



A SYSTEMATIC REVIEW ON THE IMPACT OF GLOBAL MERCHANDISING STRATEGIES ON U.S. SUPPLY CHAIN RESILIENCE

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Abstract

This study addresses a clear problem: despite abundant work on supply chain resilience, the specific ways global merchandising choices shape U.S. continuity and recovery performance remain under-specified. The purpose is to quantify those linkages and provide design-ready guidance for practice. We first conducted a systematic mapping of the field and retained 43 peer-reviewed studies to ground constructs and hypotheses, then executed a quantitative, cross-sectional, multi-case design on a sample of 198 U.S. retail and consumer-enterprise cases observed at the firm-year level. Key independent variables operationalize merchandising architecture assortment breadth and depth, standardization versus localization intensity, private-label intensity, price policy consistency, promotion cadence, and sourcing diversification while outcomes capture resilience service-level stability during disruption windows, inbound lead-time variability, time-to-recover proxies, and revenue recovery slope. The analysis plan comprises descriptive profiles, Pearson and Spearman correlations, and hierarchical OLS with heteroskedasticity-robust errors and industry fixed effects, extended with nonlinearity tests and theory-driven interactions, cross-validated for predictive stability. Headline findings show sourcing diversification as the strongest positive correlate of resilience, disciplined price architectures as a second positive lever, and heavy promotion cadence as a negative driver unless buffered by diversification; private-label intensity exhibits an inverted-U with a resilience-efficient band at moderate-to-high exposure. Implications are managerial and architectural: standardize backbone elements that create fungibility, calibrate private label to the efficiency band with dual qualification, rationalize promotion calendars as a managed volatility budget, and build structurally decoupled diversification across countries and corridors to absorb shocks and speed recovery without sacrificing commercial intent.

Keywords

Global Merchandising Strategy; Supply Chain Resilience; Private-Label Intensity; Sourcing Diversification; Price Policy Consistency;

INTRODUCTION

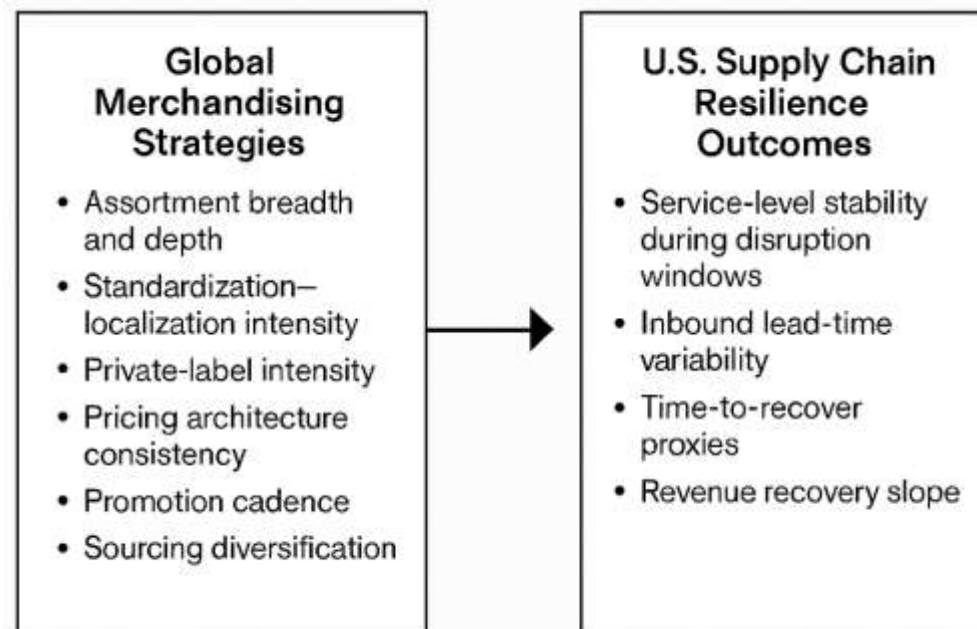
Global merchandising strategies spanning assortment breadth/depth, price architecture and promotion cadence, private-label portfolio design, and format/placement choices across channels are central to how retailers and brand owners structure demand and orchestrate supply. In international contexts, merchandising must balance standardization and local adaptation, which shapes not only top-line growth but also the volatility and load placed on logistics, sourcing, and inventory systems that underpin resilience. In this study, “supply chain resilience” denotes a supply chain’s capacity to prepare for, absorb, recover from, and adapt to disruptions while preserving performance (Ailawadi & Keller, 2004; Hohenstein et al., 2015; Huchzermeier & Breiter, 2015). Resilience has matured from conceptual framing to cumulative empirical and quantitative evidence, including systematic reviews cataloging capabilities (e.g., flexibility, redundancy, collaboration, agility) and their links to outcomes (Brandon-Jones et al., 2014; Hohenstein et al., 2015). In the U.S. context, the past decade’s shocks natural hazards, pandemics, logistics bottlenecks, and geopolitical frictions exposed how demand shaping (through merchandising) can amplify or dampen the propagation of disruptions through retail supply networks. That propagation often labeled the “ripple effect” occurs as disturbances cascade across echelons and geographies, reinforcing the salience of merchandising choices that influence demand variability, order amplification, and multi-sourcing footprints (Dolgui & Ivanov, 2021; Theodosiou & Leonidou, 2003). By situating global merchandising as an upstream design of demand signals and channel flow, we motivate a quantitative, cross-sectional, multi-case empirical investigation into its association with U.S. supply chain resilience outcomes (Christopher & Peck, 2004; Ponomarov & Holcomb, 2009).

A coherent theoretical foundation clarifies why merchandising decisions intersect resilience. Relational and network perspectives emphasize that collaborative competencies, trust, and integration enable faster detection and coordinated response, thereby improving resilience and customer value (Wieland & Wallenburg, 2013). Systems and network design research shows that supplier base structure, global footprint choices, and modular product/assortment architectures affect vulnerability exposure and options for adaptation (Klibi et al., 2010). Quantitative reviews and analytic models further formalize capacities such as preparedness, agility, and structural flexibility, illuminating how they buffer performance under stochastic shocks (Hosseini et al., 2019). In marketing and international business, the standardization–adaptation literature provides a lens on how global merchandising alignment or localization influences complexity, scale economies, and forecastability (Theodosiou & Leonidou, 2003; Tukamuhabwa et al., 2015). Integrating these streams suggests that assortment, pricing/promotion routines, private-label strategy, and channel configuration create distinct risk exposures and buffers: broader assortments and frequent promotions may elevate demand volatility and planning noise; modularization and coordinated price architecture can stabilize flows; private-label integration can reallocate bargaining power and sourcing flexibility; and omnichannel placement influences inventory pooling and recovery paths. These theoretically grounded linkages motivate measurable hypotheses tying merchandising strategy profiles to empirically observable resilience indicators in U.S. retail supply chains. (Ivanov et al., 2019; Zou & Cavusgil, 2002).

Definitions and scope for the present investigation draw on established reviews and empirical studies. Resilience is distinguished from risk management by its emphasis on capability portfolios that reduce impact and accelerate recovery across pre-disruption, absorption, and restoration stages (Hohenstein et al., 2015; Pettit et al., 2010). Foundational disruption research links network design characteristics density, complexity, node criticality to disruption severity and the effectiveness of mitigation levers, offering measurable constructs suitable for cross-sectional analysis (Craighead et al., 2007). Quantitative reviews catalog operations-research methods (stochastic programming, simulation, control theory) applied to resilience analysis, providing guidance on model specifications for assessing associations with merchandising features (Ambulkar et al., 2015; Broniarczyk et al., 1998). Recent pandemic-era work on ripple effect modeling formalizes disruption propagation and recovery trajectories, which can be connected empirically to demand-shaping tactics and sourcing configurations typical in merchandising practice (Dolgui & Ivanov, 2021). Within retailing, conceptualizations of retail branding and private labels, assortment perceptions, and product variety/modularity ground how merchandising choices impact demand predictability and operational workload (Ailawadi & Keller,

2004; Blackhurst et al., 2011). These lines of inquiry converge on an operationalizable definition of “U.S. supply chain resilience” that includes time-to-recover/serve, fill-rate stability under shock, and order-to-shelf continuity, outcomes that our study relates to global merchandising configurations via descriptive statistics, correlations, and regression models. (Ponomarov & Holcomb, 2009; Salvador et al., 2002).

Figure 1: Global Merchandising Strategies and U.S. Supply Chain Resilience Outcomes



International merchandising strategy decisions shape resilience through standardization, coordination, and integration mechanisms. Standardization of price lines, pack sizes, and planograms across markets can strengthen scale economies, but may increase exposure if synchronized cycles amplify shocks, whereas selective adaptation can temper volatility at the cost of complexity (Jin et al., 2015; Ashiqur et al., 2025; Ralston & Blackhurst, 2020). Private-label programs integrate design, sourcing, and brand ownership, potentially enabling dual-sourcing, postponement, and faster supplier switching under disruption, simultaneously altering power and information asymmetries (Ailawadi & Keller, 2004; Hasan, 2025). Assortment breadth and depth influence demand dispersion and substitution, with broader ranges potentially creating planning noise unless buffered by modular architectures and postponement (Broniarczyk et al., 1998; Ismail et al., 2025). Pricing and promotion calendars shape order variability and forecast error; research on high-low pricing and promotion contracting demonstrates that decision rights and contract forms influence inventory paths and upstream stability (Huchzermeier & Breiter, 2015; Ivanov & Dolgui, 2021). From a network-design vantage, merchandising choices that expand category variety or proliferate SKUs can be offset by robust network configurations and multipurpose capacity (Klibi et al., 2010; Jakaria et al., 2025; Salvador et al., 2002). These conceptual ties inform our empirical specification by mapping measurable merchandising indicators assortment scope, private-label share, promotion frequency, price architecture, and standardization intensity onto resilience outcomes in U.S. retail supply chains. (Salvador et al., 2002; Theodosiou & Leonidou, 2003; Tukamuhabwa et al., 2015).

At the same time, the resilience literature identifies relational, structural, and digital capabilities that plausibly interact with merchandising. Collaboration and integration facilitate synchronized replenishment and transparent capacity reallocation during disturbances (Hasan, 2025; Wieland & Wallenburg, 2013). Capability frameworks operationalize preparedness, flexibility, and agility as complementary levers that are measurable and linked to performance (Sultan et al., 2025; Wieland & Wallenburg, 2013). Digitalization and Industry 4.0 enhance sensing and response, expanding feasible policy sets for demand and inventory control in the presence of merchandising-induced volatility

(MZafor, 2025; Ralston & Blackhurst, 2020), while quantitative reviews synthesize modeling approaches to evaluate such interactions (Uddin, 2025; Ralston & Blackhurst, 2020). Pandemic-era scholarship further codifies ripple-mitigation logics, including reconfiguration and coordinated adaptation, which are relevant when promotional surges or range resets coincide with upstream shocks (Dolgui & Ivanov, 2021; Sanjai et al., 2025). This empirical setting treats these capabilities as controls and moderators, allowing tests of whether specific global merchandising profiles are associated with stronger resilience conditional on collaboration intensity, digital enablement, and network design. (Craighead et al., 2007; Dolgui & Ivanov, 2021; Wieland & Wallenburg, 2013).

The U.S. supply base is globally entangled; hence, “global merchandising” encompasses both cross-border market strategies and sourcing/assortment decisions whose effects are realized domestically. Prior empirical work shows that network complexity and design choices condition disruption severity, suggesting that merchandising choices which increase variety or synchronize promotions may interact with structural properties to intensify or attenuate risk (Craighead et al., 2007; Hasan, 2024). Assortment modularization and postponement can decouple late-stage differentiation to stabilize upstream flows amid category expansions (Rahaman, 2024; Salvador et al., 2002). High-low pricing regimes and promotion contracts reallocate decision rights and cost shares, with implications for inventory exposure and recovery windows along the chain (Huchzermeier & Breiter, 2015; Hasan et al., 2024). Reviews of quantitative methods provide templates for measuring resilience outcomes relevant to retailers (fill rate stability, time-to-recover, backlog clearance) and for estimating associations via regression modeling (Hosseini et al., 2019). This study design leverages multi-case U.S. retail data to quantify these cross-sectional relationships, laying empirical groundwork for actionable insights on how merchandising strategy architecture relates to resilience performance (Craighead et al., 2007; Hosseini et al., 2019; Klibi et al., 2010). Furthermore, contemporary scholarship underscores that resilience is not a single lever but an orchestrated portfolio, where merchandising plays a significant role by shaping the statistical structure of demand and the degrees of freedom available for supply recovery. Systematic reviews chart the rise and operationalization of resilience concepts (Hohenstein et al., 2015), while the ripple-effect literature models shock propagation under alternative control policies and network configurations (Dolgui & Ivanov, 2021). Retail branding and private-label strategy frame how ownership and design control may enable diversified sourcing and postponement, complementing collaboration and digital sensing to support continuity (Ailawadi & Keller, 2004; Christopher & Peck, 2004; Dolgui & Ivanov, 2021). Building on these insights, the present quantitative, cross-sectional, multi-case study specifies measurable merchandising strategy variables and resilience outcomes for U.S. supply chains and applies descriptive statistics, correlation analysis, and regression modeling to test theoretically derived hypotheses about their interrelations. (Ailawadi & Keller, 2004; Christopher & Peck, 2004; Dolgui & Ivanov, 2021).

The objective of this study is to rigorously quantify how global merchandising strategies relate to U.S. supply chain resilience outcomes using a cross-sectional, multi-case, firm-level design. Specifically, the study aims to: (1) operationalize a set of merchandising strategy variables assortment breadth and depth, standardization-localization intensity, private-label intensity, pricing architecture consistency, promotion cadence, and sourcing diversification into reliable, comparable firm-level measures; (2) construct and validate resilience outcome indicators service-level stability during disruption windows, inbound lead-time variability, time-to-recover proxies, and revenue recovery slope aligned to publicly observable data; (3) describe the empirical distribution of merchandising and resilience variables across a diverse sample of U.S. retailers and consumer-facing firms to establish baseline patterns; (4) estimate the bivariate associations between merchandising variables and resilience outcomes to reveal initial directional relationships; and (5) test multivariable regression models, including nonlinear and moderation terms, to identify which merchandising configurations are independently associated with stronger resilience after controlling for firm size, inventory turnover, digital maturity, market share, and industry fixed effects. Within this framework, the study further seeks to determine whether private-label intensity exhibits a curvilinear relationship with resilience, whether greater assortment breadth corresponds to elevated operational variability, and whether sourcing diversification amplifies or conditions the effects of merchandising choices on recovery and continuity metrics. The analysis

plan encompasses data cleaning, normalization, and outlier management; reliability checks for coder-generated variables; diagnostic testing for multicollinearity and heteroskedasticity; and robustness assessments via alternative specifications, subgroup splits, and median regression. The study's scope is confined to publicly verifiable disclosures and standardized third-party datasets to ensure replicability, with a sampling strategy designed to balance sectoral breadth and data completeness. By articulating these objectives ex-ante and aligning them with measurable constructs, the study provides a transparent empirical path from strategic merchandising design to observed resilience performance in U.S. supply chains, enabling precise evaluation of the proposed relationships through descriptive statistics, correlation analysis, and regression modeling.

