1 for cloud integration, whereas a statement that the firm ‘plans to migrate ERP to the cloud next year’ is coded 0. For IDG, disclosure that a board committee reviewed cyber risk and enterprise data architecture during the year is coded 1 for board technology oversight, whereas a generic statement that the board recognizes digital issues without describing a review mechanism is coded 0. For EEG, an externally verified cyber-control certification or named supplier-assurance protocol is coded 1, whereas generic language about strong partner relationships without auditable assurance detail is coded 0. Table A6 summarizes the source-to-variable mapping used in the coding protocol.

Table A6. Source-to-variable coding map.

Construct/Item Block	Primary Source	Secondary Source	Code = 1 When	Code = 0 or Missing When
DTC—Automation/analytics/cloud/interoperability/data governance	Annual report, 10-K/20-F, operating review	Investor presentation; cybersecurity or sustainability report	The disclosure states that the digital operating routine is deployed, integrated, operational, or used in production during year t.	Future plans, pilots, announced partnerships, or immaterial subsidiary-specific language do not qualify; insufficient evidence is left missing.
IDG—Board technology oversight	Proxy statement or governance report	Annual report board/governance section	A board or named committee formally reviewed digital strategy, cyber risk, or enterprise data architecture during year t.	Generic board awareness without a review mechanism is coded 0; no verifiable disclosure is missing.
IDG—Executive data-risk ownership	Proxy statement; governance report	Annual report leadership/controls section	A named executive is assigned responsibility for enterprise data governance, cyber risk, or digital-control remediation during year t.	Diffuse or aspirational responsibility language is coded 0; missing evidence stays missing.
IDG—Audit trail/disruption playbook/incentive alignment	Governance report; annual report internal-control section	Cybersecurity report; remuneration report	The firm discloses traceable digital logs, a formal cross-functional continuity playbook, or explicit incentive links tied to digital-risk or continuity objectives.	Narrative statements without an implemented mechanism are coded 0; unverifiable cases are missing.
EEG—Supplier assurance/external standards/financing continuity/third-party assurance	Supplier, sustainability, cybersecurity, annual, or financing disclosures	Investor materials released in the fiscal-year reporting cycle	A named external protocol, assurance mechanism, continuity facility, or verifiable third-party standard is in force during year t.	Vague statements about strong relationships or future financing plans are coded 0; non-verifiable cases are missing.
EEG—Institutional monitoring stability	Refinitiv ownership history	Annual report investor-relations disclosure	Institutional ownership and turnover satisfy the fixed annual stability rule used in the coding manual.	Thresholds not met are coded 0; unavailable ownership history is missing.
Supply flexibility	Annual report operations/supply-chain section	Sustainability report; investor presentation	The firm discloses implemented multisourcing, rerouting/production-transfer capability, or formal supplier-continuity planning.	Aspirational flexibility language without implementation is coded 0; missing evidence stays missing.
Data visibility	Annual report operations/technology section	Cybersecurity or sustainability report; investor presentation	The firm discloses real-time dashboards, end-to-end traceability, or structured supplier/customer data integration already in use.	Generic references to better visibility without auditable implementation are coded 0; non-verifiable cases are missing.

Note: Table A6 summarizes the source hierarchy and the positive/negative decision rule used in the coding protocol. The full keyword dictionary, ambiguity rules, translated-source verification procedure, and adjudication log are maintained in the project coding manual referenced in Appendix A.6.

Appendix A.7. Coding Reliability

The coding-reliability appendix begins by reporting the double-coding statistics for each disclosure-based construct.

Table A7. Intercooder reliability and coding reproducibility.

Construct	Coding Unit	Double-Coded Observations	Krippendorff's Alpha	Percent Agreement	Adjudication Protocol
DTC	Firm-year	1248	0.84	91.6%	Rulebook + adjudication review
IDG	Firm-year	1248	0.81	89.4%	Rulebook + adjudication review
EEG	Firm-year	1248	0.78	87.2%	Rulebook + adjudication review
SFLEX	Firm-year	960	0.76	86.3%	Rulebook + adjudication review
DVIS	Firm-year	960	0.79	88.1%	Rulebook + adjudication review
Overall	Firm-year	5664	0.80	88.9%	Rulebook + adjudication review

Note: The table reports the final reliability statistics from the double-coding exercise for the disclosure-based constructs. Krippendorff's alpha is computed on the double-coded firm-year sample, percent agreement is the pre-adjudication agreement rate, and final classifications follow the written rulebook and adjudication protocol documented in Appendix A.6.

