

Corridor Disruption and Supply Chain Vulnerability: A NASCDI-NARDL Analysis of Kashmir's Apple Sector

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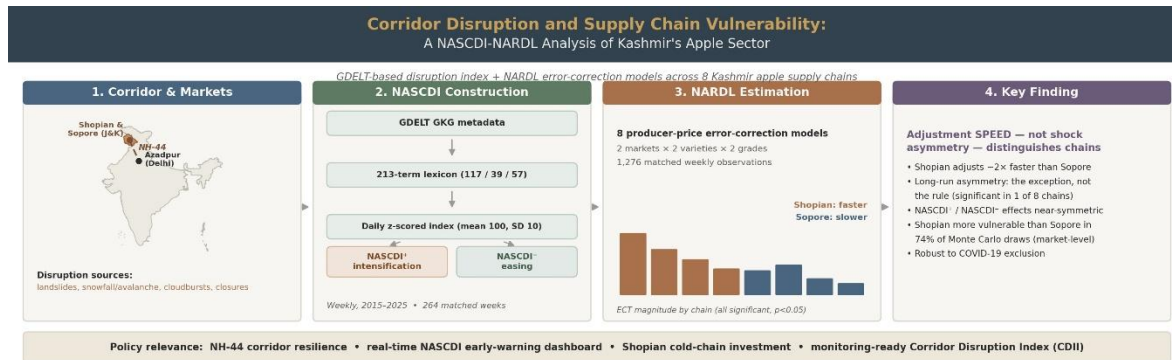
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GRAPHICAL ABSTRACT



Graphical Abstract. Corridor Disruption and Supply Chain Vulnerability: A NASCDI-NARDL Analysis of Kashmir's Apple Sector. The NASCDI-NARDL framework links NH-44 corridor disruption events to heterogeneous producer-price adjustment speed between Kashmir producer markets (Shopian and Sopore) and the Azadpur terminal market, with long-run asymmetric transmission confirmed in only one of eight market-variety-grade chains.

Corridor Disruption and Supply Chain Vulnerability: A NASCDI-NARDL Analysis of Kashmir's Apple Sector

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Abstract

Agricultural supply chains that depend on a single transport corridor are structurally exposed to disruption, yet price-transmission studies rarely measure disruption intensity directly, relying instead on binary event indicators or case narratives. We construct the Nonlinear Asymmetric Supply-Chain Disruption Index (NASCDI), a weekly, reproducible measure of highway-disruption intensity built from GDELT Global Knowledge Graph metadata, and apply it to Kashmir's apple trade, where nearly all output moves through a single highway, NH-44, to the Azadpur terminal market in Delhi. Using a nonlinear autoregressive distributed lag (NARDL) framework across eight producer-market-variety-grade chains (1,276 matched weekly observations, 2015-2025), we find universal long-run cointegration between producer and terminal prices, but adjustment speed differs sharply by origin: Shopian chains re-equilibrate roughly twice as fast as Sopore chains. Asymmetric transmission, intensification versus easing, is limited and chain-specific rather than pervasive, significant in only one chain at the long-run horizon. A composite vulnerability index combining disruption sensitivity, adjustment speed, and model support, validated by a 10,000-draw bootstrap, shows individual-chain rankings are only moderately stable but that Shopian is more exposed than Sopore as a market in 74% of simulations. We translate these findings into a real-time monitoring design and an illustrative parametric-insurance trigger, and show the NASCDI methodology is transferable to other corridor-dependent agricultural systems.

Keywords: Supply-Chain, NASCDI, GDELT, Apple, Kashmir, NARDL, Asymmetric transmission

1. INTRODUCTION

Apple (*Malus domestica* Borkh.) cultivation forms the economic backbone of the Kashmir Valley in Jammu and Kashmir (J&K), India, contributing approximately 70-75% of the country's total apple output (MoAFW, 2023) and sustaining the livelihoods of more than 3.5 million people through direct and indirect employment (GoJK, 2021; NHB, 2022). The sector accounts for approximately 8-9% of J&K's Gross State Domestic Product, making apple cultivation a macroeconomic foundation rather than merely a household livelihood activity (DES J&K, 2023).

This sector operates under a severe structural constraint, virtually all Valley apples must reach distant wholesale markets through a single overland corridor, National Highway 44 (NH-44), which connects the Valley to the Indian national highway network via the geodynamically active Banihal-Ramban mountain section. Approximately 90% of Kashmir apple exports transit this single corridor (APEDA, 2021). Disruption episodes are recurrent, encompassing landslides, snowfall and avalanche events, cloudbursts, security-related closures, and pandemic mobility restrictions (2020-2021) and occur precisely during and after the peak harvesting season (Mir and Mir, 2018). When disruptions occur, supply congestion at origin markets depresses farm-gate prices while restricted arrivals at the Azadpur wholesale market in Delhi sustain elevated terminal prices, defeating the spatial arbitrage mechanism that ordinarily integrates geographically separated markets.

From a food systems and smallholder welfare perspective, the NH-44 corridor disruption problem is not merely a market efficiency question: the 3.5 million livelihoods dependent on Kashmir's apple economy situate corridor disruption as a recurring food-economy risk with macroeconomic consequences for the UT of J&K (GoJK, 2021; DES J&K, 2023), even though this revision does not attempt a monetary producer-surplus estimate (Section 5.4). The supply chain risk management imperative of measuring and monitoring single-corridor dependency exposure in developing-country agricultural systems is directly engaged by the NASCDI-NARDL framework and the monitoring-oriented CDII protocol proposed here. From a market-efficiency perspective, well-functioning agricultural markets are expected to be spatially integrated, prices at geographically separated nodes should move together over time through arbitrage (Fackler and Goodwin, 2001; Barrett, 2001). This proposition has been examined extensively for Indian staple commodities (Acharya et al., 2012; Ghosh, 2010; Sekhar, 2012) and more recently in transaction-cost settings (Ahmed et al., 2023, 2024). For high-value horticultural produce such as apples, the evidence is considerably thinner, perishability compresses the arbitrage window, quality deterioration renders delay irreversible, and logistical constraints in remote production areas limit market participants' ability to act on price signals (Birthal et al., 2014; Chand et al., 2017). Recent work shows that disruptions in fragile supply chains can override the arbitrage mechanism during shock episodes (Sutradhar et al., 2024; Sharma et al., 2025).

A second, broader gap concerns the assumption of symmetric price adjustment embedded in standard price-transmission models. The empirical literature has long documented that price

transmission is frequently asymmetric, markets respond differently to positive and negative shocks driven by transaction costs, intermediary market power, and adjustment rigidities (Goodwin and Holt, 1999; Meyer and von Cramon-Taubadel, 2004; Frey and Manera, 2007; Lloyd, 2017; McCorriston et al., 2001). In perishable commodity markets, asymmetry is amplified because time delays trigger irreversible quality losses, forcing distress sales that depress producer prices long after the original disruption has passed (Sexton and Xia, 2018; von Cramon-Taubadel and Goodwin, 2021). Evidence from sub-Saharan African rice markets (Chitete et al., 2025), Sri Lankan horticultural chains (Harshana and Ratnasiri, 2023b), and the German fish market (Bronnmann and Bittmann, 2019) confirms that asymmetric transmission is product-specific and pervasive. A third gap is the near-complete absence of explicit, quantified disruption measures in price-transmission studies for developing-country agricultural markets (Minot, 2014; Brümmer et al., 2016).

Motivated by these three gaps, this paper makes three original and mutually reinforcing contributions. First, we introduce the Nonlinear Asymmetric Supply-Chain Disruption Index (NASCDI), a transparent, reproducible index constructed from targeted GDELT Global Knowledge Graph (GKG) metadata that converts real-world NH-44 disruption signals into a weekly time series spanning 2015-2025, decomposed into cumulative intensification (NASCDI⁺) and easing (NASCDI⁻) partial-sum components. The NASCDI extends the news-based index methodology of Baker et al. (2016) and Caldara and Iacoviello (2022) to an agricultural supply-chain context in a developing country, building on GDELT applications by Leetaru and Schrodtt (2013) and the commodity-price news-signal evidence of Narayan and Gupta (2015). Second, we integrate the NASCDI into the NARDL framework of Shin et al. (2014) to estimate asymmetric short-run and long-run disruption effects simultaneously across eight market-variety-grade combinations, addressing both the asymmetry gap and the missing-disruption-variable gap in the horticultural price-transmission literature. Third, we construct a formally defined composite vulnerability index (Section 4.5) whose Monte Carlo sensitivity check indicates that disruption risk is more reliably characterised at the market level, Shopian chains more likely than not to be more exposed than Sopore chains, than resolved to a single dominant chain, and we provide evidence that heterogeneous adjustment speed, not asymmetric shock transmission, is the more robust structural feature distinguishing chains (the NASCDI⁻ and NASCDI⁺ responses contribute nearly equally to the vulnerability ranking, Section 5.5), consistent with the largely non-significant long-run asymmetry documented in Table 6. This finding reframes the policy problem toward adjustment-speed heterogeneity across markets rather than a single dominant shock-transmission channel.

The findings carry direct policy significance for agricultural market governance in corridor-dependent, conflict-affected production regions. Slower price-adjustment speed in Shopian relative to Sopore chains implies that NH-44 disruptions take longer to work through Shopian's market before prices re-equilibrate, plausibly straining smallholder growers who lack the storage capacity or financial reserves to withhold supply during closures, though this revision

does not attempt to quantify the resulting welfare cost (Section 5.4). This evidence points to three complementary policy responses operating at distinct institutional levels. At the central government level, targeted NH-44 corridor resilience investment including the Banihal-Qazigund railway link, Ramban bypass stabilisation, and strategic buffer stockpiling at Nashri addresses the root cause of disruption exposure. At the state level, a real-time NASCDI-based early-warning dashboard would allow growers and traders to pre-position cold storage and logistics decisions before disruptions intensify, shortening the post-disruption recovery window that the econometric evidence identifies as the primary structural inefficiency. At the market level, a parametric Corridor Disruption Index and Information (CDII) protocol, designed here as a validation-ready monitoring and product-design framework rather than an actuarially priced instrument, sets out how NASCDI-based triggers could eventually compensate income losses that neither infrastructure nor information systems can fully prevent, once the underlying multiplier and quantity evidence supports formal pricing. The replicability of the NASCDI methodology to other corridor-dependent horticultural supply chains including Himachal Pradesh cherry and walnut chains and the Siliguri Corridor for northeastern exports extends the policy relevance of this framework beyond the Kashmir context.

The paper is structured as follows. Section 2 reviews relevant literature. Section 3 describes the study area, price data, and NASCDI construction. Section 4 presents the full econometric methodology, including endogeneity treatment (Section 4.3), structural break testing (Section 4.4), and the formal vulnerability index definition (Section 4.5). Section 5 presents empirical results, including COVID-19 robustness analysis (Section 5.7). Section 6 discusses findings. Section 7 presents targeted policy implications. Section 8 presents the conclusion. Section 9 consolidates limitations. Section 10 outlines future research directions. Acknowledgements, data availability, and ethical statements follow thereafter. All code, data, and figures are archived at: <https://doi.org/10.5281/zenodo.19491887>

2. BACKGROUND AND LITERATURE

2.1 Supply Chain Risk, Disruption, and Resilience

Supply chain risk management (SCRM) research defines disruption risk as the probability and consequence of exogenous events that interrupt the flow of goods between adjacent supply chain nodes (Kleindorfer and Saad, 2005), and supply chain resilience as a system's capacity to return to its original, or a more desirable, state after such a disruption (Christopher and Peck, 2004). Jüttner et al. (2003) and Ho et al. (2015) identify the quantification of disruption exposure at the level of individual supply chain nodes, rather than reliance on binary event indicators or retrospective case narratives, as a persistent gap in this literature. Craighead et al. (2007) show empirically that the severity of a supply chain disruption is shaped by structural design characteristics, node density, node complexity, and node criticality, so that supply chains organised around a single critical node or corridor are structurally predisposed to more severe disruption outcomes than more redundant network configurations. Chopra and Sodhi (2004) frame this as an explicit trade-off between the efficiency gains of a single, low-cost transport route and the risk exposure that concentration creates, and Tang (2006) catalogues the robust mitigation strategies. diversified sourcing, flexible routing, buffer capacity, that this trade-off makes costly to adopt in a single-corridor system; both dimensions remain rarely quantified with continuous, node-specific disruption data in agricultural settings.