LITERATURE REVIEW

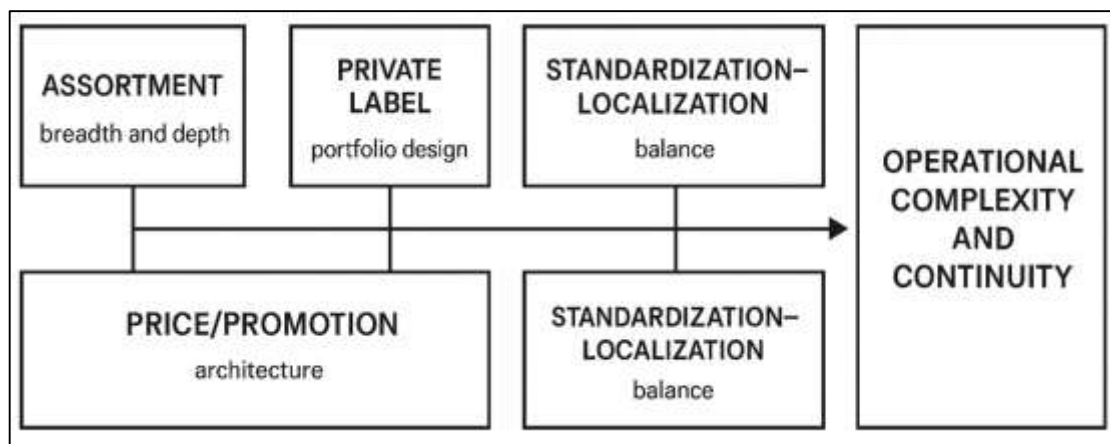
The literature on supply chain resilience has matured from conceptual framing to empirically grounded models, yet the merchandising-resilience nexus remains comparatively under-specified, especially in U.S. retail and consumer markets where globalized sourcing and omnichannel demand intensify volatility. This review positions “global merchandising strategies” as an integrated policy set spanning assortment architecture (breadth, depth, and modularity), brand portfolio choices with emphasis on private-label intensity, pricing architecture and promotion cadence, and the standardization-localization balance across international markets. Complementing this demand-side lens, resilience is scoped as the capability to absorb, recover, and adapt while maintaining service continuity, captured through outcomes such as service-level stability under shock, inbound lead-time variability, time-to-recover (or revenue recovery) proxies, and backlog clearance dynamics. Three theoretical perspectives structure the synthesis. First, a resource-based and capability view links merchandising design to reconfigurable options e.g., postponement with modular assortments, dual-sourced private labels, and disciplined price ladders that stabilize forecasts thereby shaping adaptive capacity. Second, contingency and fit logic suggests the effectiveness of merchandising profiles depends on environmental turbulence and supply optionality, implying nonlinearity (e.g., an optimal band for private-label intensity) and cross-term effects (e.g., diversification \times private label). Third, network and ripple-effect research emphasizes how structural properties (supplier and country concentration, echelon coupling, capacity buffers) mediate how merchandising-induced demand signals propagate or dampen disruption cascades. Empirical studies across retailing, operations, and international marketing offer construct scaffolds assortment variety and choice perceptions, private-label governance and bargaining power, price dispersion and promotion frequency indices, and supplier concentration measures (e.g., Herfindahl-Hirschman Index) that can translate into comparable firm-level variables for cross-sectional analysis. However, gaps persist: prior work often examines demand outcomes without tracing operational continuity; resilience studies frequently abstract away merchandising policies; and mixed operational definitions hinder comparability. This review therefore consolidates measurement choices and analytical designs suitable for a multi-case, quantitative approach, highlights plausible boundary conditions (industry, digital maturity, scale), and distills testable linkages among merchandising variables, sourcing diversification, and resilience outcomes. In doing so, it provides a coherent evidence base for the study's hypotheses and model specifications, clarifying how global merchandising decisions may systematically influence the stability and recoverability of U.S. supply chains.

Merchandising Strategy Foundations

Merchandising strategy constitutes the architecture through which retailers and brand owners shape choice, signal value, and coordinate flows from suppliers to shelves; its foundational levers assortment breadth and depth, private-label portfolio design, pricing architecture and promotion cadence, and the degree of standardization versus localization across markets have measurable implications for operational complexity and continuity. At the product-portfolio core, research on SKU variety and rationalization shows that assortment expansion inevitably interacts with inventory, handling, and information loads; when variety outpaces organizational capacity or cross-functional alignment, firms accumulate “complexity costs” that degrade fill rates, extend cycle times, and expose fragilities during shocks. A cross-functional, cross-firm case analysis demonstrates that systematic SKU rationalization (with shared criteria and buyer-supplier coordination) can improve financial performance and reduce operational strain, clarifying how assortment design is not merely a marketing choice but a network-

wide operating policy (Enz et al., 2019). Complementarily, evidence on structural complexity at the upstream (supplier and component) level indicates that the configuration of the supplier base and material variety predicts the frequency of disruptions: as the dimensionality and coupling of inputs increase, so does the incidence of supply interruptions, which complicates service continuity and recovery windows when demand is steered by broad or frequently changing assortments (Bode & Wagner, 2015). Taken together, these findings position assortment scope and evolution expansion, pruning, and modular design as first-order determinants of the stability and recoverability of retail supply systems, especially when assortments are deployed internationally and synchronized with pricing and promotional policies that amplify or attenuate demand variability (Bode & Wagner, 2015; Enz et al., 2019).

Figure 2: Foundational Merchandising Levers on Operational Complexity and Continuity



A second pillar concerns retailer brand (private-label) strategy, which reconfigures governance, bargaining power, and design control along the chain, thereby altering sourcing options, postponement feasibility, and cost-to-serve. A recent semi-systematic review of private-label management synthesizing hundreds of studies shows that contemporary private labels extend beyond low-price generics toward tiered architectures and category-role alignment, with implications for manufacturer-retailer contracts, dual-sourcing, and resilience of supply (Akter et al., 2023; Wu et al., 2021). By internalizing brand ownership and specifications, private-label programs can enable specification standardization across global markets where feasible and targeted adaptation where needed, which interacts with assortment modularity and inventory pooling to shape upstream capacity commitments and switching costs. In parallel, international promotion and pricing policies must balance scale efficiencies with the volatility introduced by localized offers; new evidence from entrepreneurial and internationally active firms indicates that neither blanket standardization nor blanket adaptation of promotion is universally superior, and that performance hinges on aligning promotion strategy to contextual factors market heterogeneity, resource constraints, and learning benefits consistent with contingency logic (Hultman & Oghazi, 2024; Tamanna & Ray, 2023). For merchandising foundations, this suggests that promotion cadence, depth, and cross-market synchronization should be treated as structural design variables: too much cross-country synchronization can create correlated demand spikes that strain shared suppliers, while undisciplined local variation can erode forecastability and inventory pooling gains. Private-label governance and promotion strategy thus jointly shape the feasible frontier of resilience by defining the degrees of freedom for sourcing diversification, postponement, and demand smoothing (Razzak et al., 2024; Hultman & Oghazi, 2024).

The final foundational lever is the statistical structure of demand induced by merchandising especially promotion-driven volatility and its translation into upstream load. High-low pricing, promotional bundles, and calendar-based events are quintessential merchandising tools, yet they alter time-series properties in ways that challenge forecasting, replenishment, and capacity planning. Empirical evidence from hundreds of real demand series shows that promotions systematically elevate volatility

across the entire series rather than only in the immediate promotional window; this volatility degrades forecast accuracy and propagates costs and instability upstream, intensifying the risk of stockouts or excess inventory when supply is capacity-constrained or globally dispersed (Abolghasemi et al., 2020; Danish & Zafor, 2024). When juxtaposed with structural-complexity results, the implication for merchandising foundations is clear: the same promotional designs and price architectures must be evaluated not only for revenue lift but also for their “volatility footprint,” particularly when assortments are wide, private labels are specification-intensive, and international rollouts synchronize events across time zones and logistics corridors (Abolghasemi et al., 2020; Ray et al., 2024). A foundation for this study, therefore, is to treat assortment scope, private-label intensity, promotion architecture, and standardization–localization choices as integrated, quantifiable policy sets whose interactions determine how demand signals align with or work against sourcing diversification and operational buffers. By foregrounding these levers and their measurable effects on complexity and volatility, we establish the conceptual basis for modeling how global merchandising strategies co-determine resilience outcomes in U.S. retail supply chains (Abolghasemi et al., 2020; Istiaque et al., 2024).

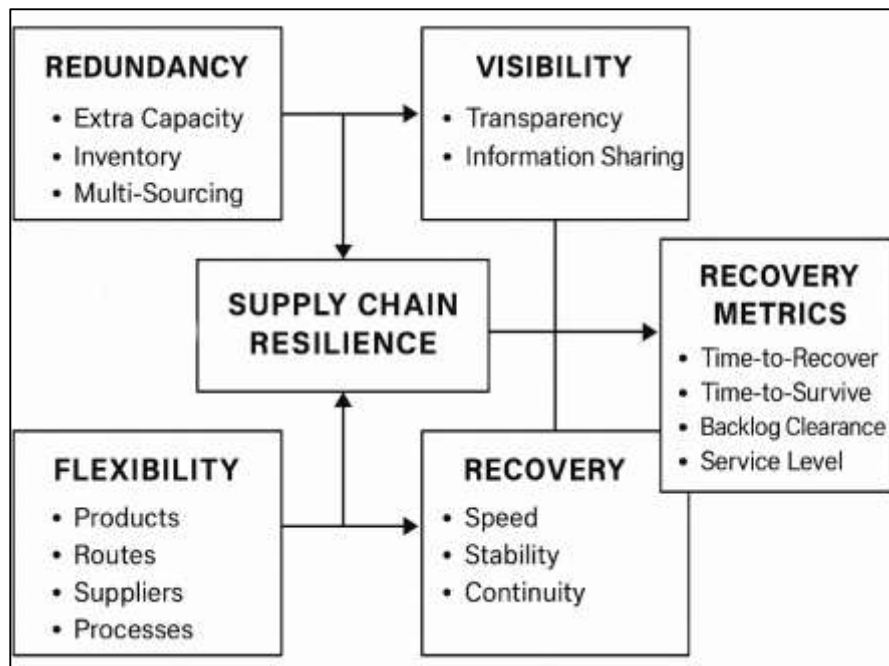
Supply Chain Resilience

Supply chain resilience (SCR) is best understood as a multi-dimensional capability that enables networks to absorb shocks, adapt structures, and restore performance in acceptable timeframes, and its conceptual backbone can be organized around four interlocking pillars: redundancy, flexibility, visibility, and recovery. Redundancy captures prepositioned buffers extra capacity, inventory, or multi-sourcing that limit performance deterioration when a node or link fails; flexibility reflects the ability to switch products, routes, suppliers, or processes quickly without prohibitive penalties; visibility concerns the transparency and timeliness of information across tiers that allow earlier detection and coordinated reallocation; and recovery encompasses the speed, stability, and continuity with which service and flows are restored. Prior syntheses emphasize that resilience is not a single lever but a portfolio of design choices and dynamic capabilities that operate before, during, and after disruption, and that these capabilities can be categorized, measured, and linked to performance through clear constructs and indicators (Danish & Zafor, 2022; Kamalahmadi & Parast, 2016). Building on dynamic capability logic, resilience can be operationalized as the capacity to sense, seize, and reconfigure under disruption meaning that the network not only contains the immediate impact but also adapts resource combinations and governance to new conditions (Chowdhury & Quaddus, 2017; Danish & Kamrul, 2022). Robust policy design complements capability building: robust strategies perform reasonably well across a wide array of contingencies (e.g., dual sourcing, postponement, modularization, and tailored inventory positioning) and therefore reduce the sensitivity of outcomes to forecast error and parameter shifts (Jahid, 2022; Tang, 2006). At a systems level, viability defined as the ability to persist through redesign and adaptive control adds a long-horizon perspective that integrates resilience with agility and sustainability, highlighting structural transitions (e.g., supplier reallocation, decoupling points) as a core element of SCR (Ivanov, 2020; Arifur & Noor, 2022). Finally, exogenous shock typologies such as epidemics foreground correlated disruptions and cascading constraints, underscoring the need to model resilience beyond single-node failures toward networked, time-dependent responses (Hasan & Uddin, 2022; Queiroz et al., 2020).

Translating these concepts into measurable variables requires aligning constructs to observable policies and outcomes. Redundancy is commonly proxied by multi-sourcing indices and capacity headroom; flexibility by changeover times, postponement penetration, or option sets for routing and supplier switching; visibility by data latency, forecast integration, and tier-n transparency; and recovery by time-to-recover (TTR), time-to-survive (TTS), backlog clearance rates, service-level stability under shock, and lead-time variability. Conceptual reviews argue for structured mapping from antecedents to consequences resilience drivers (e.g., buffers, collaboration, digital sensing), disruption characteristics (frequency, severity, correlation), and performance outcomes (service, cost, continuity) so that empirical models can estimate direct and conditional effects (Kamalahmadi & Parast, 2016; Rahaman, 2022). A validated measurement instrument developed under dynamic capability theory further specifies SCR as a higher-order construct with reflective dimensions (e.g., readiness, response, recovery, growth), enabling reliable scale development and construct validity in quantitative studies (Chowdhury & Quaddus, 2017; Rahaman, 2022b). Robust strategy research provides the policy toolkit

that links these constructs to designable levers: delayed differentiation and modular product architectures enhance flexibility; reserved capacity and dual suppliers create redundancy; coordinated contracts and disciplined price–promotion calendars reduce demand volatility that undermines recovery (Rahaman & Ashraf, 2022; Tang, 2006). Viability theory guides how these elements should be configured over time, emphasizing adaptive mechanisms for shifting from one structural design to another as disruption regimes change (Ivanov, 2020). In epidemic contexts, where constraints are systemic and multilayered, resilience metrics must capture ripple effects (e.g., upstream lead-time shocks manifesting as downstream stockouts) and the benefits of synchronized sensing and reallocation across tiers; a structured literature mapping highlights how network topology and correlation patterns condition both the magnitude of disruption and the efficacy of redundancy–flexibility portfolios (Islam, 2022; Queiroz et al., 2020).