Appendix A.8. Disclosure-Intensity Diagnostics

The disclosure-intensity diagnostics then examine whether the disclosure-based measures are mechanically related to reporting volume.

Table A8. Disclosure-bias diagnostics and reporting-intensity controls.

Panel/Test	Outcome or Construct	Disclosure Proxy	Specification	Coefficient	Std. Error	p-Value
Pairwise	DTC	Report intensity	Spearman	0.24 ***	0.011	<0.001
Pairwise	IDG	Report intensity	Spearman	0.19 ***	0.010	<0.001
Pairwise	EEG	Report intensity	Spearman	0.15 ***	0.011	<0.001
Pairwise	SFLEX	Report intensity	Spearman	0.27 ***	0.012	<0.001
Pairwise	DVIS	Report intensity	Spearman	0.29 ***	0.012	<0.001
Baseline + proxy	SRR	Report intensity	FE + proxy	0.061 ***	0.013	<0.001
Baseline + proxy	CFSI	Report intensity	FE + proxy	0.048 ***	0.011	<0.001
Alt. proxy	SRR	Doc. length/count	FE + proxy	0.059 ***	0.013	<0.001
Alt. proxy	CFSI	Doc. length/count	FE + proxy	0.046 ***	0.011	<0.001

Note: Report intensity is measured from the firm-year coding file using standardized counts of admissible disclosure documents. Alternative disclosure proxies use standardized relevant text length and document count. FE + proxy specifications retain firm fixed effects, industry-year fixed effects, and the baseline control set. The interpretation of the main coefficients therefore centers on verifiable disclosed implementation rather than simple reporting volume. *** $p < 0.01$.

Appendix A.9. Construct-Structure Diagnostics

The construct-structure appendix evaluates whether the item blocks support the separation between capability, governance, and mechanism measures.

Table A9. Principal-components and factor-structure diagnostics for disclosure-based constructs.

Item/Diagnostic	Construct Block	Component 1	Component 2	Communality	Retained Factor
Automation	DTC	0.81	0.18	0.69	Yes
Analytics	DTC	0.84	0.15	0.73	Yes
Cloud integration	DTC	0.72	0.22	0.57	Yes
Systems interoperability	DTC	0.76	0.19	0.61	Yes

Table A9. *Cont.*

Item/Diagnostic	Construct Block	Component 1	Component 2	Communality	Retained Factor
Data-governance implementation	DTC	0.68	0.31	0.56	Yes
Board technology oversight	IDG	0.29	0.78	0.69	Yes
Executive data-risk ownership	IDG	0.34	0.74	0.66	Yes
Digital audit trail	IDG	0.41	0.63	0.57	Yes
Cross-functional disruption playbook	IDG	0.37	0.71	0.64	Yes
Incentive alignment	IDG	0.28	0.67	0.53	Yes
Supplier assurance intensity	EEG	0.23	0.69	0.53	Yes
Institutional monitoring stability	EEG	0.11	0.58	0.35	Yes
External data standards	EEG	0.26	0.74	0.62	Yes
Financing continuity	EEG	0.18	0.39	0.18	No
Third-party digital assurance	EEG	0.21	0.77	0.64	Yes
KMO	All blocks	0.82	—	—	—
Bartlett test <i>p</i> -value	All blocks	<0.001	—	—	—

Note: The table reports principal-components and exploratory-factor diagnostics for the item-level disclosure matrix. Reported loadings summarize the retained structure of the disclosure-based constructs, and the summary diagnostics support the use of the composite indices as organized measurement blocks rather than ad hoc item bundles.

Appendix A.10. Alternative Ecosystem-Governance Specification

The ecosystem-governance appendix checks whether the results change when the external construct is narrowed or relabeled as a broader governance-and-continuity measure.

Table A10. Alternative treatment of ecosystem governance and continuity.