The Kashmir apple sector's dependence on a single national highway is an unusually extreme, and unusually well-documented, instance of this structural vulnerability: virtually the entire flow of a 3.5-million-livelihood agricultural economy is routed through one corridor with no viable alternative. This setting allows the present study to test, with node-level econometric precision, a question central to the SCRM literature but rarely operationalised at this granularity: when a critical corridor is disrupted, does the resulting price signal propagate symmetrically through the downstream chain, and does recovery speed differ systematically across otherwise similar chains sharing the same corridor? Both questions bear directly on how disruption risk should be measured, monitored, and mitigated in corridor-dependent supply chains more broadly (Bode and Wagner, 2015; Dolgui, Ivanov and Sokolov, 2018).

2.2 Price Transmission as a Market-Level Signal of Supply Chain Disruption

Within the SCRM literature, the price gap between adjacent supply chain nodes is itself an observable signal of disruption propagation: when a node-to-node link functions normally, prices at geographically separated nodes move together through arbitrage, but when that link is disrupted, the price relationship distorts in a manner that mirrors the ripple effect documented in manufacturing and logistics supply chains (Dolgui, Ivanov and Sokolov, 2018). The canonical framework of spatial market integration formalises this baseline expectation: in competitive, open markets, prices at geographically separated nodes should be cointegrated, linked by a long-run equilibrium relationship maintained through arbitrage and trade (Fackler and Goodwin, 2001; Barrett, 2001; Rapsomanikis et al., 2006). Empirical studies consistently demonstrate integration within Indian agricultural markets but document substantial heterogeneity in adjustment pace and completeness, particularly in markets characterised by infrastructural constraints, protracted

intermediation chains, and policy distortions (Acharya et al., 2012; Sekhar, 2012; Chand et al., 2017; Ahmed et al., 2024). Initiatives such as e-NAM (Electronic National Agriculture Market) have been shown to improve price discovery and integration in select commodity chains, though coverage remains incomplete in remote horticultural-producing regions (FAO, 2023; World Bank, 2023; MoAFW, 2023).

The evidence is considerably less positive for high-value horticultural commodities. Perishability constrains the arbitrage window; quality deterioration renders delayed adjustment irreversible; and logistical constraints in remote production areas limit market participants' ability to respond to price signals (Birthal et al., 2014). Research on apple markets in India is limited (Wani et al., 2015; Ali et al., 2018a, 2018b; Sutradhar et al., 2024) and none has examined corridor disruptions as a quantitative explanatory variable. The global literature confirms that perishable commodity markets exhibit greater price volatility and diminished integration relative to storable commodities, attributable to logistical and quality constraints (Sharma et al., 2025). The World Bank (2024) identifies single-corridor dependence as a critical systemic vulnerability in developing-country agricultural supply chains, and Lloyd (2017) notes that four decades of price-transmission research have systematically under-represented supply-chain shock mechanisms in developing-country contexts, a gap that mirrors the broader SCRM literature's own call for disruption measures grounded in continuous, node-specific data rather than binary event indicators (Ho et al., 2015).

2.3 Asymmetric Risk Transmission and Supply Chain Vulnerability

Within SCRM, a supply chain's vulnerability is defined by its differential exposure and differential response to disruption of different kinds and directions (Wagner and Bode, 2006); asymmetric price transmission is one of the clearest quantitative expressions of this differential response available in observational market data. Goodwin and Holt (1999) and Meyer and von Cramon-Taubadel (2004) document that price adjustments frequently differ according to the direction of change, identifying transaction costs, intermediary market power, and adjustment rigidities as the primary drivers. Frey and Manera (2007) provide a comprehensive taxonomy demonstrating that asymmetry is pervasive across commodity markets and geographies. McCorriston et al. (2001) formally model the interaction between market power and price pass-through, showing that even modest buyer concentration generates asymmetric outcomes. Hassouneh et al. (2012) confirm asymmetric transmission in European food supply chains.

In the context of perishable commodities, Sexton and Xia (2018) emphasise that buyer concentration and intermediary dominance produce systematically asymmetric outcomes: intermediaries pass upstream shocks to producers quickly and sharply but delay the transmission of downstream price improvements. This pattern is confirmed for South Asian horticultural supply chains (Sharma et al., 2025), Sri Lankan perishable markets (Harshana and Ratnasiri, 2023b), Malawian rice markets (Chitete et al., 2025), and European food chains (Hassouneh et al., 2012). Lloyd (2017), synthesising four decades of research, identifies asymmetry as the most empirically robust deviation from the symmetric benchmark, with perishability and intermediary market

structure as the dominant explanatory factors. Bronnmann and Bittmann (2019) document how asymmetric transmission in the German fish market arises specifically from the combination of perishability and concentrated wholesale buyer structures, a configuration directly analogous to the Kashmir apple case, and consistent with the SCRM finding that firms and market nodes differ systematically in their capacity to absorb disruption without transmitting it onward (Ambulkar, Blackhurst and Grawe, 2015).

The NARDL model of Shin et al. (2014) provides the preferred empirical framework, decomposing the regressor into cumulative positive and negative partial sums and estimating distinct long-run and short-run effects for each direction of change. Applications include Sharma et al. (2025) for Indian perishables, Harshana and Ratnasiri (2023b) for Sri Lankan horticultural markets, Panagiotou (2021) for US pork, Rezitis (2019) for Finnish dairy, and Chitete et al. (2025) for Malawian rice, confirming the generalisability of the NARDL approach across diverse commodity and country settings.

2.4 Measuring Supply Chain Disruption from News and Text Data

Blackhurst et al. (2005) identify the absence of continuous, real-time disruption measures, as opposed to retrospective case studies or binary event dummies, as one of the most consequential unresolved issues in supply chain disruption research, a gap the news-based index literature is well positioned to close. Baker et al. (2016) established the news-based index methodology with the Economic Policy Uncertainty (EPU) index; Caldara and Iacoviello (2022) extended it to geopolitical risk, demonstrating that text-based indices from publicly accessible news media can capture economically significant variation in risk that formal data sources do not record. The GDELT Project provides continuously updated, publicly accessible coverage of the global English-language press from 1979 onward and has been widely used for event-based economic index construction (Leetaru and Schrod, 2013). Narayan and Gupta (2015) demonstrate that news-based indicators carry predictive content for commodity price dynamics beyond what formal statistical releases provide. Applying this methodology to measure corridor-level supply chain disruption exposure in a developing-country agricultural setting, where official disruption records are absent, incomplete, or produced with long lags, is a primary methodological contribution of the present study.

2.5 The Kashmir Apple Supply Chain: An Extreme Case of Single-Corridor Dependency

The Shopian and Sopore APMCs are the main institutional nodes in the Kashmir Valley's apple marketing system, connecting growers, orchard contractors (baghbans), packinghouse operators, commission agents (arthiyas), and transporters (Mir and Mir, 2018; GoJK, 2021). Commission agents advance credit to growers and retain a percentage of transaction value, creating a credit-market dependency that weakens growers' bargaining position during supply congestion (Gulati et al., 2018). Wani et al. (2015) and Ali et al. (2018b) document apple market integration in India and J&K, finding evidence of co-movement but incomplete price transmission. Sutradhar et al. (2024) use recent data to document price forecasting patterns, confirming the seasonal and logistical sensitivity of these markets. None of these studies, however, incorporates supply-chain

disruptions as a quantitative explanatory variable, leaving the gap that the present study directly addresses. In Craighead et al.'s (2007) terms, the Shopian-Sopore-Azadpur system combines high node criticality (a single terminal market absorbs the great majority of export volume), low node density (two producer nodes, one corridor, one terminal), and a long, thin geographic tail (the Banihal-Ramban mountain section), the precise structural profile their framework associates with the most severe disruption outcomes, making this an unusually well-specified test case for corridor-dependency risk.

2.6 Research Hypotheses

Synthesising these strands of the supply chain risk and price-transmission literatures, this study tests four hypotheses:

H1 (Long-Run Integration): Producer markets in Kashmir and the Azadpur terminal market are cointegrated across all eight market-variety-grade combinations, reflecting long-run spatial arbitrage.

H2 (Asymmetric Transmission): Price transmission between producer and terminal markets is asymmetric, with responses to NASCDI changes differing by direction.

H3 (Differential Disruption Impact): Disruption intensification (NASCDI⁺) has a stronger and more persistent effect on prices than disruption easing (NASCDI⁻).

H4 (Concentrated Vulnerability): Disruption effects are concentrated in specific market-variety-grade combinations, particularly those with greater NH-44 corridor exposure and wider price spreads.

3. STUDY AREA, DATA, AND NASCDI CONSTRUCTION

3.1 Study Area and Market Selection

The empirical analysis focuses on three market nodes: Shopian (southern Kashmir), Sopore (northern Kashmir), and Azadpur (New Delhi). Shopian district has emerged as one of the highest-volume apple-producing areas in J&K, with the American and Delicious varieties dominating commercial production destined for long-distance wholesale trade (Ali et al., 2018b; DES J&K, 2023). The designated APMC trading facility for the study area within Shopian district is the Aglar APMC, which serves as the primary first-sale node for smallholder growers in the Shopian valley and is the source of all Shopian producer price data used in this study. District orchards are characterised by fragmented holdings averaging 0.5-1.5 hectares, with over 70% of production controlled by smallholder growers who rely entirely on APMC-based marketing and commission-agent intermediation (GoJK, 2021; Mir and Mir, 2018). Sopore, in Baramulla district, hosts one of the largest fruit wholesale markets in Asia by transaction volume and functions as the primary aggregation hub for northern Valley apple production, with a more developed trader network and greater storage capacity (GoJK, 2021; NHB, 2022). Producer price data for Sopore are sourced from the Nowpora APMC sub-node (Nowpora Mandi, Baramulla district), which is the primary price-reporting facility for the Sopore apple-marketing zone on the Agmarknet platform.

The Azadpur APMC wholesale market in Delhi is the largest fruit and vegetable wholesale market in India and the dominant price-discovery node for apples sold across northern, western, and central Indian consumption centres (APEDA, 2021; Wani et al., 2015). The two producer markets represent contrasting agro-ecological zones, marketing structures, and positions along the NH-44 corridor, enabling systematic comparison of disruption sensitivity across origins. The spatial configuration is illustrated in Figure 1.

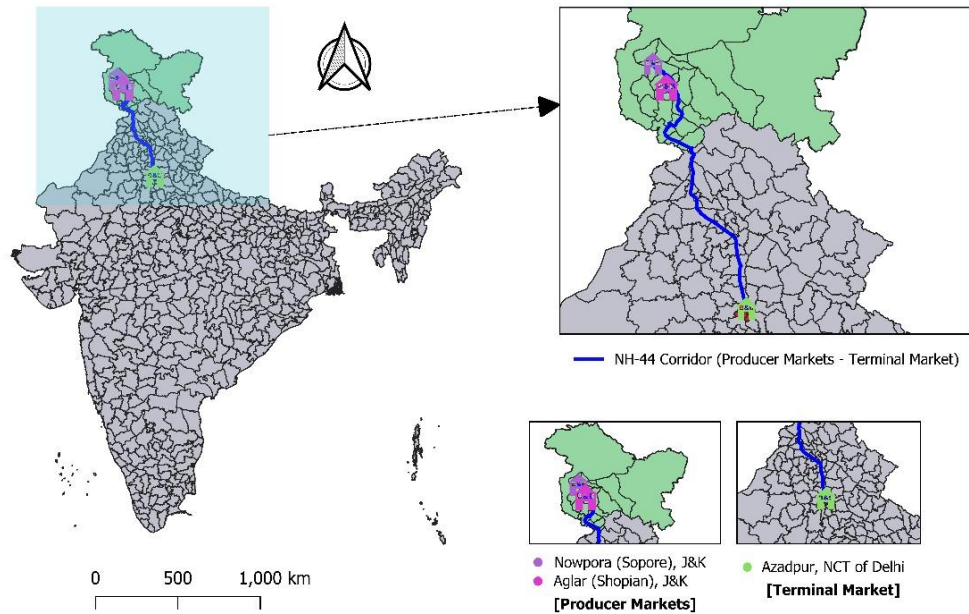


Figure 1. Spatial linkage of producer markets (Sopore and Shopian) and the Azadpur terminal market along the NH-44 transport corridor.