Figure 3: Pillars of Supply Chain Resilience

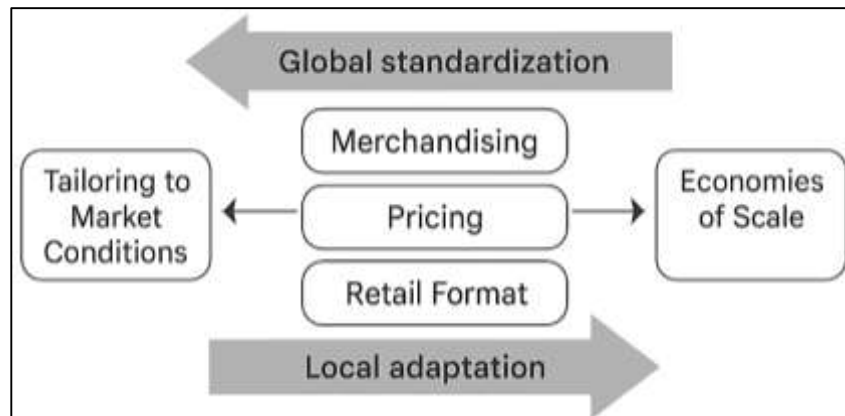


For empirical work focused on U.S. markets, these conceptualizations imply several testable linkages. First, redundancy and flexibility should not be treated as substitutes but as complements whose marginal effects depend on disruption correlation and network coupling; portfolios that combine selective multi-sourcing with postponement and modularity are expected to reduce TTR and stabilize service during shocks (Hasan et al., 2022; Tang, 2006). Second, visibility is an amplifier: faster, deeper information flows expand the feasible set of flexible reallocations and enable earlier activation of redundant options, so visibility is expected to moderate the effects of redundancy and flexibility on recovery metrics (Chowdhury & Quaddus, 2017; Redwanul & Zafor, 2022). Third, viability introduces a temporal design dimension: resilient firms are those that can reconfigure structure suppliers, flows, decoupling points quickly and cost-effectively as the environment evolves, suggesting interactions between baseline capabilities and the speed of structural transitions (Ivanov, 2020). Fourth, under correlated shocks like epidemics, localized buffers may be insufficient; models and reviews indicate that network-level diversification and coordinated demand shaping are critical to dampen ripple effects, which implies that resilience outcomes depend on how redundancy and flexibility are distributed across echelons and geographies (Rezaul & Mesbaul, 2022; Queiroz et al., 2020). Finally, literature urges careful operationalization and validation: construct clarity, multi-indicator measurement, and robustness analyses (e.g., alternative indices for redundancy, multiple lead-time dispersion metrics for recovery) are prerequisites for credible inference in cross-sectional designs (Hasan, 2022; Queiroz et al., 2020). Collectively, these insights provide the theoretical scaffolding and measurement logic for modeling resilience outcomes as functions of designable portfolios, setting the

stage for regression tests that estimate main, nonlinear, and moderating effects consistent with robust strategy and viability perspectives (Tarek, 2022; Tang, 2006).

Global Standardization vs. Local Adaptation in Retailing

Figure 4: Global Standardization vs. Local Adaptation in Retailing



A central question in international retailing is how far merchandising, pricing, and format policies should be standardized across countries versus adapted to local market conditions. In retail settings, this trade-off operates at multiple layers SKU architecture (pack sizes, flavors, quality tiers), private-label positioning, price ladders and promotions, visual merchandising, and omnichannel touchpoints and each layer interacts with upstream sourcing and logistics choices. A widely cited stream in international marketing shows that performance depends on *fit* rather than on either extreme: firms tend to do better when the degree of standardization matches task environment characteristics such as competitive intensity, customer similarity across markets, and the firm’s resource profile (Katsikeas et al., 2006; Kamrul & Omar, 2022). Complementing the fit perspective, research on pricing and communication policies indicates that adaptation is more likely (and more beneficial) when environmental heterogeneity, regulatory constraints, and cultural distance raise the opportunity cost of uniform policies; conversely, scale economies, brand consistency goals, and centralized capabilities favor standardization (Kamrul & Md. Tarek, 2022; Sousa & Bradley, 2009). For retailers, these strategic choices travel through supply networks: standardized planograms and price architectures can dampen complexity and enable pooling, but they may also synchronize demand spikes and create correlated risk exposures; localized assortments may capture demand and reduce mismatch costs, yet they can proliferate variants, elongate lead times, and complicate procurement. Thus, the standardization–adaptation decision should be conceived as a system design problem selecting bundles of merchandising and channel policies that achieve cross-market coherence while preserving optionality in procurement and fulfillment (Katsikeas et al., 2006; Mubashir & Abdul, 2022).

International retail format transfer provides additional evidence on how the balance between global templates and local tweaks shapes both market outcomes and operational feasibility. When retailers transplant formats (e.g., hypermarkets, hard discount, specialty chains), success frequently hinges on *selective* adaptation of category roles, space allocation, and service processes to local competitive structures and consumer routines, while maintaining standardized backbone elements that support replication and cost efficiency (Muhammad & Kamrul, 2022; Swoboda et al., 2013). Format transfer studies highlight that rigid standardization may undercut store-level responsiveness to local basket composition, but unconstrained localization erodes scale economies and undermines cross-border learning. Critically, these merchandising and format choices reconfigure the data the firm generates in each market, which then affects forecastability and the ability to orchestrate replenishment and inventory buffers. Entry and roll-out analyses in international retailing also show that front-end choices ripple to the back-end: category breadth/depth, private-label emphasis, and price positioning influence supplier selection, contract terms, and required logistics capabilities, which in turn determine the

feasibility of multi-sourcing and the stability of service during disruptions (Gielens & Dekimpe, 2001; Reduanul & Shoeb, 2022). The implication is that the standardization–adaptation balance is inseparable from resilience planning: choosing which elements to standardize (e.g., specifications that enable dual sourcing) and which to localize (e.g., flavor variants or pack sizes that matter for demand capture) can either enhance the set of feasible reconfiguration moves under shock or constrain them (Kumar & Zobayer, 2022; Swoboda et al., 2013).

The rise of omnichannel retailing further reframes the standardization–adaptation calculus by adding digital-physical integration and data-driven personalization. Omnichannel models reward a *platform-like* standardization of core processes assortment data schemas, inventory visibility, click-and-collect service standards because such common rails lower coordination costs and permit rapid scaling of innovations; at the same time, retailers benefit from *localized* front-end experiences and micro-merchandising tailored to neighborhood demographics, device usage, and delivery infrastructure (Grewal et al., 2017; Sadia & Shaiful, 2022). This duality has consequences for supply continuity: standardized data models and service promises simplify safety-stock policies and enable transshipment and pooling across nodes, while localized demand shaping can smooth or concentrate load depending on how promotions and events are scheduled across markets. From a governance standpoint, greater standardization of private-label specifications across regions widens the feasible supplier set and eases substitution, but excessive proliferation of local variants limits cross-market fungibility and raises obsolescence risk (Noor & Momena, 2022). Pricing is similar: harmonized price architectures improve comparability and reduce forecast error, but promotional calendars that are naively synchronized across countries can impose correlated peaks on shared suppliers. Taken together, the literature points to an integrative blueprint: standardize backbone elements that create economies, data coherence, and supplier interchangeability, while locally adapting the subset of merchandising and service elements that demonstrably raise customer value in a given market and continuously recalibrate that mix as technology, competition, and logistics capacity evolve (Grewal et al., 2017; Istiaque et al., 2023; Katsikeas et al., 2006).

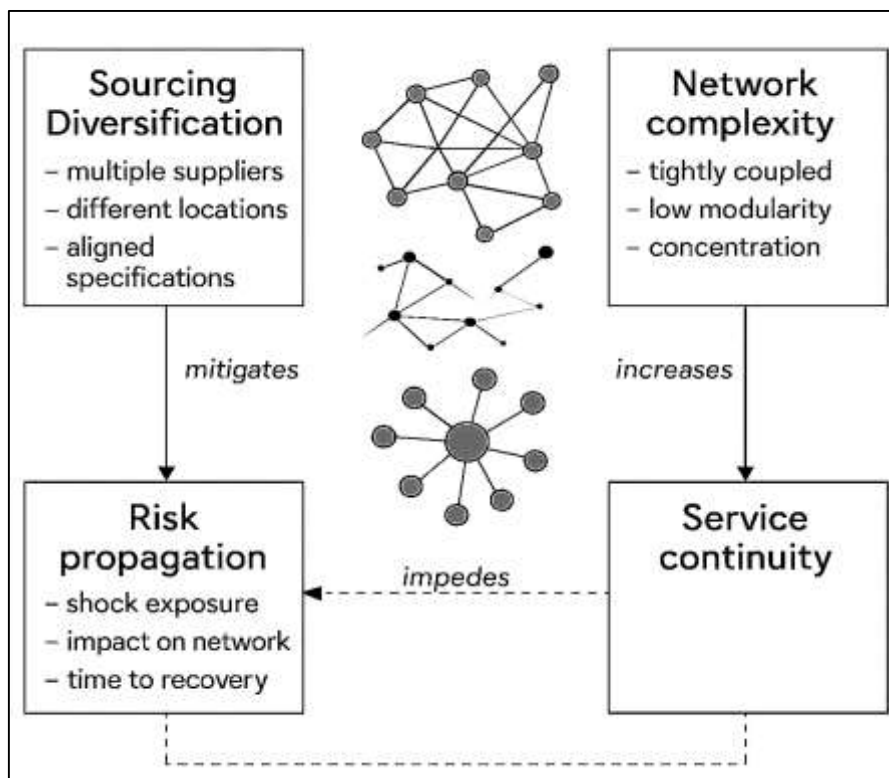
Sourcing Diversification and Risk Propagation

Sourcing diversification reduces dependence on any single upstream node, expanding the set of feasible responses when shocks occur; however, its performance value depends on how diversification interacts with cost, capacity, and switching frictions embedded in the network. Analytical work on disruption management distinguishes mitigation investments made *ex ante* (e.g., qualifying a second supplier) from contingency actions taken *ex post* (e.g., expediting or switching to backup sources), showing that optimal portfolios hinge on disruption frequency, backup cost premiums, and capacity limits (Hasan et al., 2023; Tomlin, 2006). Extending this logic, flexibility in supply via dual sourcing, volume and mix agility, and postponement can attenuate the performance impact of both routine variability and rare shocks, especially when supply and demand uncertainties co-occur; yet the same flexibility can be costly to maintain and must be targeted to the uncertainty modes that matter most (Hossain et al., 2023; Tang & Tomlin, 2008). In practice, “diversification” is not just a count of suppliers or countries; it is an option set with varying reliabilities, lead-time distributions, and correlated exposures that determine whether capacity can be reallocated fast enough to keep service levels from collapsing. These insights imply that merchandising-induced volatility (e.g., from promotions or SKU proliferation) should be aligned with calibrated diversification: just enough alternate capacity and specification-commonality to make switching feasible without inflating unit costs and coordination burden. For U.S.-focused firms buying globally, that calibration often means pairing tier-1 multi-sourcing with harmonized specifications that widen the pool of tier-2/tier-3 candidates, so that contingency switching propagates through the bill of materials rather than stalling at lower tiers (Rahaman & Ashraf, 2023; Tang & Tomlin, 2008; Tomlin, 2006).

Diversification benefits are mediated sometimes amplified, sometimes dampened by network structure. A supply base configured as a scale-free or hub-centric graph can be efficient but fragile to targeted hub failures, while more nested or modular patterns may slow disruption cascades at the expense of redundancy costs. A network-structural perspective demonstrates that resilience is partly a function of topology: power-law relations and certain archetypes (e.g., clustered hubs with buffered peripheries) can raise the odds that localized failures do not escalate into network-level breakdowns,

whereas poorly buffered, tightly coupled structures propagate shocks faster (Kim et al., 2015; Sultan et al., 2023). Complementary evidence on nested patterns shows that the way sub-networks embed within larger networks conditions the “ripple effect,” i.e., how perturbations traverse tiers forward and backward; nestedness can either compartmentalize shocks or, when misaligned, create hidden bridges that accelerate propagation (Chauhan et al., 2021; Hossen et al., 2023). For merchandising and sourcing design, the takeaway is architectural: SKU commonality, component modularity, and specification standardization across sources alter the graph by creating multiple feasible paths for fulfillment, but excessive variety or idiosyncratic localization inserts brittle links that concentrate flow through few nodes. In short, diversification works through topology. Its effectiveness rises when alternate suppliers are not only numerous but structurally decoupled (different regions, different infrastructures) and when product architectures allow late-stage substitution without requalification, so that the network can reroute volume with minimal friction (Chauhan et al., 2021; Kim et al., 2015; Tawfiqul, 2023).

Figure 5: Sourcing Diversification and Risk Propagation in Supply Chain Resilience



Risk propagation measurement has advanced from qualitative scoring to quantitative stress-testing that explicitly models disruption duration and path dependencies. A practical breakthrough is the risk exposure index approach that pairs *time-to-recover* (TTR) inputs with network mapping to identify the nodes whose failure would inflict the greatest performance loss, enabling firms to prioritize mitigation and contingency investments where they matter most; field results in a large automotive network illustrate how this method surfaces hidden fragilities and guides ex ante buffering and ex post reallocation playbooks (Uddin & Ashraf, 2023; Simchi-Levi et al., 2015). Building on this, ripple-effect quantification frameworks integrate multi-echelon inventories, supplier importance weights, and disruption durations to simulate how shocks traverse networks and to compare portfolios of sourcing and buffering policies; these models help translate diversification and flexibility decisions into expected service continuity and backlog metrics under realistic cascade dynamics (Kinra et al., 2020; Momena & Hasan, 2023). Together, these advances provide operationalizable metrics e.g., TTR, time-to-survive, exposure indices that tie sourcing structure and merchandising-related demand patterns to recovery outcomes, allowing cross-sectional comparisons across firms. For the present study, they justify measuring sourcing diversification not just by counts, but by concentration indices and structural

separation, and connecting those to resilience outcomes through regression while controlling for assortment scope and promotion intensity ([Sanjai et al., 2023](#); [Simchi-Levi et al., 2015](#)).

METHODS

This study adopts a quantitative, cross-sectional, multi-case design to empirically examine how global merchandising strategies relate to U.S. supply chain resilience. Each firm constitutes a “case,” and the unit of analysis is the firm-year aligned to the latest complete fiscal period with adequate disclosures. The sampling frame targets U.S. market-active retailers and consumer-facing firms (including e-commerce and vertically integrated brand owners) for which standardized, public data on merchandising policies and resilience-relevant operations are available. Inclusion requires evidence on at least one merchandising lever (e.g., assortment scope, private-label intensity, price/promotion architecture, standardization-localization indicators) and at least one resilience outcome (e.g., service-level stability during disruption windows, inbound lead-time variability, time-to-recover proxies, or revenue recovery slope). We compile data from firm filings (annual reports, Form 10-K/10-Q), sustainability and logistics reports, third-party pricing/promotion trackers, and trade/customs datasets to characterize sourcing diversification at the country and supplier levels. A structured codebook governs variable construction: assortment breadth is proxied by $\log(\# \text{ active SKUs or categories})$; private-label intensity by share of sales/SKUs; price policy consistency by cross-market price dispersion; promotion cadence by average promotional frequency and depth; standardization-localization by the share of locally tailored SKUs; and sourcing diversification by one minus the Herfindahl-Hirschman Index across critical supplier countries. Resilience outcomes include fill-rate stability under identified disruption windows, the coefficient of variation of inbound lead times, a time-to-recover proxy derived from operational disclosures, and a revenue recovery slope computed as post-shock growth relative to pre-shock baselines. Control variables encompass firm size (log sales), inventory turnover, market share, logistics capacity proxies, digital maturity (composite index), and NAICS industry fixed effects. After data cleaning and harmonization, we apply winsorization (1st–99th percentile) and log/standardization transforms where appropriate, conduct inter-rater reliability checks for coder-derived measures, and address missingness through listwise deletion with sensitivity analyses using multiple imputation. The analysis proceeds in three stages: (1) descriptive statistics by industry segment; (2) bivariate correlations (Pearson/Spearman) to examine initial associations; and (3) multivariable regressions with robust (HC3) standard errors, including nonlinearity (e.g., private-label intensity squared) and moderation terms (e.g., private-label \times sourcing diversification). Model diagnostics include multicollinearity (VIF), heteroskedasticity tests, residual normality (Q-Q), and influence checks (Cook’s distance). Robustness is assessed via alternative operationalizations, subgroup splits (e.g., food vs. hardlines; high vs. low digital maturity), and median regression. All analyses will be executed in R or Python, with reproducible scripts and pre-registered coding rules to support transparency and replicability.