Model	Outcome	Baseline EEG	Option A: EEG Without Financing Continuity	Option B: Ecosystem Governance & Continuity	Std. Error	Sample
1	SRR	0.017 **	0.012 *	0.016 **	0.007	57,406
2	CFSI	0.013 *	0.010	0.012 *	0.006	57,406
3	DTC × EEG on SRR	0.024 **	0.019 **	0.022 **	0.008	57,406
4	DTC × EEG on CFSI	0.019 *	0.015 *	0.017 *	0.008	57,406

Note: Option A removes the financing-continuity item from the external construct. Option B retains the broader item set and labels it ecosystem governance and continuity. All specifications use the same eligible firm-year sample and the same baseline controls as the corresponding main-text models. ** $p < 0.05$; * $p < 0.10$.

Appendix A.11. Temporal Placebo and Lag Structure

The temporal appendix reports placebo leads and stronger lags to clarify the timing pattern of the estimated association.

Table A11. Placebo tests and stronger lag structure.

Specification	Outcome	Key Regressor	Coefficient	Std. Error	Expected Sign	Interpretation
Placebo lead	SRR	Lead DTC ($t + 1$)	0.005	0.008	null	Near-zero placebo
Placebo lead	CFSI	Lead DTC ($t + 1$)	0.003	0.008	null	Near-zero placebo
One-year lag	SRR	Lagged DTC ($t - 1$)	0.054 ***	0.012	positive	Persistence
One-year lag	CFSI	Lagged DTC ($t - 1$)	0.041 ***	0.011	positive	Persistence
Two-year lag	SRR	Lagged DTC ($t - 2$)	0.032 **	0.011	positive	Stricter timing
Two-year lag	CFSI	Lagged DTC ($t - 2$)	0.025 **	0.010	positive	Stricter timing

Note: Placebo specifications replace the contemporaneous digital-capability measure with its lead, while lag specifications use one-year and two-year lags. Near-zero lead coefficients support temporal ordering, and the positive lag coefficients indicate persistence rather than reverse anticipation. *** $p < 0.01$; ** $p < 0.05$.

Appendix A.12. Restricted-Shock Design

The restricted-shock appendix focuses on disruption windows to connect the empirical design more closely to resilience under adverse conditions.

Table A12. Restricted shock-onset sample and partial difference-in-differences design.

Model	Sample	Treatment	Post Indicator	Interaction Coefficient	Std. Error	Sample
1	Severe-shock onset subsample	High DTC	Post shock-onset window	0.047 **	0.016	13,274
2	Severe-shock onset subsample	High IDG	Post shock-onset window	0.031 *	0.015	13,274
3	Severe-shock onset subsample	High EEG or alt. construct	Post shock-onset window	0.027 *	0.014	13,274

Note: The restricted sample retains firm-years around severe shock onset under the timing rule described in the main manuscript. Interaction terms capture post-onset differentials for high-capability or high-governance firms. These estimates are interpreted as supportive timing evidence rather than as experimental treatment effects. ** $p < 0.05$; * $p < 0.10$.

Appendix A.13. Mechanism and Measurement-Boundary Checks

The final appendix summarizes mechanism checks and reporting-boundary tests that qualify the interpretation of the disclosure-based mechanism variables.

Table A13. Mechanism evidence and measurement-boundary checks.

Mechanism or Boundary Test	Proxy/Variable	Source	Expected Sign	Coefficient	Std. Error
Supply flexibility	SFLEX index	Disclosure coding	positive	0.096 ***	0.022
Data visibility	DVIS index	Disclosure coding	positive	0.109 ***	0.025
Non-disclosure mechanism proxy	Inventory-turnover stability	Refinitiv Worldscope	positive	0.021 *	0.010
Reporting-intensity boundary	Document count	Coding file	attenuation/null	0.007	0.006

Note: Supply flexibility and data visibility are disclosure-based mechanism variables. Inventory-turnover stability is a non-disclosure proxy taken from Refinitiv Worldscope. The reporting-intensity boundary test adds document count to assess whether the mechanism evidence is explained by disclosure volume alone. *** $p < 0.01$; * $p < 0.10$.

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