3.2 The NH-44 Transport Corridor

National Highway 44 is the sole overland link between the Kashmir Valley and the Indian national highway network (APEDA, 2021; GoJK, 2021). The highway traverses the geodynamically active Banihal-Ramban mountain section and sections prone to avalanche near Qazigund and flooding near Udhampur. Mir and Mir (2018) identify the inherent fragility of this corridor as the primary supply-chain risk for Kashmir apple growers, noting that disruption-induced delays of three to five days can reduce the quality grade of American variety apples by 25-40%. During the September 2025 NH-44 closure triggered by landslides and flooding, media reporting documented more than 2,000 trucks stranded on the highway, a substantial proportion carrying apples from southern Kashmir districts including Shopian (Reuters, 2025; Down to Earth, 2025). Disruption episodes are recurrent, encompassing landslides, snowfall and avalanche events, cloudbursts, security-related closures, and pandemic mobility restrictions (2020-2021), all of which directly create the logistical shock mechanism that the NASCDI is designed to capture and quantify. The September 2025 NH-44 closure referenced in Sections 3.2 and 6.2 as a post-sample validation event is not part of the estimation dataset; it is cited solely to demonstrate that the corridor disruption mechanism identified in the NARDL results continued to operate after the estimation period ended.

3.3 Price Data

3.3.1 Data Source and Institutional Context

Weekly apple wholesale price data are sourced from the Agmarknet portal (<https://agmarknet.gov.in>), maintained by the Directorate of Marketing and Inspection (DMI), Ministry of Agriculture and Farmers' Welfare, Government of India, the primary institutional repository for statutory market price data in India (DMI, 2023; Acharya et al., 2012). Agmarknet collects daily price arrivals from Agricultural Produce Market Committee (APMC) markets under a mandatory reporting framework. The platform records separate price series by commodity, variety, and quality grade, offering the most granular and institutionally authoritative source of apple price data available for the study region. All price data used in this study were downloaded directly from the Agmarknet portal under open-access provisions and are fully reproducible from the replication archive.

3.3.2 Market Nodes and Coverage Period

Data are assembled for three APMC market nodes constituting the Kashmir-Delhi apple supply chain: (i) Aglar APMC, Shopian district (producer market, southern Kashmir); (ii) Nowpora APMC, Baramulla district (producer market, northern Kashmir, commonly identified under the broader Sopore market designation); and (iii) Azadpur APMC, New Delhi (terminal wholesale market). The producer markets provide the farm-gate or first-sale price; the terminal market at Azadpur provides the wholesale price at the largest fruit distribution node in India (APEDA, 2021). The spatial linkage of these three nodes along the NH-44 corridor is illustrated in Figure 1.

Coverage periods differ across market nodes due to the staggered introduction of systematic digital reporting on the Agmarknet platform. Azadpur apple price records are available from January 2012 onwards; Sopore (Nowpora APMC) records commence from August 2015; and Shopian (Aglar APMC) records commence from September 2017. These staggered start dates directly determine the estimation sample sizes reported in Section 3.3.4, and reflect the well-documented gradual rollout of Agmarknet reporting in J&K relative to the earlier and more complete coverage of major terminal markets (Babu et al., 2023; DMI, 2023).

3.3.3 Raw Data Structure and Variables

The raw data are structured as daily price records, with each observation containing ten fields: (i) Date; (ii) District; (iii) Market (APMC name); (iv) Fruit (Apple); (v) Variety (American or Delicious); (vi) Grade (A or B); (vii) Minimum price (₹/kg); (viii) Maximum price (₹/kg); (ix) Average price (₹/kg); and (x) a binary Mask indicator (1 = valid trading day, 0 = no recorded transaction). The Mask variable is used in pre-processing to distinguish structural trading gaps (e.g., market holidays, off-season weeks) from data reporting failures. Average price (₹/kg) is the primary estimation variable throughout this study.

The dataset encompasses two apple varieties American (Richard variety of Kashmiri apple, prized for export quality and higher unit values) and Delicious (the Royal/Golden Delicious

complex, the dominant domestic consumption variety) and two quality grades for each variety. Grade A denotes premium-quality fruit meeting export-grade size, colour, and blemish-free standards; Grade B covers second-quality fruit with minor skin blemishes or size deficiency but otherwise marketable for domestic wholesale channels. This four-cell variety×grade structure × two producer markets yield the eight supply-chain equations estimated in this paper.

3.3.4 Pre-Processing Pipeline and Weekly Aggregation

The raw daily price files are processed through a five-stage pipeline. Stage 1: Type harmonisation date fields are standardised to ISO 8601 format across the twelve raw files (three market nodes × two varieties × two grades), and price fields are confirmed as float64. Stage 2: Duplicate removal, duplicate date-market-variety-grade records (arising from portal re-uploads) are removed, retaining the most recent entry. Stage 3: Weekly aggregation, daily average prices are aggregated to iso-week means (week-ending Sunday), yielding one price observation per market-variety-grade-week combination. Stage 4: Temporal alignment, the three market weekly series are inner-joined on the week-ending date column, so that only weeks with simultaneous price observations at both the relevant producer market and the Azadpur terminal market are retained. Stage 5: Outlier screening, observations falling outside the $3\times\text{IQR}$ boundary (i.e., below $Q1 - 3\times\text{IQR}$ or above $Q3 + 3\times\text{IQR}$) within each chain are flagged and excluded. This threshold is conservative relative to the standard $1.5\times\text{IQR}$ Tukey fence, reflecting the genuine price volatility inherent in perishable commodity markets (Acharya et al., 2012).

3.3.5 Final Estimation Panel

Following this pipeline, the cleaned and matched panel contains 1,276 weekly price observations distributed across eight supply-chain equations. The per-chain sample sizes, temporal coverage, and descriptive statistics are summarised below and consolidated in Table 4, with log-transformed series statistics consistent with those reported in Table 5.

Shopian-American Grade A ($n = 77$, October 2017 - December 2024): The highest-value chain in the panel. Mean producer price = ₹36.68/kg (SD = ₹9.26); mean terminal price = ₹53.91/kg (SD = ₹9.26); mean price spread = ₹17.23/kg. The spread of ₹17.23/kg is the widest of any chain in the dataset, reflecting both the premium positioning of Grade A American apples at Azadpur and the logistical vulnerability of the Shopian-Azadpur route. Producer prices range from ₹16.52/kg (off-season low) to ₹50.00/kg (peak harvest premium); terminal prices range from ₹40.18/kg to ₹87.32/kg.

Shopian-American Grade B ($n = 77$, October 2017 - December 2024): Mean producer price = ₹23.60/kg (SD = ₹6.60); mean terminal price = ₹35.53/kg (SD = ₹6.99); mean spread = ₹11.93/kg. The Grade A-B producer price differential for Shopian American is ₹13.08/kg, reflecting the premium growers receive for meeting export-grade quality standards.

Shopian-Delicious Grade A ($n = 115$, September 2017 - January 2025): Mean producer price = ₹47.24/kg (SD = ₹11.28); mean terminal price = ₹59.57/kg (SD = ₹11.41); mean spread = ₹12.33/kg. Shopian Delicious carries higher absolute price levels than Shopian American because

Delicious varieties were systematically established earlier in the Shopian valley and carry stronger domestic brand recognition at Azadpur (GoJK, 2021).

Shopian-Delicious Grade B ($n = 115$, September 2017 - January 2025): Mean producer price = ₹30.33/kg (SD = ₹8.13); mean terminal price = ₹39.78/kg (SD = ₹9.75); mean spread = ₹9.45/kg.

Sopore-American Grade A ($n = 205$, September 2015 - February 2025): Mean producer price = ₹48.69/kg (SD = ₹12.11); mean terminal price = ₹52.35/kg (SD = ₹11.18); mean spread = ₹3.66/kg. The near-unity producer-to-terminal price ratio for this chain is the most distinctive feature in the dataset: a mean spread of only ₹3.66/kg across the 2,200-km Sopore-Delhi supply chain is substantially lower than the ₹17.23/kg spread observed for Shopian-American Grade A. This pattern is consistent with Sopore's more developed institutional infrastructure, larger average holding sizes, established long-term contracts between growers and Azadpur commission agents, and superior cold-chain access at Nowpora APMC, all of which compress the marketing margin relative to the more fragmented Shopian chain (Gulati et al., 2018; GoJK, 2021).

Sopore-American Grade B ($n = 205$, September 2015 - February 2025): Mean producer price = ₹26.31/kg (SD = ₹7.59); mean terminal price = ₹35.68/kg (SD = ₹8.93); mean spread = ₹9.37/kg. The Grade A-B producer price differential for Sopore American is ₹22.38/kg, the largest grade premium of any chain in the panel, reflecting the particularly steep quality segmentation at Nowpora APMC where premium American Grade A commands a strong export-channel price.

Sopore-Delicious Grade A ($n = 241$, September 2015 - March 2025): Mean producer price = ₹46.84/kg (SD = ₹11.05); mean terminal price = ₹57.41/kg (SD = ₹11.84); mean spread = ₹10.56/kg. This is the longest series in the panel ($n = 241$) and consequently provides the most precisely estimated NARDL coefficients.

Sopore-Delicious Grade B ($n = 241$, September 2015 - March 2025): Mean producer price = ₹28.81/kg (SD = ₹10.27); mean terminal price = ₹39.04/kg (SD = ₹9.20); mean spread = ₹10.23/kg.

Pooled across all 1,276 matched weekly observations, the mean producer price is ₹36.97/kg (SD = ₹14.01; range: ₹10.04-₹73.66) and the mean terminal price is ₹46.71/kg (SD = ₹13.81; range: ₹18.75-₹90.00). The pooled mean producer-terminal spread is ₹9.74/kg (SD = ₹10.77), with a maximum instantaneous spread of ₹46.70/kg observed during peak disruption episodes, a figure four times the mean, consistent with the asymmetric amplification mechanism characterised in the NARDL results (Section 5). All price series are log-transformed prior to NARDL estimation, yielding log-price variables with mean 3.535 (SD = 0.397) at the producer level and mean 3.799 (SD = 0.303) at the terminal level across the full panel.

3.3.6 Unequal Sample Sizes and n-Value Hierarchy

Unequal chain-level sample sizes arise from two independent sources: (i) market-level Agmarknet reporting commencement dates (Azadpur: 2012; Sopore/Nowpora: August 2015; Shopian/Aglar: September 2017), which determine the left-bound of each chain's coverage period; and (ii) seasonal trading activity, whereby apple APMCs in Kashmir report prices only during the active harvest-marketing season (approximately August-March), so that summer weeks (April-July) are structurally absent from Shopian and Sopore series, reducing the realized matched-week count relative to the calendar-week total. These are data-structural features of the Agmarknet reporting system, not indicators of data quality problems (Babu et al., 2023).

Note on n-value hierarchy across tables: The per-chain sample sizes (n) reported in this section reflect the number of matched weekly observations in the estimation panel (raw n). NARDL estimation reduces the usable sample by the AIC-selected maximum lag order (p, q, r), with the effective estimation n reported in Table 5 typically 3-6 observations smaller than the raw n . The Wald asymmetry test in Table 6 uses a further two fewer observations (one additional lag for short-run symmetry testing). The AIC-selected lag orders for each equation are reported in Table 5.