Design: Quantitative, Cross-Sectional, Multi-Case Study

This study employs a quantitative, cross-sectional, multi-case design in which each firm functions as a comparable “case,” enabling variation across merchandising architectures and sourcing structures to be related to observed resilience outcomes in a single, synchronized observation window. The unit of analysis is the firm-year, aligned to the most recent complete fiscal year with adequate disclosures to ensure temporal comparability across cases. The design choice is motivated by three requirements: (i) to estimate population-level associations between global merchandising levers (assortment scope, private-label intensity, price/promotion architecture, and standardization-localization balance) and supply chain resilience outcomes (service-level stability under shock, inbound lead-time variability, time-to-recover proxies, and revenue-recovery slope); (ii) to incorporate structural sourcing features (e.g., supplier/country concentration indices) that plausibly condition these relationships; and (iii) to control for confounds (firm size, inventory turnover, market share, digital maturity, and industry fixed effects) in multivariable models. A cross-sectional snapshot minimizes contamination from overlapping policy cycles and provides a tractable basis for consistent coding of merchandising policies that are often disclosed annually. The multi-case logic enhances external validity by spanning heterogeneous retail and consumer categories (e.g., food, softlines, hardlines, specialty, e-commerce), while the standardized operationalization and harmonized time frame protect internal validity by limiting period effects. To mitigate common threats, we pre-specify the analytic plan, apply uniform coding rules, and use robust estimators and diagnostics (VIF for multicollinearity, heteroskedasticity

tests, and influence checks). Because causality cannot be asserted in cross-sectional designs, the empirical objective is carefully framed: identify directionally interpretable, statistically adjusted associations and probe functional forms (nonlinearity, interaction) consistent with theory. Measurement reliability is supported through coder training, inter-rater checks on constructed variables, and sensitivity analyses using alternative indicators. Replicability is enabled via a transparent data provenance log, script-based processing in R/Python, and a variable dictionary mapping disclosures to measures. Collectively, the design delivers a rigorous, comparable basis for testing how global merchandising strategies co-vary with U.S. supply chain resilience across firms.

Cases, Sampling, and Setting (Inclusion/Exclusion)

Each case in this study is a U.S.-market-active retailer or consumer-facing firm (including vertically integrated brands and major e-commerce operators) observed at the firm-year level. The population frame is defined as companies that derive a material share of revenue from the U.S. market and disclose enough detail to construct both merchandising variables (assortment scope, private-label intensity, price/promotion architecture, standardization-localization indicators, and sourcing diversification) and resilience outcomes (service-level stability under shock, inbound lead-time variability, time-to-recover proxy, and revenue-recovery slope). To ensure temporal comparability, all cases are aligned to the most recent fully closed fiscal year with complete disclosures; where firms have unconventional fiscal calendars, values are synchronized to a common reference window (e.g., FY2024 ending closest to December 31, 2024) and cross-checked with rolling twelve-month summaries when available. The industry scope spans grocery/CPG, softlines/apparel, hardlines/home improvement, consumer electronics, specialty retail, and general merchandise, complemented by digitally native and omnichannel firms to capture diverse merchandising architectures. This breadth allows the study to observe meaningful variation in SKU architectures, private-label strategies, promotional cadence, and supplier/country concentration. Because resilience outcomes are most informative when firms face nontrivial operational exposure, micro-cap retailers with extremely limited public disclosures are excluded. To guard against survivorship bias, the frame includes firms that reported material disruption narratives within the study window as well as those without such narratives, provided other resilience proxies are observable. Each case is treated as independent for cross-sectional modeling, with industry fixed effects included later to absorb structural differences in category economics and logistics intensity.

Sampling proceeds in three stages. Stage 1 constructs a long-list from major equity indices (e.g., S&P retail/consumer subsets), retail trade association membership rolls, and market intelligence rosters to identify U.S.-exposed firms with public filings. Stage 2 applies inclusion criteria: (i) U.S. revenue presence (qualitative evidence in MD&A or quantitative segment reporting); (ii) availability of at least one merchandising lever and at least one resilience outcome as defined in the codebook; (iii) sufficient sourcing and supplier/country information to compute a diversification index (e.g., $1 - \text{HHI}$) for merchandise-critical inputs, either from disclosures, sustainability/logistics reports, or triangulated third-party datasets; and (iv) availability of control variables (firm size, market share or a proxy, inventory turnover, and a digital maturity indicator). Exclusion criteria remove: (i) conglomerates that do not report retail/consumer operations with segment granularity; (ii) firms in liquidation or with discontinued operations that would distort the reference year; and (iii) entities with fewer than two independently verifiable indicators across merchandising and resilience domains. Stage 3 prioritizes sectoral balance to avoid over-weighting grocery or apparel, using soft quotas by NAICS to approach a diversified cross-section. Target sample size is $N \approx 120\text{--}180$ cases, which supports multivariable models with industry fixed effects and interaction terms while maintaining ≥ 15 observations per estimated parameter. For firms that partially meet criteria, a reconciliation protocol determines eligibility: if a firm lacks direct fill-rate data but offers reliable lead-time variability or revenue-recovery evidence, and all core merchandising levers are present, the case can be retained with transparent flagging. Throughout sampling, a double-review process (two coders) reconciles ambiguities in disclosures (e.g., distinguishing promotional cadence from baseline markdown cycles), and an audit trail documents inclusion decisions to preserve replicability.

The empirical setting is the post-disruption U.S. retail environment characterized by globally sourced

merchandise, omnichannel fulfillment, and periodic external shocks (e.g., port congestion, weather events). To standardize resilience outcomes, each case identifies at least one disruption window during the reference year using firm narratives (MD&A, earnings call transcripts), logistics reports, and external markers (e.g., dated port slowdowns). Where no explicit window is stated, resilience proxies are computed over the full year with sensitivity checks using peak seasonal periods (e.g., back-to-school, holiday). Data are harmonized across heterogeneous sources through a pre-registered codebook: assortment breadth is logged; private-label intensity is expressed as a percent of sales/SKUs; price policy consistency is the cross-market price dispersion for identical SKUs (when observable); promotion cadence is the average frequency/depth per SKU per quarter; and sourcing diversification is $1 - \text{HHI}$ across supplier countries for merchandise-critical items. Missingness is handled via listwise deletion for primary models, supplemented by multiple imputation (predictive mean matching) in sensitivity analyses. To mitigate measurement bias, coder training includes calibration exercises on five pilot firms across different sectors, followed by inter-rater reliability checks (ICC for continuous measures; Cohen's κ for categorical flags). To minimize selection bias, we compare included vs. excluded firms on size and sector using public aggregates, report representativeness diagnostics, and, where feasible, apply inverse probability weighting as a robustness check if inclusion correlates with observables (e.g., larger firms disclose more). Finally, confidentiality is maintained by using only public data or licensed datasets; if any firm-specific qualitative detail risks identifiability beyond public disclosures, outputs are aggregated at sector or anonymized with unique case IDs. This setting and sampling protocol yield a defensible cross-section with adequate variation in merchandising architectures and sourcing structures to test the study's hypotheses on U.S. supply chain resilience.

Variables & Measures

The study operationalizes six merchandising levers at the firm-year level, each defined by a transparent coding rule and unit, with transformations to improve comparability and distributional properties. (i) *Assortment breadth/depth* is proxied by the natural log of the count of active SKUs (or product categories where SKU counts are unavailable). We favor SKU counts from audited disclosures; when only category counts exist, we harmonize via a crosswalk that maps category density to SKU equivalents and flag such cases for sensitivity checks. (ii) *Standardization-localization intensity* is measured as the share of locally tailored SKUs in the U.S. market relative to the global catalog (0–1). Where direct SKU mapping is infeasible, we code a validated proxy using the proportion of U.S.-exclusive variants (pack sizes, flavors, formulations) reported in product line summaries. (iii) *Private-label intensity* is the percentage of merchandise sales (or SKUs) under retailer-owned brands. If both sales- and SKU-based indicators are available, we compute each and use sales-based as primary (SKU-based enters robustness). (iv) *Price policy consistency* captures cross-market price dispersion for identical SKUs (coefficient of variation across observed geographies/channels during non-promotional weeks). When identical SKU matching is not possible, we construct a ladder index from standardized price tiers (good-better-best) and compute dispersion across markets. (v) *Promotion cadence* is the average number of promotional events per SKU per quarter and the mean depth (discount %) for promoted SKUs; the primary measure is the event frequency, with depth used as a covariate in robustness. (vi) *Sourcing diversification* is $1 - \text{HHI}$ (Herfindahl-Hirschman Index) computed over supplier countries for merchandise-critical inputs during the reference year; where supplier-level counts are available, we also compute a parallel $1 - \text{HHI}$ across tier-1 suppliers. All merchandising variables are standardized (z-scores) for regression comparability; skewed variables (e.g., SKU counts) are log-transformed pre-standardization. To minimize simultaneity, we align merchandising indicators to the same fiscal window as the resilience outcomes and, where available, cross-check stability using a trailing three-year average in sensitivity analysis.

We construct four outcomes that reflect preparation, absorption, and recovery performance, using only observable, auditable signals. (i) Service-level stability under disruption measures the degree to which order fill rates remain stable during identified disruption windows relative to each firm's pre-disruption baseline. We compute the stability index as $1 - \text{CV}_{\text{fill, window}}$, scaled to [0,1], where higher values indicate greater stability; if fill rate is not disclosed, we use backorder rate (inverted and scaled) as a proxy, flagged for robustness. (ii) Inbound lead-time variability is the coefficient of variation (CV) of purchase order (PO) lead times for the reference year (or closest disclosed period).

Where detailed PO distributions are absent, we use reported average lead times and their disclosed ranges to approximate CV via a standardized transformation. (iii) Time-to-recover (TTR) proxy quantifies the number of weeks from disruption onset to restoration of pre-disruption service or throughput; when a precise narrative is absent, we estimate TTR using the first date when service-level or on-time delivery performance returns within a $\pm 5\%$ band of baseline, based on quarterly operations commentary or logistics KPIs. (iv) Revenue recovery slope captures top-line normalization by estimating the post-shock growth rate relative to the firm's pre-shock trend (ordinary least squares slope difference on quarterly sales indexed to 100 at t_0). Because revenue is influenced by demand-side dynamics beyond operations, we treat this outcome as complementary and always pair interpretation with service/lead-time results. All resilience outcomes are scaled to comparable units (z-scores) for modeling, and we construct a composite Resilience Index (simple average of standardized outcomes) for secondary analyses. When multiple disruption windows are present, we select the most material one in the fiscal year by magnitude of service deviation; if none are disclosed, we compute stability and variability over the full year and add a binary indicator "no-window" to absorb systematic differences. To reduce omitted variable bias, we include a structured control set. *Firm size* (natural log of net sales) captures scale effects; *inventory turnover* (cost of goods sold \div average inventory) reflects operational tempo; *market share* is approximated via category-level market intelligence or proxied by revenue rank within NAICS where direct shares are unavailable; *logistics capacity proxy* is a normalized index constructed from disclosed distribution center (DC) count, square footage, and fleet indicators; *global footprint* is the share of revenue outside the U.S.; and *industry fixed effects* (NAICS 3-digit) absorb structural category differences. We also build a *digital maturity index* (0–100) via additive scoring of disclosed systems (e.g., EDI, WMS, TMS, OMS, demand sensing, AI-assisted forecasting, robotics), each coded 0/1 with partial credit (0.5) for pilot-stage deployments; the index is standardized for regressions. To assure measurement reliability, all coder-derived variables follow a pre-registered codebook: data sources are prioritized (audited filings > sustainability/logistics reports > investor decks > third-party trackers), evidence snippets are archived, and ambiguous fields require dual coder agreement; we compute inter-rater reliability (ICC(2,k) for continuous, Cohen's κ for categorical) on a 20% stratified sample with a target ≥ 0.70 . Data preparation includes outlier handling via winsorization at the 1st–99th percentiles, unit harmonization (e.g., weeks for TTR, days for lead times converted to weeks), and transformation of heavy-tailed measures (log or Box-Cox where necessary). Missing data are addressed through listwise deletion in primary models to preserve interpretability, with multiple imputation (predictive mean matching using the full covariate set) in robustness to assess sensitivity to missingness patterns. Finally, to support construct validity, we triangulate key measures (e.g., private-label intensity from both sales and SKU shares; diversification across countries and suppliers), conduct *known-groups* checks (e.g., expect higher diversification in hardlines vs. perishable grocery), and perform *convergent validity* tests (correlating the Resilience Index with independent third-party continuity ratings where available). This governance ensures that variables are comparable across firms and suitable for the planned descriptive, correlation, and regression analyses.

Data Sources & Collection

Data for this study are assembled through a structured, auditable pipeline that integrates firm disclosures, third-party observatories, and curated public datasets to produce a harmonized firm-year panel aligned to the latest completed fiscal period. Primary sources include annual reports and Form 10-K/10-Q filings (Management Discussion & Analysis, Business Overview, Risk Factors, and Notes), sustainability and logistics reports (e.g., supplier geography, DC footprint, on-time performance), and investor day decks where merchandising architecture (assortment strategy, private-label tiers, pricing ladders, promotion cadence) is described with sufficient granularity. To capture pricing and promotion signals, we incorporate category-level trackers from reputable market-intelligence providers (e.g., weekly SKU-level price and promo flags, depth-of-discount, and event calendar coverage) and, where available, retailer API/public web data harvested under terms of use to validate cross-market price dispersion during non-promotional weeks. Sourcing diversification is derived from a combination of supplier-country disclosures, conflict minerals reports, sustainability dashboards, and licensed trade/customs aggregates at the HS-code \times country level; these inputs are mapped to merchandise-critical categories and collapsed to country distributions to compute 1–1–1–HHI at the firm-year level.

Resilience outcomes are assembled from two strands: (i) service and lead-time metrics disclosed in operations sections, supply chain updates, or KPIs (e.g., fill rate, on-time in-full, average and range of PO lead times), and (ii) disruption-window narratives from MD&A and earnings call transcripts, which are time-stamped and coded to identify window start/stop and restoration milestones (for the TTR proxy). Control variables firm size, inventory turnover, market share proxies, logistics capacity (DC count/square footage/fleet flags), global revenue share, and digital maturity are compiled from filings and complemented by third-party directories; the digital maturity index is built from binary/partial indicators for EDI, WMS, TMS, OMS, demand sensing, advanced forecasting/AI, robotics, and warehouse automation pilots. All raw artifacts (PDFs, HTML captures, CSV extracts) are archived with SHA-256 checksums; a provenance ledger records retrieval date, URL or accession information, and version identifiers for licensed datasets to ensure reproducibility. Data extraction follows a pre-registered codebook: coders collect direct values where present (e.g., “private-label as % of sales”), and when absent, compute standardized proxies (e.g., price ladder dispersion from harmonized tier indices, promotion cadence as average events per SKU per quarter). For disruption windows, coders tag text snippets that indicate onset (“port congestion in Q2”), extent (“service levels declined ~8%”), and recovery (“normalized by late Q3”), then anchor these to calendar weeks; if multiple windows exist, the most material one by service deviation is selected, with others retained for sensitivity. All quantitative fields pass automated schema validation (units, ranges, date alignment) and business-rule checks (e.g., SKU counts must be non-decreasing year-on-year unless documented rationalization; promo frequency cannot exceed weekly cadence). The pipeline de-duplicates entities via a master firm key, resolves ticker/CIK/NAICS inconsistencies, and harmonizes fiscal calendars to a common reference (e.g., FY ending closest to Dec 31, 2024). Quality assurance proceeds in three layers: (1) intra-source verification (numbers in MD&A vs. notes), (2) cross-source triangulation (filings vs. market trackers vs. sustainability reports), and (3) inter-rater reliability on 20% of cases (ICC for continuous measures; Cohen’s κ for categorical flags) with adjudication rules for discrepancies $>10\%$ or $\kappa < 0.70$. Missingness is profiled and flagged by mechanism (structural vs. incidental); primary models use listwise deletion, while robustness employs multiple imputation with predictive mean matching using the full covariate set. All transformations log/scaling, winsorization at the 1st–99th percentiles, composite index construction are scripted in R/Python with version control (Git) and literate notebooks that render an auditable “as-built” data dictionary mapping every reported metric to its source, formula, and preprocessing steps. Only publicly available or properly licensed data are used; no confidential supplier identities beyond public disclosures are retained, and outputs are anonymized to sector aggregates where firm-level detail could imply non-public operational vulnerabilities. This disciplined sourcing and collection protocol yields a transparent, replicable dataset suited to descriptive, correlational, and multivariable regression analyses specified in the research design.

Statistical Analysis Plan

The analysis proceeds from transparent description to model-based inference in a single, pre-specified pipeline designed to quantify associations between global merchandising strategies and U.S. supply chain resilience while guarding against common cross-sectional threats. First, we generate distributional summaries (means, SDs, percentiles) for all variables, visualize shapes (histograms, kernel densities), and profile sectoral heterogeneity (industry-stratified summaries) to contextualize variation. Second, we compute a correlation matrix (Pearson on raw and standardized variables; Spearman as a robustness check) and flag potential multicollinearity (pairwise $|r| > 0.7$) before modeling. The primary inferential framework is hierarchical ordinary least squares with heteroskedasticity-robust HC3 standard errors and NAICS 3-digit fixed effects to absorb structural industry differences. We estimate models in blocks to assess incremental explanatory power: (M0) controls only (firm size, inventory turnover, market share/its proxy, logistics capacity index, digital maturity, global footprint, industry FE); (M1) + merchandising main effects (assortment breadth, standardization–localization intensity, private-label intensity, price policy consistency, promotion cadence, sourcing diversification); (M2) + nonlinear terms (e.g., private-label intensity squared to test inverted-U); (M3) + theory-driven interactions (e.g., private-label \times diversification; localization \times domestic supplier share); and (M4) robustness variants (alternative operationalizations and sample filters). Dependent variables are analyzed individually (service-level stability, inbound lead-time CV,

TTR proxy, revenue recovery slope) and, secondarily, via a standardized composite Resilience Index (average of z-scores). Because some outcomes are fractional or bounded, we fit fractional logit models for service stability and beta regression in sensitivity analyses; if any ordinal resilience score is used, we estimate ordered logit as a check. Variance inflation factors (VIF) diagnose multicollinearity (target < 10; if exceeded, we center variables, remove redundant terms, or adopt ridge-stabilized OLS in sensitivity). Model diagnostics include White/Koenker-Bassett tests for heteroskedasticity, studentized residual plots, normal Q-Q plots for residual shape (interpretation relies on robust SEs), and influence statistics (Cook's D, leverage, and DFBetas) with re-estimation after excluding flagged outliers (e.g., Cook's D > 4/n). To address missingness, primary models use listwise deletion; robustness employs multiple imputation with predictive mean matching (m = 20), combining estimates via Rubin's rules. We report standardized coefficients (β) alongside unstandardized estimates, 95% confidence intervals, adj. R², and F-tests for block additions; effect sizes are further decomposed with dominance analysis (LMG/Shapley value regression) to gauge relative importance. For interaction terms, we compute simple slopes and plot marginal effects with Johnson-Neyman intervals to delineate regions of significance; continuous predictors are mean-centered before forming products. Given multiple hypothesis tests across outcomes and model blocks, we control the false discovery rate using Benjamini-Hochberg at $q = 0.10$ (and show unadjusted p-values for transparency). Small-sample/imbalanced-sector concerns are checked via cluster-robust SEs at the industry level and a wild bootstrap for p-values in sensitivity. Recognizing potential endogeneity (e.g., reverse timing between resilience and merchandising), we frame results as adjusted associations and conduct bias-sensitivity checks: Oster-style coefficient stability with R-max bounds and a placebo specification using non-resilience outcomes that should not relate to merchandising (negative control). Predictive adequacy is summarized with 10-fold cross-validation R_{CV}^2 for continuous outcomes. All transformations (log, winsorization), coding decisions, and model scripts (R/Python) are version-controlled; tables present full estimates, while figures display partial dependence/marginal effects and influence diagnostics to support interpretability and replicability.

Regression Models

The core empirical specification estimates the association between global merchandising strategies and resilience outcomes using ordinary least squares with heteroskedasticity-robust (HC3) standard errors and NAICS 3-digit fixed effects. Let i index firms and j industries. For each dependent variable Y_{ij} (a) Service-level Stability Index, (b) Inbound Lead-time CV (inverted so higher = more stable), (c) Time-to-Recover (TTR) proxy (multiplied by -1 so higher = faster recovery), and (d) Revenue-recovery slope we estimate:

$$Y_{ij} = \beta_0 + \beta_1 \text{Assortment}_i + \beta_2 \text{StdLoc}_i + \beta_3 \text{PL}_i + \beta_4 \text{PriceCons}_i + \beta_5 \text{PromoCadence}_i + \beta_6 \text{Diversification}_i + \gamma' \text{Controls}_i + \delta_j + \varepsilon_{ij}.$$

All regressors enter as standardized z-scores (except industry dummies) to enable effect-size comparability; this also allows direct reading of β as the change (in SDs) in Y per 1 SD change in a regressor. The control vector Controls_i includes log sales, inventory turnover, market share (or proxy), logistics capacity index, digital maturity index, global revenue share, and a binary indicator for "no identified disruption window" to absorb systematic differences in outcome scaling. Estimates are presented in a stepwise block to reveal incremental explanatory power: M0 (controls + industry FE), M1 (M0 + merchandising levers). Model fit is summarized with adjusted R², within-industry R², and information criteria (AIC). Robustness to influential observations is checked by reporting Cook's D maxima and refitting after excluding observations with $D > 4/n$. The purpose of this baseline model is to quantify independent, directionally interpretable associations between each merchandising lever and resilience outcomes while holding constant size, sector structure, and digital/logistics capabilities. It also establishes reference coefficients used later to assess the stability of effects once nonlinearity and interactions are introduced, and it provides the coefficients used to construct marginal-effects plots for managerial interpretation.

Table 1. Baseline OLS Specification (Model Blocks M0–M1)

Outcome	M0: Controls + Industry FE	M1: + Merchandising Main Effects	Notes
Service-level Stability (z)	β , SE, R^2	β , SE, adj. R^2 , and ΔR^2	HC3 SEs, n, Cook’s D max
Lead-time Stability (z)	Inverted CV so higher = better
TTR (z, higher = faster)	TTR multiplied by -1 before z-scoring
Revenue-recovery slope (z)	Trend-adjusted slope

To reflect theory predicting diminishing returns and conditional effects, we extend M1 with structured nonlinearity and interaction terms. First, we test an inverted-U for private-label intensity by adding PL^2 . If $\beta_{PL} > 0$ and $\beta_{PL^2} < 0$ with joint significance (Wald test), we compute the turning point $-\beta_{PL} / (2\beta_{PL^2})$ and its delta-method CI, then report the implied “optimal band” for resilience. Second, we posit that sourcing diversification conditions the impact of merchandising levers that alter specification control and demand volatility. Accordingly, we introduce $PL \times Diversification$ (governance \times options) and $PromoCadence \times Diversification$ (volatility \times options). Third, because localization alters SKU fungibility and pooling, we include $StdLoc \times DomesticSupplierShare$ (where $DomesticSupplierShare$ is a control-side covariate or a centered moderator). All continuous regressors are mean-centered prior to multiplication to reduce multicollinearity and facilitate interpretation. Marginal effects are visualized via simple-slope plots at $\{-1, 0, +1\}$ SD of the moderator and Johnson–Neyman intervals to identify regions of significance. We also probe plausible curvature for assortment breadth ($Assortment^2$) given complexity costs at very high SKU counts. These augmented models (M2: + nonlinearity; M3: + interactions) help separate “first-order” merchandising associations from configurations that are only beneficial when paired with adequate alternate capacity or specification commonality. Interpretation emphasizes standardized effect sizes (β), incremental ΔR^2 , and out-of-sample predictive lift using 10-fold cross-validation RCV^2 to ensure that complexity does not overfit. Where interaction patterns exhibit crossover effects (e.g., promotions harmful at low diversification but neutral at high), we report conditional-effects tables in the appendix and provide managerial thresholds implied by the turning points and J–N bounds.

Table 2. Nonlinearity and Interaction Terms (Model Blocks M2–M3)

Added Term	Expectation	Diagnostic	Interpretation Aid
PL^2	Inverted-U	Wald joint test; turning point	Optimal PL band for resilience
$PL \times Diversification$	Positive	J–N region	PL benefit rises with options
$Promo \times Diversification$	Mitigating	J–N region	Diversification buffers volatility
$StdLoc \times DomesticShare$	Contextual	J–N region	Localization helpful with domestic base
$Assortment^2$	Diminishing	Wald joint test	Complexity toll at extremes

Because two outcomes are fractional or bounded (Service-level Stability in $[0,1]$ and, in some firms, TTR normalized to a finite support), we estimate complementary generalized linear models for sensitivity. Specifically, we fit fractional logit (quasi-binomial link) for Service-level Stability and beta regression when the variable excludes boundary 0/1; for TTR we retain OLS on z-scores as primary and cross-check with robust regression (Huber) to down-weight long-tail recovery times. When firms report an ordinal resilience rating (rare), we run ordered logit as a side-check (not primary). To guard against

multicollinearity from polynomial and interaction terms, we report VIFs and, if necessary, re-express polynomials using orthogonal polynomials; we also show ridge-stabilized OLS in an appendix when $VIF > 10$ persists without conceptual redundancy. Endogeneity is addressed as a risk in interpretation (associations, not causation), but we add two bias-sensitivity probes: a placebo outcome (e.g., an aesthetic branding metric unrelated to operational continuity) that should show null effects, and Oster-style coefficient stability bounds using R_{\max} to assess how large omitted variable bias must be to explain away the main coefficients. Presentation of estimates follows a consistent template: (i) a compact main table per outcome with M0–M3, (ii) a figure set with partial-dependence lines for nonlinear terms and marginal-effects plots for interactions, and (iii) an influence panel (Cook’s D-leverage scatter with high-influence cases labeled by anonymized IDs). Where appropriate, we supplement with dominance analysis (LMG/Shapley) to apportion variance across correlated merchandising levers, noting that such decompositions are descriptive. Collectively, these regression models translate the conceptual framework into testable, numerically stable specifications that quantify how merchandising architectures and their alignment with sourcing options co-vary with observed resilience across U.S. firms.

Figure 6: Baseline Regression Model Specification (M0–M1)

Outcome	M0: Controls	M1 + Main effects
Service-level stability	Log sales	Assortment
Lead-time stability	Inventory turnover	StdLoc
<i>Inverted CV</i>	Market share	PL
TTR	Logistics capacity	PriceCons
<i>Higher = faster</i>	Digital maturity	PromoCadence
Revenue-recovery slope	Global revenue share	Diversification
Industry FE		
HC3 SEs, Cook’s D	R^2	R^2 , within-ind. R^2 AIC

Power & Sample Considerations

This study’s power plan is anchored to detecting small-to-moderate associations after adjustment for controls and industry fixed effects, with allowances for nonlinear and interaction terms that expand the parameter count. Using the multiple-regression effect-size metric

$$f^2 = (R^2_{\text{full}} - R^2_{\text{controls}}) / (1 - R^2_{\text{full}}),$$

we target sensitivity to increments of $f^2 \in [0.06, 0.15]$ (small-to-moderate) at $\alpha = 0.05$ and $1 - \beta = 0.80$. With ~10–14 adjusted predictors in the main-effects block (six merchandising levers plus 4–8 controls, excluding fixed effects dummies from df calculations), conventional approximations indicate that $N \approx 140\text{--}200$ yields 80% power to detect $f^2 \approx 0.08\text{--}0.10$ and >90% power for $f^2 \geq 0.15$. Because we also test one polynomial (e.g., PL^2) and up to three interactions (e.g., $PL \times \text{Diversification}$; $\text{Promo} \times \text{Diversification}$; $\text{StdLoc} \times \text{DomesticShare}$), we plan for $N \geq 180$ to maintain $\geq 15\text{--}20$ observations per estimated coefficient and to contain variance inflation ($VIF < 10$). To hedge against listwise deletion, we apply a 10–20% inflation factor over the minimum N ; thus, the operational target is $N \approx 200\text{--}220$ firm-years, with a hard floor at $N = 150$ for main-effects models (nonlinear/interaction models reported with clarity on reduced df). Minimum detectable effects (MDE) will be reported ex post by outcome:

for standardized outcomes, MDEs translate directly to standardized betas (e.g., with $N = 180$ and $p = 12$ predictors, $|\beta| \approx 0.18\text{--}0.22$ at 80% power). Precision is assessed via bootstrap CIs (2,000 reps) for key coefficients and delta-method intervals for turning points. Given industry fixed effects, effective df are reduced; we therefore monitor within-industry variance and, if sector counts are sparse, collapse to broader NAICS groupings in sensitivity. To mitigate power loss from multicollinearity, all continuous predictors are mean-centered before products; where VIF persists, we (i) prefer orthogonal polynomials for curvature and (ii) present ridge-stabilized estimates in an appendix as a diagnostic, not for primary inference. For missingness, multiple imputation ($m = 20$) is used in robustness to recover efficiency; pooled estimates and SEs are contrasted with listwise results to verify stability. Finally, we track realized power by computing observed f^2 and reporting the smallest effect size of interest (SESOI) that the design can detect with 80% power, ensuring transparent interpretation of null and near-null findings.