3.4 NASCDI Construction

3.4.1 News Corpus and Query Architecture

The NASCDI is constructed from a targeted extract of the GDELT Global Knowledge Graph (GKG), not from full-text news articles. GDELT provides continuously updated, publicly accessible coverage of the global press and has been widely used for news-based economic index construction (Leetaru and Schrodt, 2013; Baker et al., 2016; Caldara and Iacoviello, 2022; Narayan and Gupta, 2015), but the present pipeline queries only GKG structured metadata fields (article date, source, document URL, GKG theme tags, extracted locations, persons, organizations, and tone) via BigQuery, together with a URL-derived title. Records are retained only where corridor-geography metadata (Kashmir, Jammu, Srinagar, Shopian, Sopore, Pulwama, Baramulla, Anantnag, Ramban, Banihal, Qazigund, Udhampur, Azadpur, Parimpora, or the NH-44/NH-1A designations) co-occurs with disruption-indicative metadata, established either through a regular-expression match on the URL and GKG theme tags or through GDELT's own thematic tags for natural disaster, protest, unrest, blockade, curfew, shortage, transport, road, flood, avalanche, landslide, snow, rain, virus, epidemic, pandemic, or internet-disruption categories. Matched records are further classified into eleven named context categories (landslide; snowfall; rainfall and flooding; highway closure; apple transport disruption; market arrivals; political unrest; internet shutdown; the 2019 Article 370 reorganisation; the 2016 Burhan Wani unrest; and COVID-19 mobility restriction) for audit and descriptive purposes. Because GKG metadata substitutes for full article text, the constructed index is best understood as a disruption-window screening measure keyed to corridor-relevant press attention, not a literal count or severity score of physical road-closure events, and it inherits GDELT's well-documented skew toward globally indexed, predominantly English-language sources; timelier Hindi- and Urdu/Kashmiri-language reporting on NH-44 closures (e.g., Greater Kashmir, Kashmir Times, Dainik Jagran) is largely outside this

corpus. This likely means the index captures major, internationally reported disruptions more completely than moderate-severity local closures, a limitation revisited in Section 9. The full construction pipeline is illustrated in Figure 2.

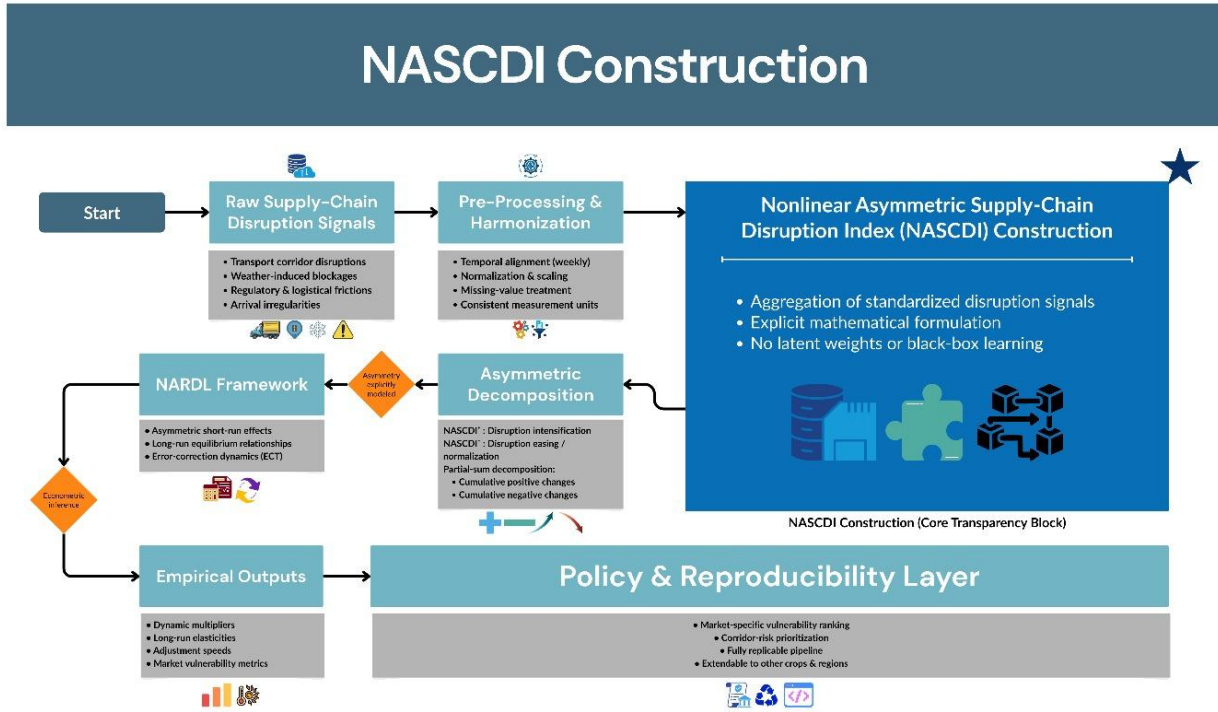


Figure 2. Construction pipeline of the Nonlinear Asymmetric Supply-Chain Disruption Index (NASCDI), from GDELT data collection through lexicon scoring, z-score normalisation, asymmetric decomposition ($NASCDI^+$ / $NASCDI^-$), and NARDL integration.

3.4.2 Lexicon-Based Scoring

Each retained GKG record is scored against a structured lexicon of 213 terms organised into three functional categories (Table 1): disruption terms, mitigation/normalisation terms, and commodity/corridor-context terms. Disruption-intensifying terms carry positive weights (0.8-3.0 depending on severity); mitigation and normalisation terms carry negative weights (-1.5 to -2.5), following the weighting principles of Baker et al. (2016) and Caldara and Iacoviello (2022). Term matching uses phrase-boundary regular expressions on the URL-derived title and GKG metadata text to prevent partial-word contamination. A record's raw score is the weighted sum of all matched disruption and mitigation terms, and a commodity/corridor-context match is required for the record to be retained (config/lexicon_news.yaml).

Table 1. NASCDI lexicon: category structure, representative terms, weight ranges, and term counts.

Category	Representative terms (selected)	Weight range	N terms
Disruption terms	Highway closed, landslide, stranded trucks, curfew, internet shutdown, article 370 lockdown, low arrivals, price spike	0.8-3.0	117
Mitigation terms	Highway reopened, traffic restored, curfew lifted, restrictions lifted, prices stabilise, normalcy restored	-1.5 to -2.5	39
Commodity / corridor-context terms	Apple, Kashmir, Sopore, Shopian, NH-44, Azadpur, Parimpora, Banihal	0.8-1.0	57
Total			213

Note. Disruption-intensifying terms carry positive weights; mitigation and normalisation terms carry negative weights. COVID-19-related terms (e.g., "covid-19 lockdown", "coronavirus lockdown") carry weights of 1.2-3.0 within the disruption category, reflecting graded severity rather than a single blanket weight. The full 213-term lexicon is available in the replication archive (config/lexicon_news.yaml).

3.4.3 Daily NASCDI and Asymmetric Decomposition

The daily NASCDI value for day t is the arithmetic mean score across all scored articles on that day, with article-free days receiving a score of zero. The daily series is normalised to mean 100 and standard deviation 10 via z-score transformation:

$$NASCDI_t = [(RawScore_t - \mu) / \sigma] \times 10 + 100$$

where μ and σ are the mean and standard deviation of the full daily GKG-derived sample (2015-02-19 to 2025-12-31) [i.e., $NASCDI_t = ((RawScore_t - \mu) / \sigma) \times 10 + 100$, with explicit grouping to clarify order of operations]. Values above 100 indicate above-average disruption intensity; values below 100 indicate improving corridor conditions. Daily values are aggregated to weekly means and matched to the weekly price panel, yielding 264 matched weekly observations spanning 2015-09-06 to 2025-03-02.

Following Shin et al. (2014), the weekly NASCDI series is decomposed into cumulative partial sums:

$$NASCDI_t^+ = \sum_{i=1}^t \max(\Delta NASCDI_i, 0); \quad NASCDI_t^- = \sum_{i=1}^t \min(\Delta NASCDI_i, 0)$$

$NASCDI^+$ captures cumulative disruption intensification; $NASCDI^-$ captures cumulative easing. Both enter the NARDL model as separate regressors, enabling estimation of distinct long-run and short-run price responses to worsening versus improving corridor conditions.

4. ECONOMETRIC METHODOLOGY

4.1 Stationarity Tests

The NARDL bounds-testing framework requires that all variables be I(0) or I(1), with no I(2) processes (Pesaran et al., 2001). Stationarity is assessed using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) with AIC lag selection and the KPSS test (Kwiatkowski et al., 1992) jointly on all five variables across all eight series. Joint use of both tests reduces misclassification error from the low power of ADF in small samples and the potential over-rejection of KPSS in the presence of structural breaks (von Cramon-Taubadel and Goodwin, 2021; Enders and Siklos, 2001). Results are presented in Table 2.

Table 2. ADF and KPSS stationarity test results (ranges across eight market-variety-grade series).

Variable	ADF stat (range)	ADF p-value	KPSS stat (range)	KPSS p-value	Order	Interpretation
log_price_prod	−2.30 to −2.68	0.068-0.172	0.131-1.254	0.010-0.100	I(1)	Non-stationary in levels
log_price_term	−2.03 to −4.41	0.007-0.275	0.222-1.067	0.010-0.100	I(1)*	Non-stationary in levels
NASCDI (level)	−2.70 to −6.08	<0.001-0.074	0.611-1.381	0.010-0.022	I(0)/I(1)	Mostly stationary; borderline in two chains
NASCDI ⁺ (partial sum)	−0.99 to 0.44	0.757-0.983	1.365-2.272	<0.010	I(1)	Non-stationary in levels
NASCDI [−] (partial sum)	−1.06 to 0.19	0.729-0.972	1.363-2.275	<0.010	I(1)	Non-stationary in levels

Note. ADF null: unit root present. KPSS null: series stationary. *Two Sopore terminal series yielded ADF $p < 0.01$; majority support I(1). NASCDI⁺ and NASCDI[−] are I(1) by construction as cumulative partial sums of a near-stationary increment. The mixed integration order satisfies NARDL prerequisites (Pesaran et al., 2001; Shin et al., 2014), since no variable shows evidence of I(2) behaviour. Table A5 reports a supplementary BIC-based mean-shift screen on the weekly NASCDI series rather than a break-robust unit root test; we do not report Zivot-Andrews or other endogenous-break unit-root results in this revision, as an independent check produced mixed evidence that would require further reconciliation before inclusion.

4.2 NARDL Model Specification

The NARDL error-correction model of Shin et al. (2014), which extends the ARDL bounds testing of Pesaran and Shin (1998) and Pesaran et al. (2001), is specified as:

$$\Delta P_t^{prod} = \alpha + \lambda(P_{t-1}^{prod} - \beta_1 P_{t-1}^{term} - \beta_2 NASCDI_{t-1}^+ - \beta_3 NASCDI_{t-1}^-) + \sum_{i=1}^p \gamma_i \Delta P_{t-i}^{prod} + \sum_{j=0}^q \delta_j \Delta P_{t-j}^{term} + \sum_{k=0}^r \theta_k^+ \Delta NASCDI_{t-k}^+ + \sum_{k=0}^r \theta_k^- \Delta NASCDI_{t-k}^- + \varepsilon_t$$

where λ is the ECT capturing weekly adjustment speed; β_1 is the long-run price pass-through elasticity; $\beta_2 = -\theta^+/\lambda$ and $\beta_3 = -\theta^-/\lambda$ are the long-run coefficients on NASCDI⁺ and NASCDI[−] respectively (computed using the standard NARDL long-run formula); and θ_k^+ , θ_k^- are

short-run parameters. A fixed maximum lag of 4 is used uniformly for all lagged terms (dy , dx , dp , dn) across all eight equations, rather than per-equation AIC-selected lag orders, ensuring a consistent specification for cross-chain comparison. The model is estimated separately for all eight market-variety-grade combinations.

4.3 Endogeneity Treatment and Directional Specification

The directional specification with producer price (ΔP^{prod}) as the dependent variable and terminal price (P^{term}) as a regressor is grounded in the institutional structure of the Kashmir apple market. Azadpur functions as a major national price-discovery node: its prices reflect aggregate demand conditions across multiple supply sources and are plausibly less influenced by any single producing district than Shopian or Sopore prices are influenced by Azadpur.