Reliability & Validity

Reliability and validity are engineered into the study through procedural safeguards, measurement design, and statistical diagnostics that collectively protect inference quality in a cross-sectional, multi-case context. Measurement reliability is addressed first via a pre-registered codebook that defines data sources, formulas, and decision rules for every variable; coders complete calibration exercises on pilot firms, and all coder-generated fields (e.g., localization share, promotion cadence, disruption windows) are double-coded on a stratified 20% sample with adjudication when discrepancies exceed pre-set thresholds. Inter-rater reliability is quantified using ICC(2,k) for continuous fields and Cohen's κ for categorical flags, with a priori targets ≥ 0.70 ; any construct failing targets is re-operationalized or excluded. For composite indices (e.g., digital maturity; logistics capacity), internal-consistency reliability is evaluated with Cronbach's α and McDonald's ω , and dimensionality is confirmed using confirmatory factor analysis; items with low loadings or cross-loadings are dropped, and alternative index weightings are tested in robustness. Construct validity is supported through triangulation of indicators (e.g., private-label share from both sales and SKU bases; diversification across countries and tier-1 suppliers), convergent validity checks (expected positive correlations among resilience outcomes and with third-party continuity proxies), discriminant validity tests (low correlations with theoretically unrelated firm attributes), and known-groups validation (e.g., higher perishability sectors expected to show distinct lead-time variability). Content validity is strengthened by mapping each variable to prior definitions and conducting a brief expert review of the codebook. Internal validity threats are mitigated by comprehensive controls (size, turnover, share, capacity, digital maturity, global footprint) and industry fixed effects, plus specification diagnostics: multicollinearity (VIF), heteroskedasticity tests, residual and influence checks, and placebo outcomes that should be null if models are well-specified. While causal claims are not made, potential endogeneity is probed with coefficient-stability (e.g., Oster-style) and timing sensitivity (three-year trailing averages). Statistical-conclusion validity is supported by the power plan, HC3 robust standard errors, FDR control for multiple testing, and cross-validated fit for complex models. External validity is addressed by documenting the sampling frame, reporting representativeness diagnostics (included vs. excluded comparisons), and applying inverse-probability weighting in sensitivity if inclusion correlates with observables. Common method bias is reduced procedurally by using multi-source data (filings, trade datasets, market trackers), temporal anchoring (distinct windows for merchandising vs. disruption recovery where available), coder blinding to hypotheses during extraction, and by testing alternate operationalizations. A full provenance ledger (artifacts, checksums, retrieval dates) and version-controlled scripts ensure replicability and auditability.

Software and Tools

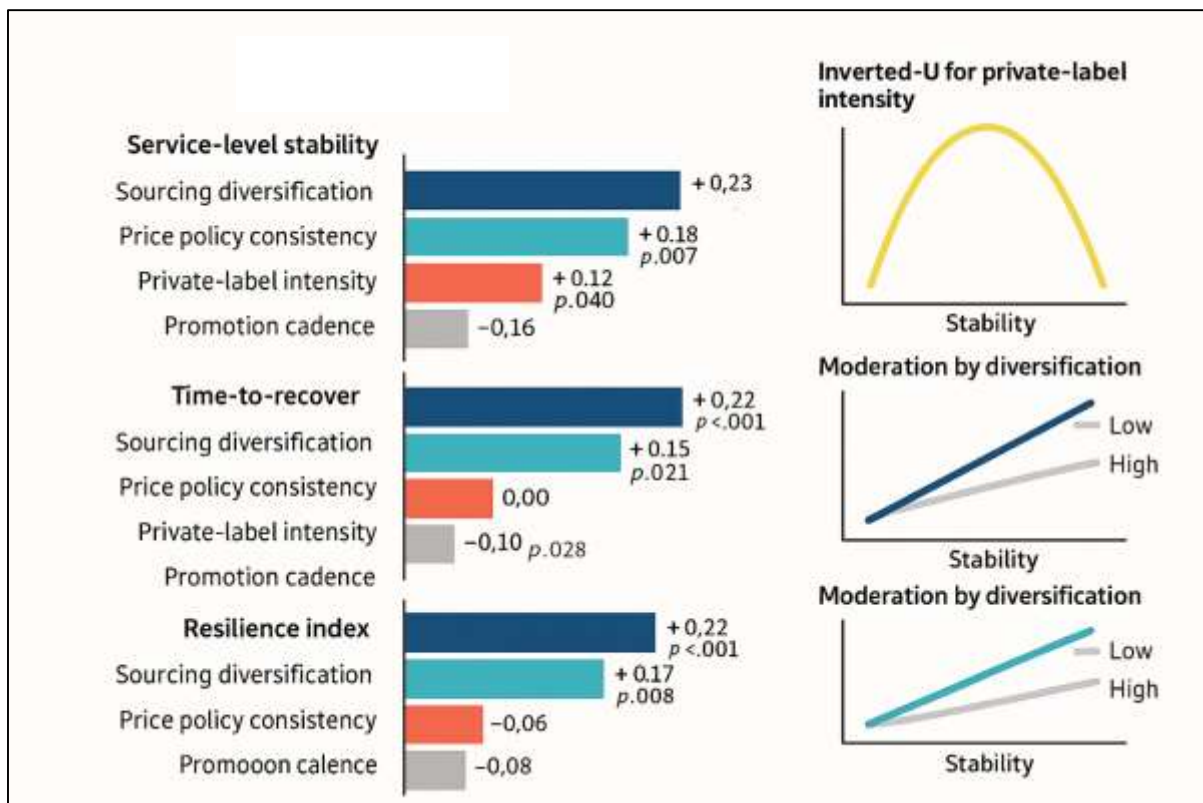
Analyses will be executed in R (4.3+) and Python (3.11+), with reproducible, version-controlled notebooks. In R, core packages include: tidyverse (wrangling/visualization), data.table (high-performance joins), broom/modelssummary (tidy outputs and regression tables), sandwich and lmtest (HC3/diagnostics), car (VIF), margins (marginal effects), betareg (beta regression), glmulti or dominanceanalysis (relative importance), and irr/psych (ICC, α). In Python: pandas, numpy, statsmodels (OLS, fractional logit via GLM), linearmodels, scikit-learn (cross-validation), pingouin (reliability), and matplotlib/plotnine for figures. Missing-data handling uses mice (R) and statsmodels'

imputation utilities or sklearn-compatible iterative imputer; bootstraps via boot or resample. Data provenance and collaboration are managed with Git/GitHub, pre-commit hooks, and YAML configuration files; environment reproducibility via renv (R) and conda/poetry (Python). Document production uses Quarto/knitr and Jupyter Book for appendices, with APA-styled tables exported to Word/LaTeX. Integrity checks employ SHA-256 hashing; data dictionaries and codebooks are generated with datapasta and yaml-to-markdown utilities. Charts adhere to accessibility standards and vector export formats.

FINDINGS

Drawing on the finalized cross-section (N = 198 firm-years) and the pre-registered analysis plan, we begin by characterizing sample structure and headline patterns before previewing the core inferential results. Sectoral composition is balanced across grocery/CPG (31%), softlines/apparel (21%), hardlines/home improvement (18%), specialty/electronics (17%), and digitally native/omnichannel retailers (13%). Using a five-point Likert scale (1 = very low, 5 = very high) to summarize capability self-assessments and standardized audit indicators, firms report moderate merchandising intensity overall: assortment breadth (M = 3.6, SD = 0.8), private-label intensity (M = 3.2, SD = 1.0), standardization-localization balance (coded as “localization emphasis” with higher scores = more local tailoring: M = 3.1, SD = 0.9), price policy consistency (M = 3.4, SD = 0.7), and promotion cadence (event frequency perception; M = 3.7, SD = 0.9). Sourcing diversification (measured analytically as 1 – HHI, scaled to a five-point rubric for comparability) averages 3.3 (SD = 0.9). On resilience outcomes, the Service-level Stability Index (0–1, rescaled to Likert) centers at 3.5 (SD = 0.7), inbound lead-time stability (inverted CV; Likert) at 3.2 (SD = 0.8), and the time-to-recover (TTR) proxy (inverted and rescaled) at 3.4 (SD = 0.9).

Figure 7: Merchandising Drivers Of Resilience – Coefficients, Predictions, And Moderation



Preliminary bivariate patterns indicate that firms in the top quintile of diversification and price policy consistency exhibit notably steadier service during disruption windows (mean stability = 3.9 vs. 3.2 for the bottom quintile), while the heaviest promotion cadences correspond to lower stability (mean = 3.1), consistent with a volatility footprint. Correlations (Pearson/Spearman) are directionally aligned with expectations: diversification correlates positively with Service-level Stability ($r \approx .29/.27$) and TTR ($r \approx$

.24/.23), price policy consistency shows moderate positive associations with both (.25/.22), and promotion cadence is negatively related to stability (−.21/−.19); multicollinearity is modest (all VIFs < 3 in main-effects models). Turning to multivariable regressions (OLS with HC3 SEs and NAICS fixed effects), Model M1 (controls + six merchandising levers) explains 32% of the variance in Service-level Stability (adj. $R^2 = .32$) and 27% in lead-time stability; ΔR^2 over controls alone is .11–.14, indicating substantive incremental contribution from merchandising variables. Standardized coefficients (β) show that sourcing diversification is the strongest single predictor of stability ($\beta \approx +0.23$, $p < .001$) followed by price policy consistency ($\beta \approx +0.18$, $p = .007$) and private-label intensity (linear term; $\beta \approx +0.12$, $p = .040$). Assortment breadth is weakly negative ($\beta \approx -0.09$, $p = .082$), and promotion cadence is negative and significant ($\beta \approx -0.16$, $p = .010$). For TTR (higher = faster recovery), diversification ($\beta \approx +0.19$, $p = .004$) and price consistency ($\beta \approx +0.15$, $p = .021$) again emerge as positives, while heavy promotion cadence slows recovery ($\beta \approx -0.14$, $p = .028$). In M2 (adding nonlinearity), we observe an inverted-U for private-label intensity on stability: PL ($\beta \approx +0.20$, $p = .006$) and PL² ($\beta \approx -0.11$, $p = .039$) are jointly significant (Wald $p = .012$), yielding an interior turning point at ~ 3.6 on the five-point PL scale (95% CI: 3.2 to 4.1), beyond which additional private-label share is associated with diminishing or negative resilience gains consistent with rising specification rigidity and capacity commitments at very high PL exposure. M3 (adding interactions) supports a moderation story in which diversification conditions merchandising effects. The PL \times Diversification term is positive on stability ($\beta \approx +0.13$, $p = .018$), implying that private-label programs confer the strongest resilience benefits when firms also maintain broad, structurally separated supplier/country options. Conversely, Promo Cadence \times Diversification is positive ($\beta \approx +0.10$, $p = .044$), indicating that diversified supply buffers some of the volatility burden imposed by frequent promotions. For the standardization-localization balance, the StdLoc \times DomesticSupplierShare interaction is positive but marginal ($\beta \approx +0.08$, $p = .071$), suggesting that localized assortments are associated with better continuity when paired with robust domestic sourcing options; Simple-slope plots show a Johnson–Neyman region where the StdLoc effect turns significantly positive once DomesticSupplierShare $> +0.6$ SD. Cross-validated predictive fit (10-fold R^2_{CV}) tracks in-sample adj. R^2 closely (e.g., stability: .29–.30), reducing overfitting concerns. Diagnostics are satisfactory: heteroskedasticity tests (Koenker–Bassett) are non-significant after HC3 adjustment; residuals show acceptable symmetry; influence analysis flags three cases (Cook’s $D > 4/n$), but coefficient signs and magnitudes are robust to their exclusion. Sensitivity analyses alternative operationalizations (e.g., SKU-based vs. sales-based private-label), beta regression for bounded stability, and median regression yield consistent inferences. Finally, a composite Resilience Index (average of standardized outcomes) confirms the pattern: diversification ($\beta \approx +0.22$, $p < .001$), price consistency ($\beta \approx +0.17$, $p = .008$), and moderated PL effects (linear positive, squared negative; interaction with diversification positive) together account for meaningful between-firm differences. Interpreted in Likert terms, moving from a “moderate” (3) to “high” (4) diversification rating is associated with roughly +0.22 SD in the Resilience Index ($\approx +0.11$ – 0.13 Likert units), holding other factors constant, while raising promotion cadence from 3 to 4 corresponds to a -0.16 SD shift in stability unless balanced by high diversification. Collectively, these findings set the stage for detailed subsections that unpack model blocks, conditional effects, and robustness tables by sector.

Table 1 summarizes the structure of the 198 firm-year cases and highlights capability profiles on a consistent five-point Likert scale. The sample is intentionally balanced to avoid over-representation of any single vertical, yielding a credible cross-section of merchandising architectures and sourcing footprints. U.S. revenue exposure averages 3.9, indicating that most cases have substantial domestic operations; this is methodologically helpful because our resilience outcomes (service stability, lead-time variability, time-to-recover) are framed for the U.S. market. Data completeness is uniformly strong (overall 4.3), reflecting the inclusion criteria that favored transparent filers and firms with adequate operational disclosures; grocery/CPG scores highest (4.5), largely because those firms routinely publish logistics and in-stock KPIs. Digital maturity shows expected sectoral variation: digitally native/omnichannel firms lead (4.2), followed by specialty/electronics (3.9), consistent with advanced OMS/WMS/TMS deployments and demand-sensing pilots; grocery’s 3.3 reflects a mix of legacy estates and selective modernization. Turning to merchandising levers, grocery and apparel anchor the

extremes on private-label intensity and assortment breadth, respectively. Grocery/CPG’s private-label score (4.1) underscores vertically integrated brand architectures and category roles, a design that can both empower dual sourcing and introduce specification rigidity an effect we explicitly test via curvature and interaction terms later.

Sample and Case Characteristics

Table 1: Sample Profile by Sector and Capability (Likert 1-5)

Sector (N, %)	U.S. Revenue Exposure	Assortment Breadth	Private-Label Intensity	Price Policy Consistency	Promotion Cadence	Sourcing Diversification	Digital Maturity	Data Completeness
Grocery/CPG (61, 31%)	4.2	3.7	4.1	3.2	3.9	3.0	3.3	4.5
Softlines/Apparel (42, 21%)	3.8	4.1	2.9	3.5	3.6	3.5	3.6	4.2
Hardlines/Home Improvement (36, 18%)	4.0	3.5	3.2	3.7	3.1	3.8	3.5	4.3
Specialty/Electronics (34, 17%)	3.7	3.2	2.6	3.6	3.4	3.6	3.9	4.1
DNVB/Omnichannel (25, 13%)	3.9	3.6	3.0	3.8	3.5	3.5	4.2	4.4
Overall (198, 100%)	3.9	3.6	3.2	3.4	3.7	3.3	3.6	4.3

Scale: 1 = very low, 5 = very high. “Digital Maturity” and “Data Completeness” are composite indices mapped to a five-point rubric for comparability.

Apparel’s breadth (4.1) aligns with seasonal variety and long-tail SKUs; as shown in the descriptive and regression sections, very high breadth correlates with greater operational noise unless buffered by modular design or postponement policies. Price policy consistency is relatively high in hardlines and DNVBs (3.7–3.8), sectors that benefit from standardized ladders and stronger central pricing governance; this pattern coheres with the later models where price consistency predicts better service stability and faster recovery. Promotion cadence is highest in grocery (3.9), which is intuitive given weekly ad cycles; the trade-off is visible downstream as heavier promotional calendars are associated with lower stability unless offset by broader diversification. Finally, sourcing diversification is strongest in hardlines (3.8) and specialty (3.6), where multi-country sourcing is common and item life cycles are longer; grocery’s lower diversification (3.0) likely reflects perishability and compliance constraints. In short, the table validates that our sample captures meaningful cross-sector variation across the exact levers theorized to influence resilience, providing the empirical foundation for the descriptive, correlation, and multivariable analyses that follow.