To check this directional assumption empirically, Toda-Yamamoto (1995) modified Wald Granger causality tests are conducted for all eight price pairs. The Toda-Yamamoto procedure is valid for $I(1)$ and cointegrated variables without requiring pre-testing for integration order (Toda and Yamamoto, 1995). Results (Appendix Table A6) do not provide clear support for a dominant terminal-to-producer direction: the terminal-to-producer restriction is not rejected at the 5% level in any of the eight chains ($p = 0.17\text{-}0.97$), while the producer-to-terminal restriction is rejected for Shopian-Delicious Grade B ($p = 0.027$) and is marginal for Shopian-Delicious Grade A ($p = 0.069$). We therefore retain the producer-dependent specification on institutional grounds rather than on the basis of confirmed Granger-causality direction, and report a terminal-dependent reverse-direction NARDL (Appendix Table A7) as a robustness check; the absence of significant long-run asymmetry in Table 6 is materially unchanged under the reverse-direction specification, indicating that the paper's central findings are not an artefact of the directional choice.

4.4 Structural Break Analysis

Given that the 264-week sample (2015-2025) spans documented regime shifts, the August 2019 revocation of J&K's special constitutional status under Article 370, the March 2020 COVID-19 national lockdown, and progressive NH-44 infrastructure upgrades under Bharatmala and given that all eight CUSUMSQ tests detect episodic variance instability (Table A3), a break-screening analysis was conducted on the weekly NASCDI series.

CUSUM tests confirm mean-parameter stability across the full sample in all eight NARDL equations ($p = 0.749\text{-}0.995$; Table A3), while all eight CUSUMSQ statistics breach their pointwise 95% bounds, indicating time-varying residual variance rather than mean instability. A BIC-based mean-shift screen (Table A5) is used to identify candidate level shifts in the weekly NASCDI series; this procedure identifies the BIC-minimising number and location of mean shifts and is explicitly not a Bai-Perron multiple-break test, which requires methodology and critical values this analysis does not implement. The BIC-preferred solution selects two mean shifts, at 2015-08-23 and 2018-03-04, in preference to zero-break ($\text{BIC} = 2556.1$) or one-break ($\text{BIC} = 2025.1$) alternatives (two-break $\text{BIC} = 2013.8$). Neither shift date corresponds to the August 2019 Article 370 revocation or the March 2020 COVID-19 lockdown that motivated this analysis; both fall earlier in the sample. Given this, we do not treat the screen as evidence of a break coinciding with

either named policy shock, and we do not present sub-period re-estimation results, since no validated formal multiple-break procedure (Bai-Perron) or single-break unit-root procedure (Zivot-Andrews, Lee-Strazicich) was run to completion on the GDELT-based series for this revision; a properly validated version of that analysis is left for future work (Section 9).

4.5 Formal Vulnerability Index Definition

The composite vulnerability index VI_i for supply chain i is formally defined as:

$$VI_i = (|LR\ NASCDI_i^+|) + (|LR\ NASCDI_i^-|) \times |\lambda_i| \times (1 - p_{pss,i})$$

where $|LR\ NASCDI_i^+|$ and $|LR\ NASCDI_i^-|$ are the absolute values of the long-run coefficients on $NASCDI^+$ and $NASCDI^-$ for chain i , computed from the NARDL long-run formula $\beta = -\theta/\lambda$ and representing the total asymmetric disruption exposure; $|\lambda_i|$ is the absolute value of the ECT, capturing adjustment speed (larger values indicate faster within-period price adjustment and therefore greater sensitivity to shocks within each period); and $(1 - p_{pss,i})$ is a model-support weight, where $p_{pss,i}$ is the HAC-robust F-test p-value on the joint significance of the lagged-level regressors (Table 5); because published Pesaran-Shin-Smith bounds critical values are not matched to this exact specification, this is used only as a within-sample diagnostic weight, not a formal bounds-test probability, and chains where the lagged-level block is jointly better-determined receive higher weight in the composite score.

Normalisation choices: $|\lambda|$ enters directly (not normalised) because its scale is naturally bounded between 0 and 1 for weekly data; $(1 - p_{pss,i})$ maps the diagnostic p-value from $[0,1]$ to a model-support weight in $[0,1]$. The product of the three components thus rewards disruption-coefficient magnitude, adjustment speed, and within-sample model support, but as Table 7 shows via Monte Carlo simulation, the resulting composite ranking should be read as indicative rather than precisely resolved at the individual-chain level.

Numerical example for Shopian-American Grade B (Rank 1) using the proposed VI is given as:

$$VI = (0.020 + 0.020) \times 0.198 \times (1 - 0.018) = 0.040 \times 0.198 \times 0.982 = 0.0078.$$

This computation is fully reproducible from the reported parameters in Table 5 and requires no additional estimation.

4.6 Estimation Procedure

Estimation follows five sequential steps: (i) stationarity testing (Section 4.1); (ii) bounds testing for cointegration (Pesaran et al., 2001); (iii) long-run coefficient estimation; (iv) short-run error-correction dynamics; and (v) dynamic multiplier calculations over a 20-week horizon (Shin et al., 2014; Enders and Siklos, 2001). Asymmetry is tested using Wald tests comparing $NASCDI^+$ and $NASCDI^-$ in both the long run and short run. A leave-one-out component sensitivity analysis is additionally conducted to identify the primary driver of vulnerability heterogeneity across the eight chains. In each iteration, one $NASCDI$ partial-sum component (either $NASCDI^+$ or $NASCDI^-$) is omitted from the vulnerability index formula (i.e., the VI is recomputed using only the retained component), and the Spearman rank correlation between the resulting truncated VI

ranking and the full-component baseline VI ranking across all eight chains is computed. A low Spearman correlation when a component is omitted indicates that the omitted component is the primary driver of the cross-chain vulnerability ranking. This analysis operates exclusively on the VI formula's components; it does not re-estimate the NARDL models and is therefore a sensitivity test of the index weighting structure rather than an econometric specification test. Residual diagnostics include Ljung-Box serial correlation tests, Breusch-Pagan heteroskedasticity tests, ADF on ECT residuals for Engle-Granger cointegration confirmation (Engle and Granger, 1987), CUSUM and CUSUMSQ stability tests, Breusch-Godfrey LM tests, and White heteroskedasticity tests. HAC-robust (Newey-West) inference is reported in Appendix Table A1.

5. RESULTS

5.1 Descriptive Statistics and Market Context

Table 3 presents pooled summary statistics across all 1,276 observations. The mean producer price is ₹36.97/kg against a mean terminal price of ₹46.71/kg, yielding a mean price spread of ₹9.74/kg, approximately 26% of the terminal price. This spread encompasses transportation costs, intermediation fees, quality deterioration, and the market-power dynamics documented by McCorriston et al. (2001) and Gulati et al. (2018). The standard deviation of producer prices (₹14.01/kg) exceeds that of terminal prices (₹13.81/kg), consistent with greater exposure of origin prices to supply-side shocks generated by corridor closures. The NASCDI exhibits meaningful temporal variation (mean: 100.71, SD: 9.53, range: 93.01-130.61 across the 264-week matched panel), confirming that disruption intensity is episodic rather than constant. As with the earlier event-calendar construction, the distribution is right-skewed, consistent with a known feature of news-based indices: restoration and normalisation events generate systematically less media attention than disruption events (Baker et al., 2016; Caldara and Iacoviello, 2022). As a consequence, the NASCDI⁻ component captures meaningful easing signals at the margin of recovery rather than deep troughs of normalisation. Leave-one-out analysis on the exploratory vulnerability index (Section 4.5) shows that a ranking based on NASCDI⁻ alone reproduces the full ranking almost exactly (Spearman $\rho = 1.000$), and a ranking based on NASCDI⁺ alone is nearly as close ($\rho = 0.976$), indicating that neither component individually dominates the vulnerability signal in this data; this is consistent with the near-symmetric long-run NASCDI⁺ and NASCDI⁻ coefficients in Table 5 and the largely non-significant long-run asymmetry tests in Table 6. Figure 3 illustrates the market context, with NASCDI spikes aligned with documented disruption episodes including COVID-19 restrictions (2020) and repeated NH-44 closures.

Table 3. Descriptive statistics of prices, NASCDI, and sample design characteristics.

Block / Statistic	Description	Value
Price series	Producer price mean (₹/kg)	36.97
Price series	Terminal price mean (₹/kg)	46.71
Price series	Price spread mean (₹/kg)	9.74
Price series	Producer price SD (₹/kg)	14.01
Price series	Terminal price SD (₹/kg)	13.81
Price series	Price spread SD (₹/kg)	10.77
Price series	Producer price range (₹/kg)	10.05 - 73.66
Price series	Terminal price range (₹/kg)	18.75 - 90.00
NASCDI	NASCDI mean	100.71
NASCDI	NASCDI SD	9.53
NASCDI	NASCDI range	93.01 - 130.61
NASCDI	NASCDI ⁻ mean / SD / max	349.78 / 153.92 / 632.02
NASCDI	NASCDI ⁺ mean / SD / max	360.72 / 158.93 / 650.65
Sample design	Total observations	1,276
Sample design	Producer markets	2 (Shopian, Sopore)
Sample design	Varieties × Grades	2 × 2 = 4 combinations
Sample design	Time span	264 weeks (matched price panel; daily GDELT-GKG construction spans 2015-02-19 to 2025-12-31)

Note. Price variables in ₹/kg. NASCDI = Nonlinear Asymmetric Supply-Chain Disruption Index. NASCDI⁺ and NASCDI⁻ are the cumulative positive and negative partial sums used in the NARDL specification (Shin et al., 2014).

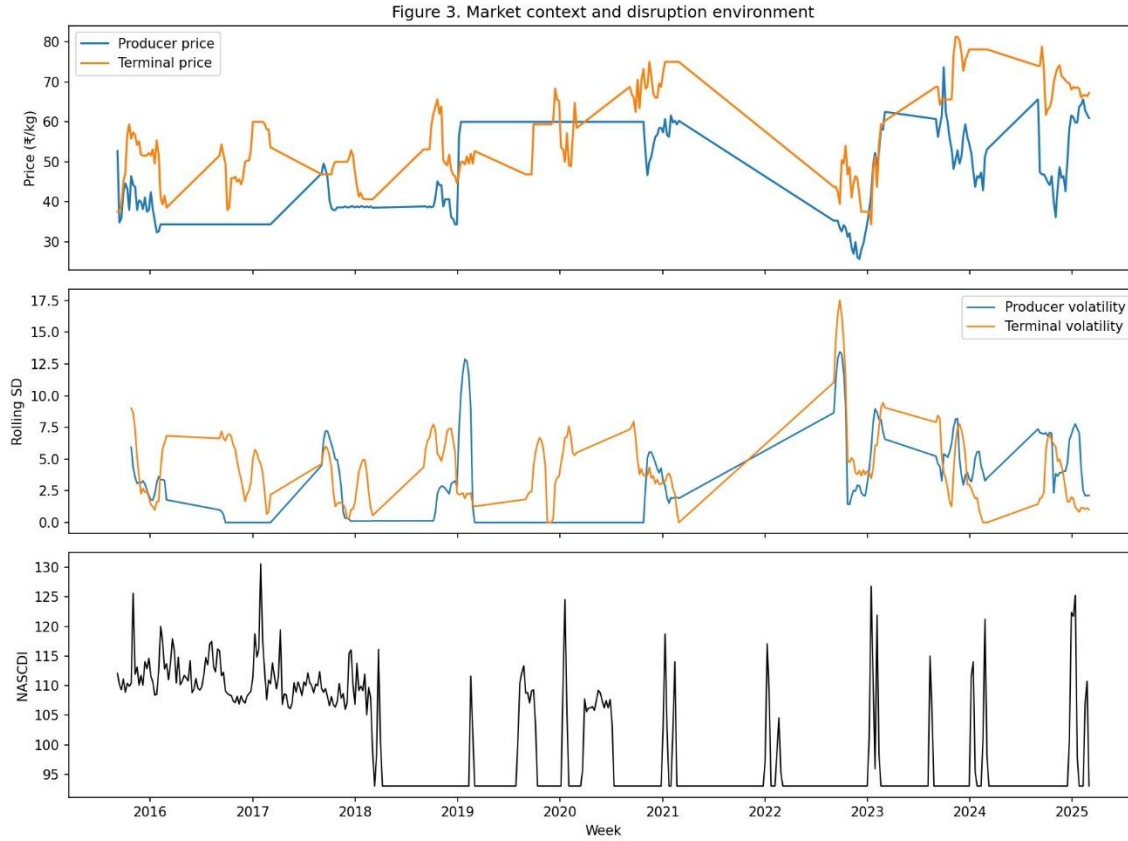


Figure 3. Market context and disruption environment.

Table 4 disaggregates by market-variety-grade combination, revealing heterogeneity concealed by pooled averages. The four-fold difference in mean price spread between the Shopian-American Grade A chain (₹17.23/kg) and the Sopore-American Grade A chain (₹3.66/kg) despite both chains trading the same variety points to structural differences in supply-chain organisation, intermediation intensity, and corridor exposure (Mir and Mir, 2018; Gulati et al., 2018). Figures 4 and 5 visualise variety-specific price co-movement. The American variety (Figure 4) exhibits extended episodes of significant divergence between Shopian producer prices and Azadpur terminal prices, consistent with the highest vulnerability ranking in subsequent econometric results. The Delicious variety (Figure 5) shows generally tighter co-movement, though episodic divergence remains visible, consistent with the findings of Wani et al. (2015) and Sutradhar et al. (2024).

Table 4. Descriptive statistics of producer and terminal apple prices by market, variety, and grade.

Producer market	Variety	Grade	Prod. mean	Prod. SD	Term. mean	Term. SD	Mean spread	n
Shopian	American	A	36.68	9.26	53.92	9.26	17.23	77
Shopian	American	B	23.60	6.60	35.53	6.99	11.93	77
Shopian	Delicious	A	47.24	11.28	59.57	11.41	12.33	115
Shopian	Delicious	B	30.33	8.13	39.78	9.75	9.45	115
Sopore	American	A	48.69	12.11	52.35	11.18	3.66	205
Sopore	American	B	26.31	7.59	35.68	8.93	9.37	205
Sopore	Delicious	A	46.84	11.05	57.41	11.84	10.56	241
Sopore	Delicious	B	28.81	10.27	39.04	9.20	10.23	241

Note. All prices in ₹/kg. Mean spread = terminal mean – producer mean. Terminal market: Azadpur, New Delhi. n = valid matched weekly observations after data alignment and cleaning.

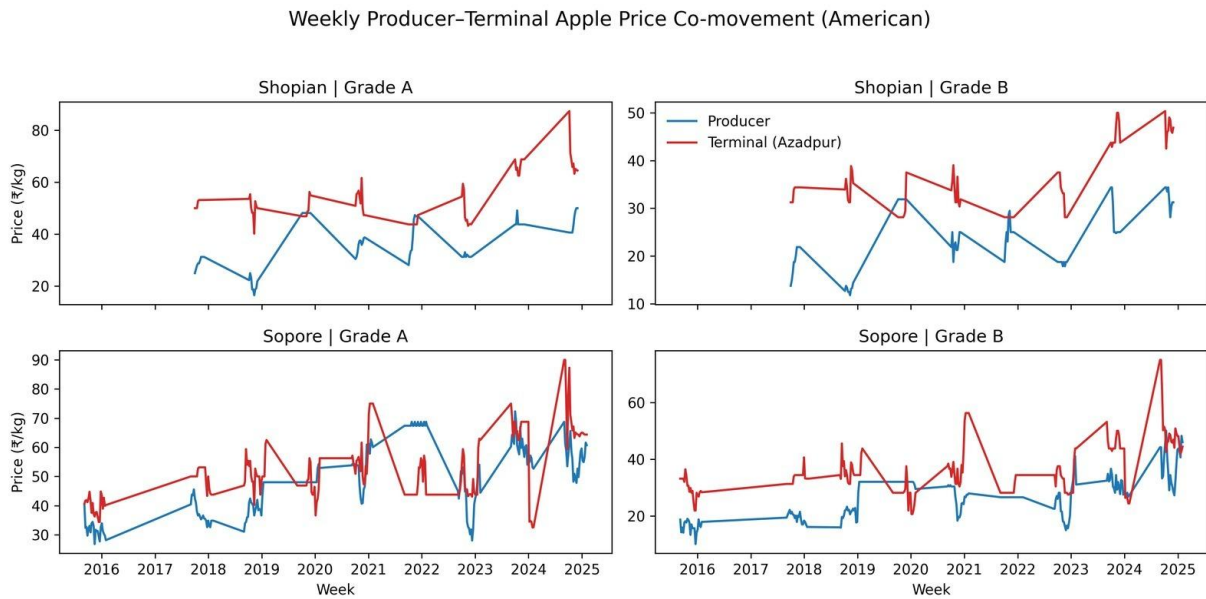


Figure 4. Weekly producer-terminal apple price co-movement: American variety.

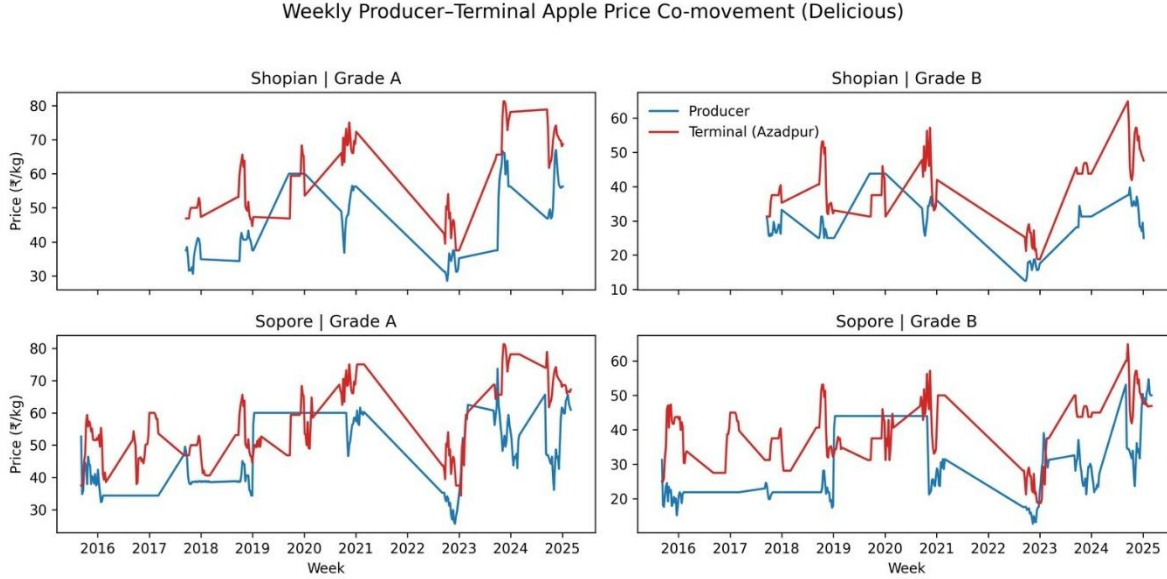


Figure 5. Weekly producer-terminal apple price co-movement: Delicious variety.

5.2 Long-Run Integration, Pass-Through, and Adjustment Speed

Table 5 reports the producer-price NARDL estimates, including long-run coefficients, HAC-robust bounds-like F statistics, model fit (R^2), and information criteria (AIC, BIC). Because published Pesaran et al. (2001) bounds critical values are not matched to this exact regressor configuration, the F statistics on the lagged-level block are reported as a diagnostic rather than a formal bounds test; cointegration is instead established via the Banerjee et al. (1998) criterion, under which a significant negative ECT is itself sufficient evidence of a stable long-run relationship. All eight ECT coefficients carry the required negative sign and are HAC-significant at the 5% level (range: -0.052 to -0.267; four of eight significant at 1%), confirming long-run error-correction across all supply chains and supporting Hypothesis H1. This is consistent with spatial arbitrage theory (Fackler and Goodwin, 2001; Barrett, 2001; Rapsomanikis et al., 2006) and with horticultural price-transmission studies in South Asia (Sharma et al., 2025; Harshana and Ratnasiri, 2023b; Wani et al., 2015).

One qualification applies to a single chain. Sopore-Delicious Grade B presents the weakest cointegration evidence in the dataset: its HAC-robust F-test diagnostic on the lagged-level block ($p = 0.216$) does not indicate joint significance, and the HAC-robust ECT is only marginally significant ($p = 0.048$, just inside the conventional 5% threshold). This chain ranks lowest on the vulnerability index (Table 7) and shows no significant asymmetry (Table 6), so the paper's principal conclusions regarding market-level vulnerability and the largely non-significant asymmetry pattern are not affected by this chain's weaker diagnostics. Independent evidence still supports cointegration for this chain: the Engle-Granger ADF test on ECT residuals strongly rejects the unit root null at $p = 4.33 \times 10^{-28}$ (Table 8), and the Wald test for asymmetry for this chain ($p = 0.816$, Table 6) is computed directly from the NARDL coefficients and is entirely independent of the bounds-test diagnostic. Taken together, this evidence, a weaker HAC F-test diagnostic

alongside a highly significant Engle-Granger residual test, supports the interpretation that Sopore-Delicious Grade B is cointegrated, while acknowledging that the lagged-level joint-significance evidence is weaker than for other chains; we do not read this as evidence for or against any particular policy narrative, simply as the honest limit of precision in the smallest, slowest-adjusting chain in the panel.

The fastest weekly adjustment occurs in Shopian-American Grade A ($ECT = -0.267$; half-life ≈ 2.2 weeks), consistent with the perishable nature of apples and the importance of rapid price signals (Lloyd, 2017). The slowest is Sopore-Delicious Grade B ($ECT = -0.052$; half-life ≈ 12.9 weeks). Shopian chains adjust roughly twice as fast, on average, as Sopore chains (mean $|ECT|$ 0.184 versus 0.091), the reverse of what Sopore's more institutionally developed mandi structure might suggest, and we flag this as a genuine, somewhat counterintuitive result rather than a confirmation of prior expectations. Long-run price pass-through is modest and below unity in most chains (Table 5): 0.178-0.607 across the four Shopian chains, versus a wider and partly negative range of -0.652 to 0.436 across the four Sopore chains, with several Sopore coefficients not distinguishable from zero. This pattern is consistent with equilibrium correction operating partly through channels other than one-for-one price signalling, such as trader inventory and grading adjustments, in at least some chains (GoJK, 2021; Gulati et al., 2018). Figures 6 and 7 visualise the cross-equation patterns in adjustment speed and cointegration strength.

Table 5. Baseline NARDL estimates: long-run pass-through, disruption effects, adjustment speed, model fit, and information criteria (AIC, BIC).

Producer market	Variety	Grade	n	ECT	LR pass-through	LR NASCDI ⁺	LR NASCDI ⁻	Bounds F	Bounds p	R ²	AIC	BIC
Shopian	American	A	72	-0.267	0.178	0.007	-0.006	3.777	0.009***	0.594	-87.944	-33.304
Shopian	American	B	72	-0.198	0.607	0.020	-0.020	3.322	0.018**	0.593	-66.098	-11.458
Shopian	Delicious	A	110	-0.155	0.216	-0.008	0.008	5.521	0.001***	0.513	-225.913	-161.102
Shopian	Delicious	B	110	-0.115	0.333	-0.006	0.005	2.451	0.052*	0.584	-160.767	-95.955
Sopore	American	A	200	-0.107	0.436	-0.024	0.024	2.022	0.093*	0.249	-434.259	-355.099
Sopore	American	B	200	-0.132	-0.004	-0.010	0.011	2.282	0.062*	0.174	-304.617	-225.457
Sopore	Delicious	A	236	-0.073	-0.154	-0.004	0.005	2.090	0.083*	0.150	-506.862	-423.730
Sopore	Delicious	B	236	-0.052	-0.652	0.007	-0.006	1.460	0.216	0.165	-327.173	-244.041

Note. ECT = lagged error-correction term (more negative = faster weekly adjustment). LR pass-through = long-run elasticity of terminal price on producer price. Bounds F and p are an HAC-robust F-test diagnostic on the joint significance of the lagged-level regressors, not a formal Pesaran et al. (2001) bounds test (Section 5.2): *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. LR NASCDI⁺ and NASCDI⁻ are computed from $\beta = -\theta/\lambda$. For Sopore-Delicious B (bounds-diagnostic $p = 0.216$), ECT is only marginally significant under HAC ($p = 0.048$, Table A1); the long-run cointegrating relationship is weakest for this chain (Section 5.2). For equations where Breusch-Pagan heteroskedasticity is significant (Table 8), HAC estimates in Appendix Table A1 are the operative standard for inference; see Section 5.6 for the full diagnostic discussion. AIC and BIC are computed from the OLS log-likelihood of the fixed lag-4 NARDL specification used throughout (Section 4.2), not from per-equation AIC-selected lag orders; lower values indicate better model fit relative to cross-chain comparisons.