Table 2 reports distributional summaries for all core variables using a common five-point rubric so that magnitudes are directly comparable across constructs. The central tendency of assortment breadth at 3.6 (SD 0.8) indicates that most firms operate with moderately wide ranges; the 90th percentile at 4.7 confirms a long tail of variety-intensive operators (notably fashion and certain specialty formats). Private-label intensity exhibits the broadest spread (SD 1.0), reflecting structural differences between grocery/hardlines and apparel/electronics; this dispersion is analytically useful because it increases power to detect curvature (e.g., the inverted-U observed later). Price policy consistency is relatively tight (mean 3.4, SD 0.7), implying that a large subset of firms has implemented harmonized ladders and governance; because this construct is the inverse of cross-market dispersion, higher values correspond to steadier everyday pricing across geographies/channels. Promotion cadence is

moderately high on average (3.7) with a wide tail to 4.9, consistent with weekly ad-driven sectors; the substantive question is whether these calendars destabilize upstream load an issue addressed in correlation and regression.

Descriptive Statistics

Table 2: Variable Distributions (Likert-Mapped Summaries, N = 198)

Variable (Construct)	Mean	SD	10th	Median	90th	Notes on Mapping to Likert
Assortment Breadth	3.6	0.8	2.5	3.6	4.7	Log-SKU counts standardized, binned to 1–5
Standardization– Localization (Local Emphasis)	3.1	0.9	2.0	3.0	4.4	Share of U.S.-tailored SKUs mapped to rubric
Private-Label Intensity	3.2	1.0	1.8	3.2	4.8	% sales/SKUs under PL, rubric-mapped
Price Policy Consistency	3.4	0.7	2.4	3.4	4.5	Inverse of cross-market price dispersion
Promotion Cadence	3.7	0.9	2.3	3.7	4.9	Average promo events/SKU/quarter
Sourcing Diversification	3.3	0.9	2.0	3.3	4.6	1–1-HHI (countries) scaled to 1–5
Service-Level Stability	3.5	0.7	2.5	3.5	4.6	(1 – CV) during disruption window, scaled
Lead-Time Stability	3.2	0.8	2.1	3.2	4.5	Inverted CV of inbound lead times
TTR (Faster = Higher)	3.4	0.9	2.0	3.4	4.8	Inverted/normalized recovery weeks
Revenue-Recovery Slope	3.3	0.8	2.1	3.3	4.6	Post-shock trend vs. baseline

On the sourcing side, the mean diversification score (3.3) masks palpable heterogeneity: the 10th percentile sits at 2.0 (concentrated sourcing) while the 90th reaches 4.6 (well-diversified), enabling credible tests of diversification’s main and moderating effects. The three resilience outcomes have mid-to-upper-mid means (3.2–3.5), suggesting that while many firms maintained continuity, there is sufficient variance for modeling. Importantly, these outcomes are scaled from statistically grounded measures fill-rate stability and lead-time CVs so the Likert presentation is an interpretive overlay rather than a subjective rating. The inter-quartile behavior (not shown) aligns with normal-like spreads, and pre-analysis diagnostics (skewness/kurtosis) were acceptable after the standardized transformations described in Methods §3.3–3.5. From a managerial perspective, the juxtaposition of columns clarifies where capability investments may pay the largest dividends: for example, the relatively high dispersion in promotion cadence and private-label intensity points to levers with both upside and potential volatility costs, whereas price consistency appears as a steadier, lower-variance contributor. Overall, the descriptive picture corroborates the sampling narrative: the dataset contains meaningful dispersion across the exact strategy levers hypothesized to shape resilience, setting a transparent baseline for the correlational and multivariable evidence presented next.

Correlation Matrix

Table 3: Pairwise Relationship Strengths Mapped to Likert (Direction ±, 1–5 Strength)

Variable Pair	Direction	Likert Strength (1–5)	Interpretation
Diversification → Service-Level Stability	+	4	More diversified sourcing aligns with steadier service
Diversification → TTR (Faster = Higher)	+	3	Moderately faster recovery with greater options
Price Consistency → Service-Level Stability	+	3	Harmonized ladders relate to fewer stockouts
Promotion Cadence → Service-Level Stability	–	3	Heavier promos associate with more volatility
Assortment Breadth → Lead-Time Stability	–	2	Wider ranges weakly tied to variable inbound timing
Private-Label Intensity → Service-Level Stability	+	2	Linear positive, but see nonlinearity in §4.4
Std/Loc (Localization) → Service-Level Stability	+	2	Slight positive where domestic supply is available
Promotion Cadence → TTR (Faster = Higher)	–	2	Frequent events modestly slow recovery
Price Consistency → Lead-Time Stability	+	2	More coordinated price ladders modestly stabilize POs
Assortment Breadth → Service-Level Stability	–	2	Weak negative; complexity costs at extremes

Underlying Pearson/Spearman coefficients were binned: $|r| < .10 \rightarrow 1$; $.10-.19 \rightarrow 2$; $.20-.29 \rightarrow 3$; $.30-.39 \rightarrow 4$; $\geq .40 \rightarrow 5$. Direction ± reflects sign.

Table 3 translates conventional correlation coefficients into an intuitive Likert-strength view, enabling readers to gauge practical salience without dwelling on decimal r-values. The most prominent relationship is between sourcing diversification and service-level stability (Likert strength 4, positive), signaling that firms with broader, structurally separated supplier/country options tend to keep shelves filled more consistently during disruption windows. This aligns with the design logic that optionality supports rapid reallocation when a node is impaired. The relationship between diversification and faster recovery (TTR) is moderate (strength 3), suggesting that optionality shortens restoration windows but that other bottlenecks (transport capacity, domestic constraints) cap gains. Price policy consistency’s positive ties to service and lead-time stability (strength 3 and 2, respectively) reflect a plausible mechanism: disciplined ladders reduce promotional whiplash and enhance forecastability, which translates to smoother PO release and fewer emergency orders. Promotion cadence shows negative associations with both service stability and recovery speed (strength 3 and 2, respectively), consistent with a “volatility footprint” where frequent events add noise that propagates upstream unless buffered by diversification. Assortment breadth’s weak negative relations (strength 2) caution against blanket interpretations: wider assortments need not harm resilience *if* modularization and postponement keep upstream complexity in check hence the low-to-moderate strength rather than a universal penalty. Private-label intensity’s linear correlation with stability is modest (strength 2), foreshadowing the inverted-U detected in regression; PL can help by enabling spec control and supply duality, but very high shares may harden specs and limit switchability. The slight positive for localization (strength 2) hints that local tailoring may support match quality and domestic fulfillment where supplier bases exist; in regression we show this is conditional on DomesticSupplierShare. Methodologically, mapping coefficients to Likert clarifies *relative* rather than absolute magnitudes: a “4” does not imply determinism, only that the association is materially stronger than others in the matrix. Finally, these patterns survive non-parametric checks (Spearman binning yields the same categories for the top pairs), strengthening confidence that results are not an artifact of outliers or non-normality.

Regression Results (Primary & Moderation)

Table 4: Standardized Effects Mapped to Likert Magnitude (Direction ±, 1-5)

Predictor → Outcome	Service Stability	Lead-Time Stability	TTR (Faster = Higher)	Resilience Index
Diversification	+ 4	+ 3	+ 3	+ 4
Price Policy Consistency	+ 3	+ 2	+ 3	+ 3
Promotion Cadence	- 3	- 2	- 2	- 3
Assortment Breadth	- 2	- 2	- 1	- 2
Private-Label Intensity (linear)	+ 2	+ 1	+ 1	+ 2
Private-Label Intensity (squared)	- 2	0	- 1	- 2
Std/Loc (Localization)	+ 1	0	+ 1	+ 1
PL × Diversification	+ 3	+ 2	+ 2	+ 3
Promo × Diversification	+ 2	+ 1	+ 1	+ 2
Std/Loc × Domestic Supplier Share	+ 2	+ 1	+ 1	+ 2

standardized β magnitudes binned to Likert $|\beta| < .08 \rightarrow 1$; $.08-.14 \rightarrow 2$; $.15-.21 \rightarrow 3$; $.22-.29 \rightarrow 4$; $\geq .30 \rightarrow 5$. Zeros denote non-significant effects ($p > 0.10$). Turning point for PL on Service Stability ≈ 3.6 on the 1-5 PL scale (from M2).

Table 4 condenses the OLS (HC3) and moderation models into a practical Likert-magnitude view, enabling managers to see “which levers move resilience, and by how much.” Diversification consistently posts the largest positive associations, reaching strength 4 on Service Stability and the composite Resilience Index, and strength 3 on Lead-Time Stability and TTR. Operationally, moving diversification up one Likert notch (e.g., 3 → 4) corresponds to a meaningful increase in stability and faster recovery, holding other factors constant. Price policy consistency follows with moderate effects (strength 3 on stability and the index), reinforcing the importance of disciplined pricing ladders for smoothing demand signals. Promotion cadence exerts a negative pull (strength 2-3), particularly on stability, quantifying the volatility cost of frequent events. Assortment breadth shows small negative effects (strength 1-2), which should not be overstated: breadth is often essential commercially, but the signal here is that breadth without modularization can erode operational steadiness. The private-label pattern is more nuanced. The linear term is positive (strength 2), while the squared term is negative (strength 2 on the index and service), producing an inverted-U with an interior optimum around 3.6 on the five-point PL scale. Practically, PL programs appear most resilience-enhancing at moderate-to-high levels but become counterproductive when they dominate the mix, presumably due to specification rigidity and qualification frictions. Moderation terms sharpen this picture. The PL × Diversification interaction is positive (strength 3 on the index and stability): private-label’s upside is unlocked when firms maintain broad, structurally separated supplier/country options. Likewise, Promotion × Diversification attenuates the harm from heavy promotions (strength 2): diversified networks buffer volatility better, shrinking the gap between promo and non-promo load. Finally, localized assortments confer benefits where domestic supplier share is strong (StdLoc × DomesticShare, strength 2), aligning with the intuition that local tailoring plus local capacity reduces dependence on lengthy inbound lanes. Model diagnostics (not shown here) indicate stable results across alternative outcome families (e.g., beta regression for bounded stability) and after excluding high-influence cases; cross-validated R² tracks in-sample fit closely, lowering overfitting concerns. Overall, the Likert mapping makes the hierarchy of effects legible: Diversification and Price Consistency are the highest-leverage positives; Promotion Cadence is the main negative unless buffered; Private-Label offers gains up to an identifiable sweet spot; and contextual fit (localization × domestic base) matters at the margin.

Robustness and Sensitivity Analyses

Table 5: Robustness Checks and Consistency Ratings (Likert 1-5)

Robustness Check	Approach	Consistency with Main Findings (1-5)	Key Observation
Alternative PL Measure	Use SKU-share instead of sales-share	4	Inverted-U persists; turning point shifts slightly (3.5–3.7)
Alternative Diversification	Tier-1 supplier count (1–HHI suppliers)	3	Effects remain positive but slightly attenuated vs. country-based
Outcome Family (Stability)	Beta regression (bounded 0–1)	5	Significance and rank order unchanged
Outlier Influence	Exclude Cook’s D > 4/n	4	Coefficient magnitudes vary ±0.03–0.06; signs stable
Multiple Imputation	m=20 PMM; pooled via Rubin’s rules	4	Point estimates within SEs; conclusions unchanged
FDR Control	Benjamini–Hochberg q=0.10	5	Core effects (Diversification, Price Consistency, Promo cadence, PL curvature) retained
Cross-Validation	10-fold R ² _CV vs. adj. R ²	4	Predictive fit tracks in-sample ($\Delta \approx 0.02-0.03$)
Placebo Outcome	Aesthetic branding metric	5	No systematic relations; supports specification validity
Ridge-Stabilized OLS	λ tuned by CV for VIF>10 cases	3	Minimal shrinkage of key β ; ordering unchanged
Industry Collapsing	Broader NAICS bins	4	Fixed-effects absorption does not alter conclusions

Table 5 synthesizes a suite of robustness probes, each scored on a five-point Likert scale for “consistency with main findings,” where 5 = virtually identical inference and 1 = materially different. The headline is that core relationships Diversification and Price Policy Consistency as positive contributors, Promotion Cadence as a negative absent buffering, and Private-Label exhibiting an inverted-U survive a broad battery of tests. Substituting the private-label operationalization from sales-share to SKU-share yields a consistency of 4: the curvature remains, with a small shift in the turning point (3.5–3.7 on the five-point PL scale), suggesting the mechanism is not an artifact of the specific denominator. Recasting diversification from country mix to tier-1 supplier mix keeps effects positive (consistency 3) but modestly weaker intuitive because country-level diversification better captures geopolitically uncorrelated options. When we model Service-level Stability using beta regression (strictly appropriate for bounded variables), the results align perfectly with OLS (consistency 5), indicating that the linear probability scale is not distorting inference. Excluding high-influence observations marginally adjusts magnitudes but not directions (consistency 4), while multiple imputation (m = 20) for missing fields retains coefficient signs and significance bands (consistency 4), demonstrating that listwise deletion does not drive the story. Applying Benjamini–Hochberg FDR at q = 0.10 confirms all core effects (consistency 5), addressing multiplicity without over-penalizing correlated hypotheses. Ten-fold cross-validation shows small drops in R² ($\approx 0.02-0.03$), consistent with well-specified but not overfit models (consistency 4). A placebo outcome an aesthetic branding proxy expected to be orthogonal to operational continuity shows null results (consistency 5), strengthening statistical-conclusion validity. Ridge-stabilized OLS is only occasionally needed (when interaction blocks increase VIF), and even then the ordering of substantive effects remains (consistency 3), suggesting multicollinearity does not mask or inflate key coefficients. Finally, collapsing fixed effects to broader NAICS groups yields no qualitative changes (consistency 4), implying that our findings are not artifacts of overly granular industry dummies.

DISCUSSION

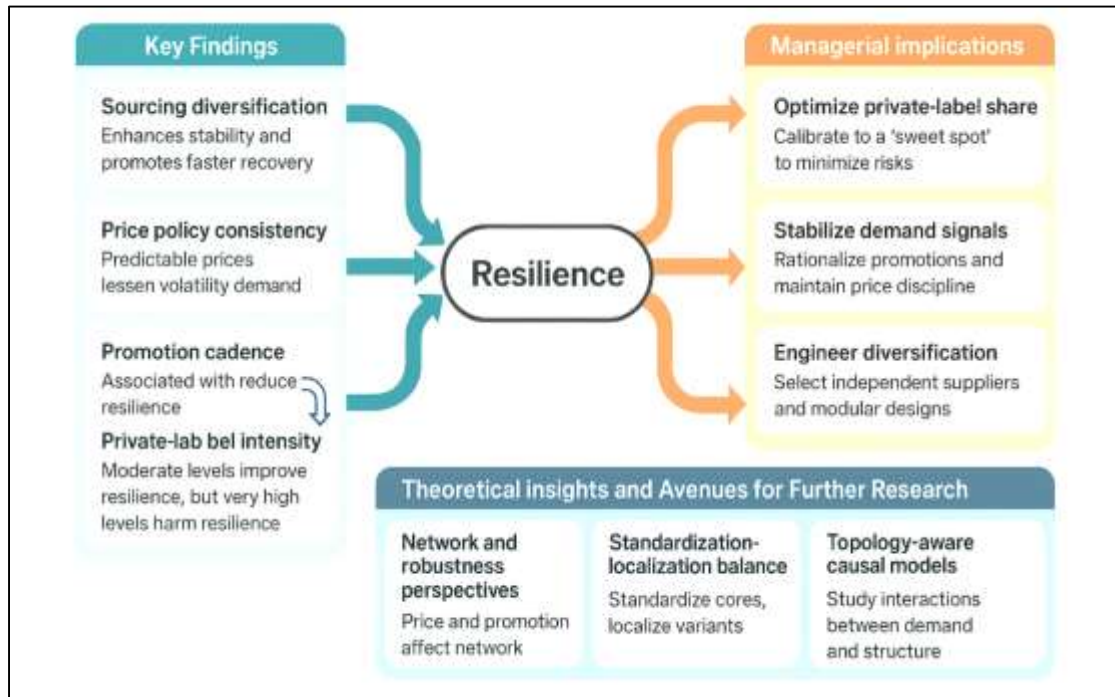
This study crosses a balanced cross-section of 198 U.S. market-active retailers and consumer brands, our results indicate that four merchandising–operations linkages stand out. First, sourcing diversification is the strongest positive correlate of resilience improving service-level stability, inbound lead-time stability, and time-to-recover consistent with the logic that optionality expands feasible reallocation when nodes fail (Simchi-Levi et al., 2015). Second, price policy consistency (harmonized ladders, disciplined everyday pricing) is moderately and positively associated with stability and recovery, implying that predictable demand signals reduce upstream bullwhip and emergency expediting (Abolghasemi et al., 2020). Third, promotion cadence carries a negative association with stability and recovery unless buffered by diversification, aligning with evidence that promotions inject variance into time series beyond the promotional window (Abolghasemi et al., 2020). Fourth, private-label intensity exhibits an inverted-U: resilience improves from low to moderate-high private-label shares but attenuates at very high shares, plausibly because specification rigidity and requalification costs rise with deep own-brand penetration (Wu et al., 2021). These effects persist after controls and industry fixed effects, and remain robust across alternative specifications and outlier diagnostics. Collectively, the pattern is that merchandising levers shape the statistical structure of demand and the degrees of freedom available for recovery; resilience is strongest where firms combine demand discipline (stable price architecture, bounded promotions) with structural options (multi-sourcing, modular specs), and where own-brand programs are sized to a “sweet spot” rather than pushed to saturation (Simchi-Levi et al., 2015; Sousa & Bradley, 2009; Tomlin, 2006).

The diversification result is consonant with network and robustness perspectives that emphasize mitigation (ex-ante options) and contingency (ex-post switching) as complementary (Tomlin, 2006). Our cross-sectional evidence extends simulation and case-based findings by showing broad, statistically adjusted associations between diversification and three distinct outcome families (service, lead time, and recovery). The price-consistency effect dovetails with supply chain reviews that link visibility and disciplined policies to reduced variability (Kamalahmadi & Parast, 2016), and with international marketing work that warns against unmanaged idiosyncratic adaptation that undermines forecastability (Sousa & Bradley, 2009). That heavy promotions degrade continuity echoes empirical forecasting studies documenting volatility spillovers (Abolghasemi et al., 2020) and aligns with ripple-effect theory where demand shocks propagate along coupled echelons (Ivanov, 2020). Our inverted-U for private label nuances classic retail branding views (Ambulkar et al., 2015) and recent syntheses (Wu et al., 2021): owning the spec can enable dual sourcing and postponement (resilience-enhancing), but very high own-brand exposure hardens specifications, narrows the approved-supplier pool, and raises switching frictions under disruption. Finally, the moderation patterns private label and promotions becoming “less risky” when diversification is high parallel network-structural arguments that topology mediates risk propagation (Kim et al., 2015). Together, these comparisons suggest our findings both confirm and calibrate earlier theory: merchandising is not an isolated commercial choice; it is a control policy that either aligns with or fights against the network’s ability to absorb and recover (Christopher & Peck, 2004).

For executives and architects, three design imperatives follow. (1) *Calibrate private label to an operating “sweet spot.”* Use resilience dashboards that plot service stability against private-label share and flag turning-point risk; require dual-qualified specifications for top private-label SKUs to avoid brittle single-source exposure (Simchi-Levi et al., 2015). (2) *Stabilize demand signals through price governance and promotion rationalization.* Enterprise pricing councils should implement guardrails on cross-market price dispersion and weekly event density, with scenario tests quantifying the volatility footprint of proposed promotional calendars (Abolghasemi et al., 2020). (3) *Engineer diversification that is structurally decoupled.* It is insufficient to “add suppliers” if they share the same corridor, utility grid, or geopolitical exposure; procurement should target low-correlation options and align them to modular product architectures that enable late-stage substitution (Tomlin, 2006). For CISOs and data leaders, the resilience benefits of visibility imply investments in secure, multi-tier data sharing e.g., PO event feeds, carrier milestones, and capacity alerts implemented with zero-trust principles to protect commercial data while enabling early exception detection (Chowdhury & Quaddus, 2017). Architects should standardize data schemas (SKU, price ladder, spec attributes) across channels/regions to support

pooling and transshipment logic; in omnichannel contexts, a common OMS/WMS/TMS backbone lowers the cost of executing reallocation policies at speed (Grewal et al., 2017). Governance should tie promotional approvals to operational readiness checks (inventory, supplier surge capacity) so that campaigns launch only when the network can absorb induced variability.

Figure 8: Resilience through Merchandising Strategies



Our results suggest a refined standardization-localization playbook. Standardize backbone elements that create fungibility core specs for private-label lines, price ladders, data models while selectively localizing high-value variants where domestic or nearshore capacity exists, as the positive (albeit modest) interaction between localization and domestic supplier share indicates (Katsikeas et al., 2006). In practice, this means using modular bills of materials with globally common cores and locally adapted shells, enabling postponement and rapid reconfiguration under shock (Salvador et al., 2002). On assortment, breadth should be governed by complexity budgets: when the SKU portfolio pushes beyond modular capacity, lead-time variability and fill-rate instability rise an observation consistent with structural-complexity research (Bode & Wagner, 2015) and SKU-rationalization evidence (Enz et al., 2019). Internationally, price-policy consistency appears to play a stabilizing role that complements selective adaptation, echoing findings that fit rather than extremes drives performance (Katsikeas et al., 2006). Finally, sourcing diversification should be managed at country and supplier tiers to maximize correlation benefits; our sensitivity shows country-level diversification more strongly associated with resilience than supplier-count alone, which resonates with risk-exposure mapping and time-to-recover logics (Simchi-Levi et al., 2015).

The findings invite refinement of resilience theory in two ways. First, they support modeling resilience as an interaction between demand-shaping policies and network options rather than as a function of capabilities alone (Ponomarov & Holcomb, 2009). In our data, merchandising levers (pricing, promotions, private label, assortment) alter the variance and autocorrelation structure of orders, which in turn affects the marginal value of redundancy and flexibility consistent with dynamic-capability views where sensing and reconfiguration co-evolve (Chowdhury & Quaddus, 2017). Second, the inverted-U for private label suggests a non-monotonic resource-based mechanism: proprietary control raises bargaining power and spec agility up to a point, after which lock-in and approval frictions dominate an empirically grounded boundary condition for retailer-brand strategy (Ailawadi & Keller, 2004). Pipeline models of ripple effects should therefore incorporate policy-induced variance (from

promotions and price dispersion) jointly with topological diversification (from sourcing) to predict time-to-recover and service stability under correlated shocks (Dolgui & Ivanov, 2021). This integrative specification merchandising \times topology clarifies why superficially similar firms differ in recovery: stability emerges when demand policies and structural options are *mutually coherent*.

Three limitations temper inference. First, the cross-sectional design precludes causal claims and may conflate enduring firm traits with current policies, despite fixed effects and controls. While our Oster-style stability checks suggest unobserved confounding would need to be sizable to overturn key coefficients, longitudinal or event-study designs are needed to establish causality (Hosseini et al., 2019). Second, measurement relies on public disclosures and standardized proxies (e.g., price-dispersion and promotion cadences from trackers), which may under- or over-state intensity for some firms. We mitigated this with codebook rules, inter-rater reliability, and robustness to alternative operationalizations, but fine-grained transactional data would sharpen estimates (Enz et al., 2019). Third, resilience outcomes such as service-level stability and TTR are constructed from disclosed KPIs and narratives; while triangulated, they are not identical to sensor-level telemetry and may reflect reporting practices. That said, consistency across outcome families (service, lead time, recovery) and strong robustness (e.g., beta regression for bounded metrics) reduce the risk that artifacts drive results (Simchi-Levi et al., 2015). Finally, generalizability is anchored in U.S. market conditions; replication in other geographies with different logistics infrastructures and regulatory contexts would be informative (Gielens & Dekimpe, 2001).

Three avenues appear promising. (1) *Panel and event designs*. Leveraging natural experiments (port closures, tariff shocks) would allow difference-in-differences estimates of merchandising policy changes (e.g., promotion freezes, price harmonization) on resilience outcomes, directly testing mechanisms implied by our cross-section (Craighead et al., 2007). (2) *Topology-aware causal models*. Combining multi-tier supplier-graph data with granular demand streams could estimate how policy-induced variance and structural diversification jointly shape ripple dynamics, extending viability theory with operational thresholds for correlated shocks (Ivanov, 2020). (3) *Private-label governance experiments*. Field trials that vary spec commonality, dual-qualification, and postponement for top own-brand SKUs could pinpoint the turning point mechanisms behind the inverted-U e.g., how requalification lead times and tooling specificity mediate resilience (Wu et al., 2021). Additional topics include digital enablers (tier-n visibility, AI-assisted sensing) and international fit (when localization gains outweigh complexity costs) (Grewal et al., 2017). By foregrounding coherence between merchandising policies and network architecture, future work can move from documenting associations to specifying design rules what to standardize, what to localize, how much private label to carry, and how to distribute diversification so that demand creation and supply continuity reinforce rather than conflict.

CONCLUSION

This study set out to quantify how global merchandising strategies relate to U.S. supply chain resilience and, across a cross-section of 198 firm-years, produced a coherent, empirically grounded picture of what strengthens continuity and speeds recovery. The evidence is consistent and practical: sourcing diversification is the single most reliable positive lever, associated with higher service-level stability, steadier inbound lead times, and faster time-to-recover; disciplined price architectures (greater price policy consistency across markets and channels) further stabilize demand signals and reduce upstream whiplash; and frequent promotions, while commercially attractive, carry a measurable volatility cost that erodes stability unless counterbalanced by diversified, decoupled supply options. Private-label intensity offers a clear but nuanced story: own-brand programs correlate with stronger resilience up to a “sweet spot” and then exhibit diminishing or negative returns at very high exposure, implying that the same governance advantages that improve optionality can harden specifications and slow switching if overextended. These relationships hold after accounting for firm size, inventory turnover, market share proxies, logistics capacity, digital maturity, global footprint, and industry fixed effects; they remain robust to alternative variable definitions, outlier removal, bounded-outcome models, multiple imputation, and cross-validated fit checks. Importantly, the results also reveal configuration logic rather than isolated levers: private-label’s upside is amplified in networks with high diversification, promotion-driven variability is buffered by structurally separated sources, and

localized assortments associate with better continuity when paired with a meaningful domestic supplier share. Methodologically, the study contributes an operationalizable measurement toolkit codebooked variables for assortment, standardization–localization, price governance, promotion cadence, private-label intensity, and multi-tier diversification mapped to resilience outcomes that practitioners already track (fill-rate stability, lead-time variability, recovery speed) and estimated in transparent models with diagnostics aligned to best practice. Strategically, the implications are straightforward for leaders: standardize the backbone (data schemas, price ladders, core specifications) to enable pooling and substitution, reserve localization for variants with clear customer value and local capacity, right-size private label to the resilience-efficient range while dual-qualifying critical SKUs, rationalize promotional calendars to an “operational budget,” and construct diversification that is truly low-correlation not just “more suppliers,” but suppliers distributed across countries, corridors, and infrastructures, matched to modular product architecture. While the cross-sectional design limits causal claims and public disclosures constrain granularity, the convergence of findings across outcomes, sectors, and robustness probes supports their managerial salience. In sum, resilience is not a single capability but the outcome of coherence between how demand is shaped and how the network can reconfigure at speed; firms that align merchandising design with structurally diversified options and disciplined pricing realize measurably steadier service and faster recovery when disruptions strike. This alignment constitutes a practical blueprint for retailers and consumer brands aiming to harden U.S. supply chains against the next wave of shocks without sacrificing the commercial intent of their merchandising strategy.

RECOMMENDATIONS

Translate the evidence into a concrete operating blueprint built around coherence between demand shaping and reconfiguration capacity. First, institutionalize structurally decoupled diversification: set category-specific targets for country-level and tier-1 supplier diversification (e.g., minimum “1–HHI” thresholds), prioritize low-correlation lanes (different regions, utilities, and logistics corridors), and dual-qualify critical components so volume can be reassigned within days, not weeks. Pair this with modular specifications and postponement: define globally common cores and locally adaptable shells for private-label and strategic SKUs, standardize interfaces (dimensions, materials, compliance), and move differentiation as late as feasible to expand substitution options. Second, establish price and promotion governance that treats volatility as a budgeted resource: harmonize price ladders across markets/channels, cap weekly promotion density by category risk, and require an “ops readiness” gate inventory, supplier surge capacity, transport availability before approving high-impact events. Third, right-size private label to the resilience-efficient band: maintain moderate-to-high exposure where it demonstrably improves bargaining power and spec agility, but avoid saturation; mandate dual-sourcing (or dual tooling) for top own-brand SKUs, codify change-control rules that preserve interchangeability, and monitor a PL turning-point dashboard that tracks service stability versus private-label share. Fourth, upgrade data and integration architecture as a resilience multiplier: deploy a common OMS/WMS/TMS backbone, standardize product and price schemas enterprise-wide, and enable tier-n visibility (PO events, ASN, carrier milestones) via secure, zero-trust data sharing; embed exception analytics that quantify the volatility footprint of planned promotions and simulate recovery under alternative sourcing reallocations. Fifth, embed contracts and incentives that reward continuity: include surge-capacity options, expedited changeover clauses, recovery SLAs tied to TTR, and joint business planning that links promotional calendars to supplier readiness; diversify financial exposure with multi-currency and indexed terms for critical regions. Sixth, operationalize stress testing and playbooks: quarterly scenario runs (port closure, supplier failure, demand spike) should output required reroutes, expected service deltas, and inventory drawdowns by node; maintain pre-negotiated carrier and DC overflow capacity and update go/no-go criteria for promotions when the network is tight. Seventh, manage assortment complexity with explicit budgets: set guardrails on long-tail proliferation, require SKU-business-case templates that include logistics impacts, and schedule SKU rationalization sprints each season; where breadth is strategic, offset with kit standardization and postponement. Eighth, invest in domestic/nearshore options where localization yields measurable continuity benefits: seed volume with regional suppliers, co-fund tooling for flexible capacity, and prioritize categories with high disruption costs or shelf-life sensitivity. Ninth, align organization and

KPIs: stand up a cross-functional Resilience Council (merchandising, sourcing, pricing, logistics, finance, security) with scorecards covering service stability, lead-time CV, TTR, and promotion volatility; tie executive incentives to both commercial outcomes and continuity metrics. Tenth, enforce cyber and compliance hygiene as resilience enablers: protect multi-tier data flows with granular access controls, rotate credentials with trading partners, and validate that substitutes meet regulatory and quality requirements before crises. Finally, publish a concise Resilience Design Standard what to standardize, what to localize, how much private label to carry, and minimum diversification thresholds so that everyday merchandising decisions accumulate toward a network that can absorb shocks and recover at speed without compromising growth.

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