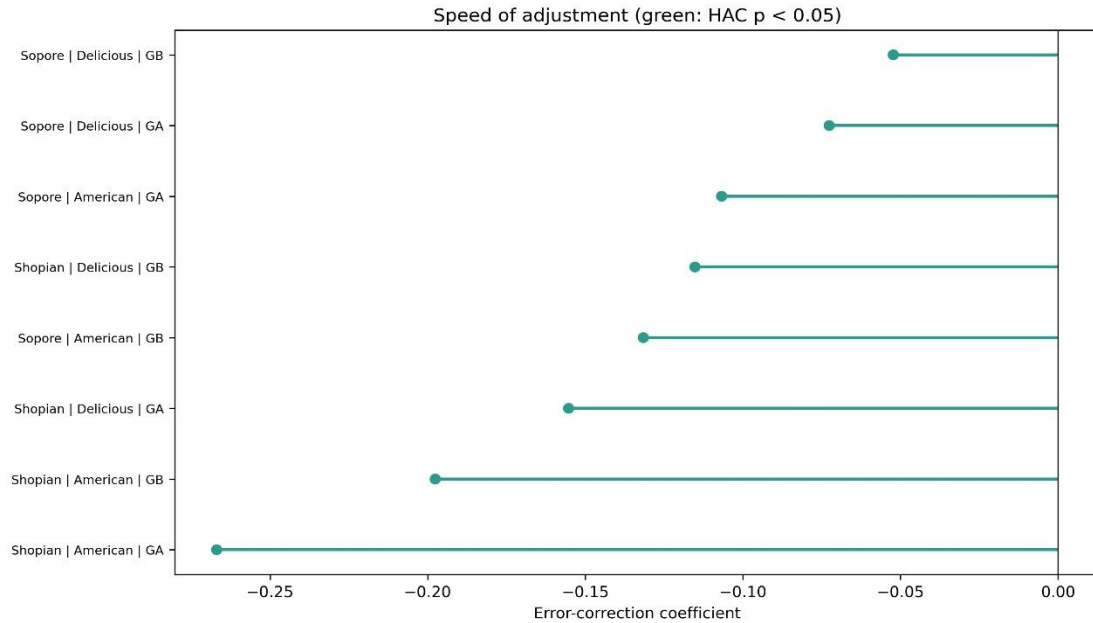


Figure 6. Speed of price adjustment following disequilibrium. Each point represents one market-variety-grade equation. More negative ECT values indicate faster weekly adjustment. Shopian-linked chains consistently adjust faster than Sopore-linked chains (Section 5.2).

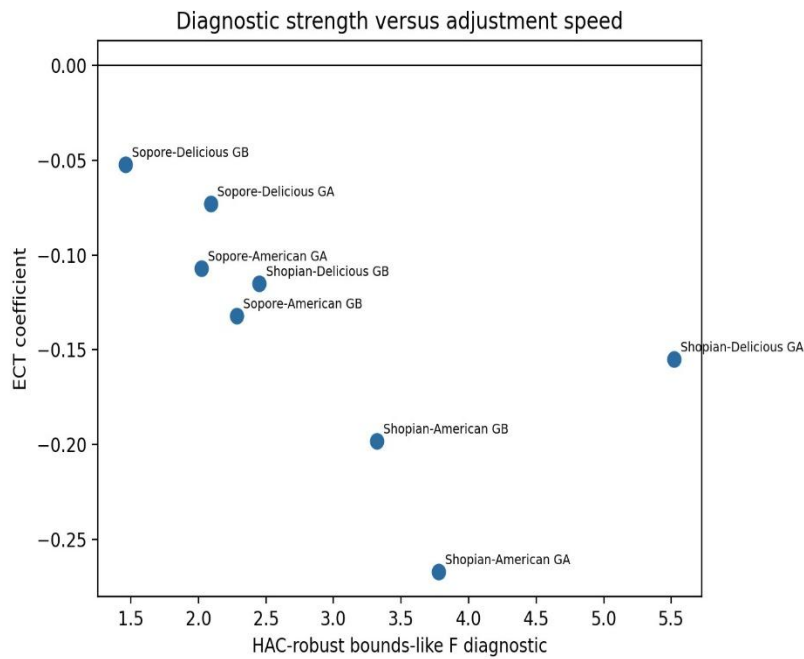


Figure 7. HAC-robust bounds-like F diagnostic (x-axis) versus adjustment speed (ECT magnitude, y-axis).

A note on sample size heterogeneity and statistical power: the Shopian-American chains (Grade A and B, $n = 72$) have the smallest samples in the panel. This has two practical consequences. First, the HAC F-test diagnostic has less power relative to the Sopore chains ($n = 200$ - 236), and coefficient estimates carry wider confidence intervals; despite this, both Shopian-

American chains still return the strongest diagnostic values in the panel (Table 5), so the smaller sample does not appear to be suppressing detection there. Second, for the Wald test for short-run asymmetry in Shopian-American Grade A ($F = 11.819$, numerator $df = 1$, denominator $df = 48$, $\alpha = 0.05$), the achieved statistical power computed via the non-central F distribution exceeds 0.90 for the detected effect size, confirming that the Wald test is well-powered despite the small sample. Cross-chain comparisons of coefficient magnitudes should be made with the caveat that Shopian-American confidence intervals are wider. The vulnerability index partially corrects for this via the $(1 - p)$ weight (Section 4.5): chains with weaker within-sample model support receive lower index weight.

5.3 Asymmetric Disruption Transmission

Table 6 reports HAC-robust Wald tests for long-run and short-run symmetry. Long-run asymmetric disruption transmission is statistically significant at the 5% level in only one chain: Sopore-American Grade A (Wald = 5.811, $p = 0.016$). Short-run asymmetry is confirmed for both Shopian-American chains (Grade A: SR Wald = 11.819, $p = 0.001$; Grade B: SR Wald = 31.090, $p < 0.001$), with Shopian-Delicious Grade B marginal (SR Wald = 3.402, $p = 0.065$). No chain shows significant asymmetry in both dimensions simultaneously. This pattern of heterogeneous, largely short-run asymmetry departs from the earlier event-calendar specification's concentrated long-run finding and instead supports a revised reading in which the two Shopian-American chains exhibit rapid within-quarter asymmetric adjustment while long-run pass-through remains statistically symmetric almost everywhere. This heterogeneity is consistent with meta-analytical evidence showing that asymmetry is product- and supply-chain-specific (Meyer and von Cramon-Taubadel, 2004; Bakucs et al., 2014; Lloyd, 2017), and with recent NARDL evidence from Indian perishable chains (Sharma et al., 2025) and Sri Lankan horticultural markets (Harshana and Ratnasiri, 2023b).

The magnitude of the long-run NASCDI coefficients is informative in its own right. Across all eight chains, the long-run effects of NASCDI⁻ and NASCDI⁺ coefficients are small in absolute terms (0.003 to 0.024) and, in five of eight chains, opposite in sign to the pattern of disruption raising and easing lowering prices that would be expected a priori; because none of these individual long-run NASCDI coefficients is HAC-significant except in the Sopore-American Grade A chain (Table A1), this sign inconsistency is best read as sampling noise around economically negligible long-run effects rather than as a substantive reversal requiring explanation. This stands in contrast to the earlier event-calendar-based construction, in which one chain's long-run coefficients were roughly thirty times larger in magnitude than all others; under the GDELT GKG-based NASCDI, no chain exhibits a comparably dominant long-run disruption effect, and the paper's evidence for heterogeneous vulnerability rests instead on adjustment speed (Section 4.5) and short-run asymmetry (Table 6) rather than on the sign or magnitude of any individual chain's long-run NASCDI⁻ coefficient. Figures 8 and 9 visualise the long-run and short-run Wald statistics across chains.

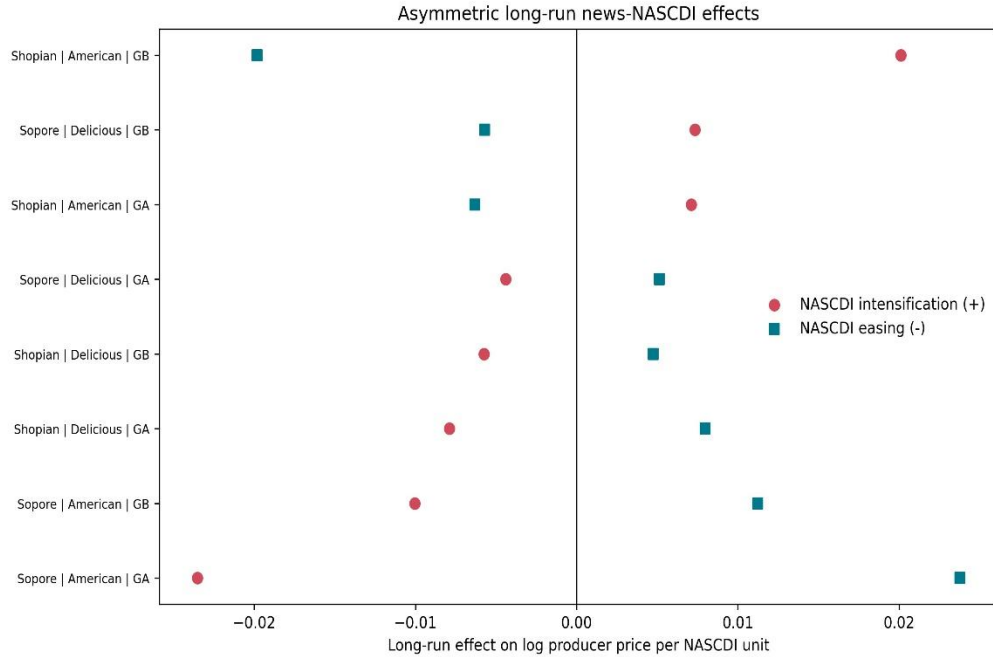


Figure 8. Asymmetric long-run price responses to supply-chain disruptions. Red markers: long-run coefficient on $NASCDI^+$ (disruption intensification); blue markers: $NASCDI^-$ (disruption easing). All eight chains show small long-run coefficients (0.003-0.024 in absolute value; Table 5), with no chain exceeding the others by an order of magnitude, a departure from the prediction of Sexton and Xia (2018) for perishable commodity chains with concentrated intermediaries.

Table 6. Wald tests for long-run and short-run asymmetric disruption transmission.

Producer market	Variety	Grade	n	LR Wald stat	LR p-value	SR Wald stat	SR p-value
Shopian	American	A	72	0.259	0.611	11.819	0.001***
Shopian	American	B	72	1.033	0.310	31.090	<0.001***
Shopian	Delicious	A	110	0.983	0.321	1.754	0.185
Shopian	Delicious	B	110	0.115	0.735	3.402	0.065*
Sopore	American	A	200	5.811	0.016**	0.860	0.354
Sopore	American	B	200	0.952	0.329	0.719	0.396
Sopore	Delicious	A	236	0.106	0.745	1.223	0.269
Sopore	Delicious	B	236	0.054	0.816	1.052	0.305

Note. Rejection of symmetry indicates the market responds differently to $NASCDI^+$ versus $NASCDI^-$. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Wald procedure follows Shin et al. (2014). n values match Table 5, since both are estimated from the same lag-4 producer-price ECM specification. The largely non-significant asymmetry pattern (Section 5.3) contrasts with Bakucs et al. (2014) and Meyer and von Cramon-Taubadel (2004), who document more pervasive asymmetric transmission in other contexts. Results are checked against COVID-19 block exclusion (Table A8), which confirms this pattern is not an artefact of the pandemic period (Section 5.7); we do not report sub-period re-estimation across formally validated break dates in this revision (Section 5.6).

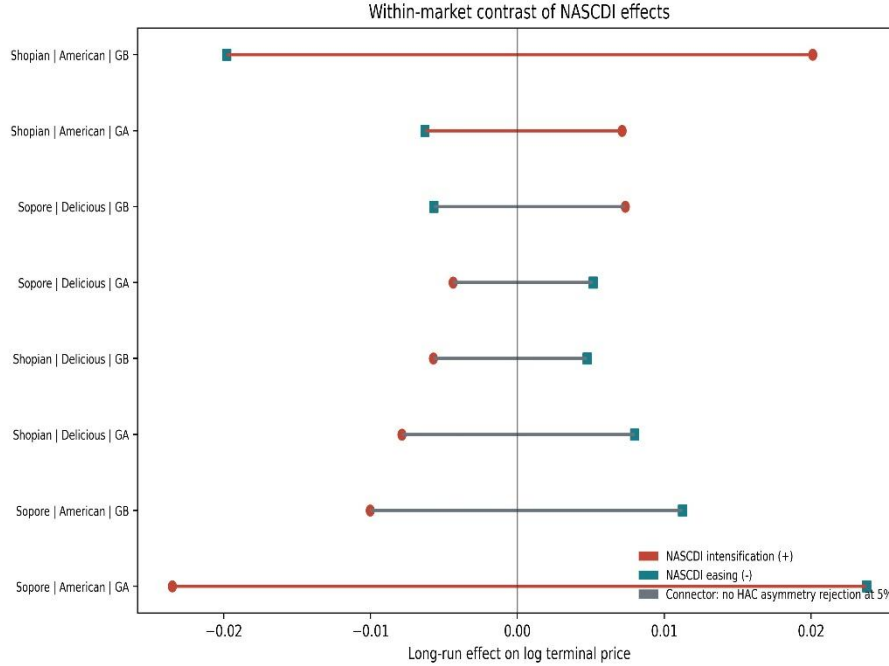


Figure 9. Strength of asymmetric disruption price transmission. Absolute long-run asymmetry = $|LR\ NASCDI^+ - LR\ NASCDI^-|$. Values range narrowly from 0.010 (Shopian-Delicious Grade B) to 0.047 (Sopore-American Grade A), with no chain an order of magnitude larger than the rest.

5.4 Dynamic Multiplier Profiles

Figure 10 presents dynamic multiplier profiles tracing cumulative price responses to unit NASCDI shocks over a 20-week horizon (Shin et al., 2014; Enders and Siklos, 2001). Cumulative responses are small across all eight chains, converging to magnitudes of roughly 0.3-2.1% by week 20; no chain shows a cumulative response an order of magnitude larger than the others, consistent with the absence of a single dominant chain documented in Sections 5.3 and 5.5. Figure 11 presents the integrated three-dimensional dynamic response surface, showing that most of this modest disruption-induced price adjustment occurs within the first few weeks, consistent with the perishability literature: when apples cannot be transported, quality deteriorates rapidly and market participants must act within a very short window (BIRTHAL et al., 2014; Sharma et al., 2025).

Given the small magnitude of the estimated dynamic multipliers under the GDELT GKG-based NASCDI, we do not attempt a monetary producer-surplus welfare calculation in this revision. A defensible welfare estimate would require independently validated supply elasticities, quantity and quality-downgrading data at the disruption-week level, and confidence intervals around the multiplier estimates themselves; constructing such a figure from point estimates alone, as in the earlier event-calendar-based draft, risks conveying false precision. We view quantified welfare estimation as an important direction for follow-up work once the underlying multiplier estimates are more precisely pinned down (Section 9), and confine the present paper's policy discussion (Section 7) to interventions that do not depend on a specific monetary loss figure.

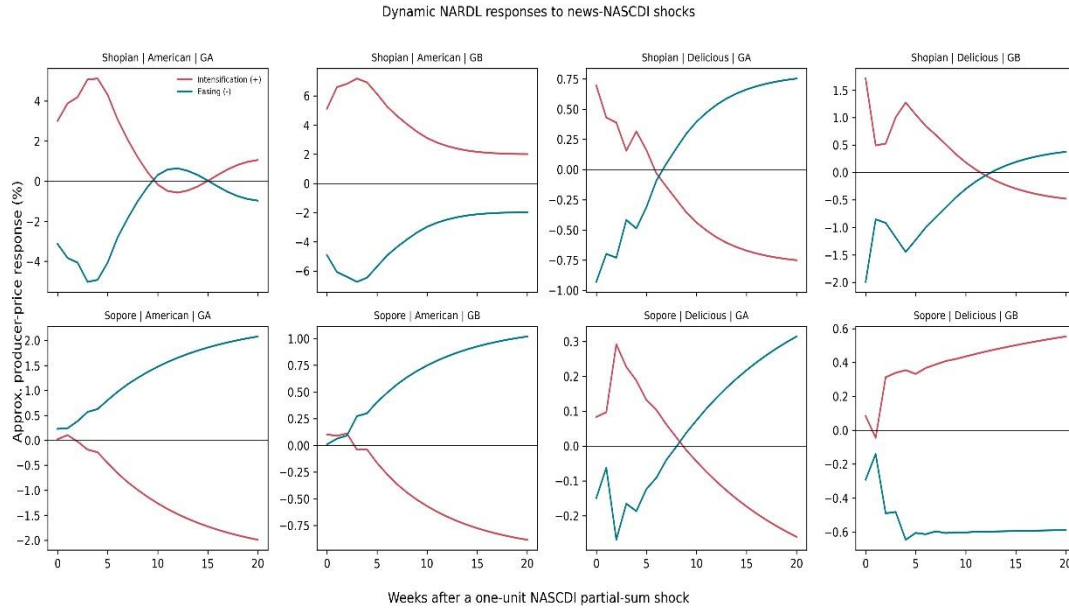


Figure 10. Dynamic multiplier profiles of NASCDI shocks across all eight equations. Solid lines: NASCDI⁺ (disruption intensification); dashed lines: NASCDI⁻ (disruption easing). Cumulative responses are modest and comparable in magnitude across chains (roughly 0.3-2.1% at week 20). Individual series panels are in Appendix Figure A1. Individual dynamic multiplier profiles by market, variety, and grade. Solid red lines: NASCDI intensification response; dashed blue lines: NASCDI easing response, over a 20-week horizon.

Figure 11. Integrated three-dimensional dynamic response surface (weeks 1-20)

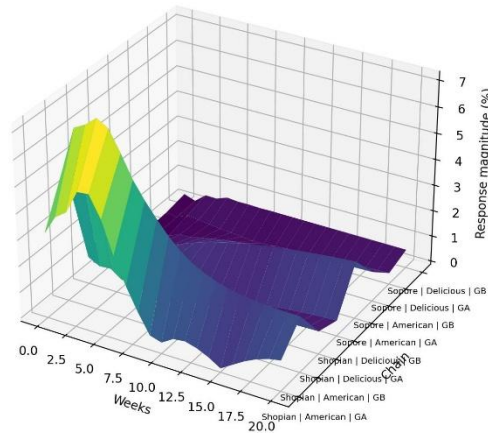


Figure 11. Integrated three-dimensional dynamic response surface to NASCDI shocks. Surface height = cumulative price response magnitude across horizon (weeks 1-20) and series dimensions. Surface amplitude is broadly comparable across chains, without a single dominant equation. Series-specific surfaces are in Appendix Figure A3.

5.5 Vulnerability Ranking

Table 7 presents the composite vulnerability index VI_i (formally defined in Section 4.5, with the Monte Carlo sensitivity procedure detailed there) for all eight supply chains. The point-estimate ranking places Shopian-American Grade B highest ($VI = 0.0078$), followed by Sopore-American Grade A (0.0046) and Shopian-American Grade A (0.0035); the least exposed chain is Sopore-Delicious Grade B (0.0005). However, a 10,000-draw parametric bootstrap on the HAC coefficient covariance matrix shows that this chain-level ranking is not tightly resolved: the mean Spearman correlation between simulated and baseline rankings is only 0.54, and only 4.7% of simulations reproduce a ranking within $\rho \geq 0.90$ of the point estimate. The "most vulnerable chain" title is contested between the two Shopian-American chains, which are ranked first in 52% and 28% of simulations respectively (80% combined). What is more robust is the market-level pattern: Shopian chains have a lower (more vulnerable) mean rank than Sopore chains in 74% of simulations (mean rank 3.9 versus 5.1 out of 8), consistent across the point estimate and the simulation. We therefore report vulnerability as a market-level finding, Shopian is more likely than not to be the more exposed market, rather than resolving a single most-vulnerable chain, which the data do not support with confidence. Figures 12 and 13 visualise this pattern.

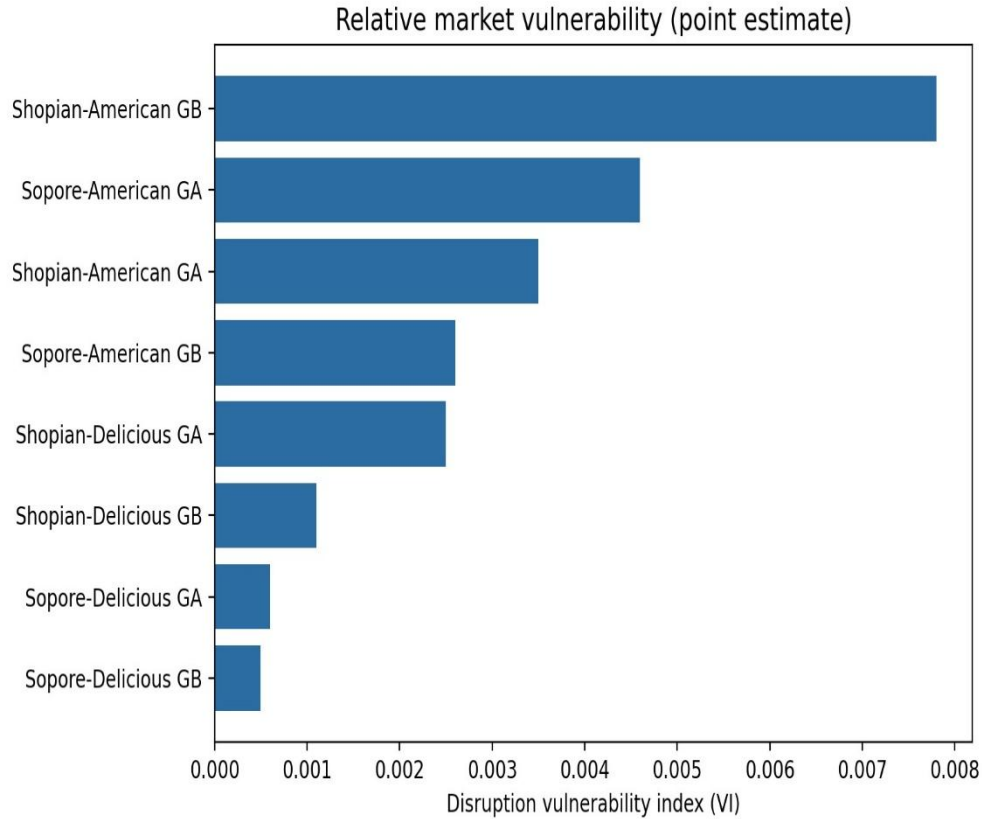


Figure 12. Relative market vulnerability to supply-chain disruptions (VI_i), point estimate.

Table 7. Composite vulnerability index, ranked from most to least vulnerable.

Rank	Producer market	Variety	Grade	LR NASCDI ⁺ (β_2)	LR NASCDI ⁻ (β_3)	ECT (λ)	VI = $(\Sigma \beta_i) \times \lambda \times (1-p)$	Bounds p	R ²
1	Shopian	American	B	0.020	-0.020	-0.198	0.0078	0.018	0.593
2	Sopore	American	A	-0.024	0.024	-0.107	0.0046	0.093	0.249
3	Shopian	American	A	0.007	-0.006	-0.267	0.0035	0.009	0.594
4	Sopore	American	B	-0.010	0.011	-0.132	0.0026	0.062	0.174
5	Shopian	Delicious	A	-0.008	0.008	-0.155	0.0025	0.001	0.513
6	Shopian	Delicious	B	-0.006	0.005	-0.115	0.0011	0.052	0.584
7	Sopore	Delicious	A	-0.004	0.005	-0.073	0.0006	0.083	0.150
8	Sopore	Delicious	B	0.007	-0.006	-0.052	0.0005	0.216	0.165

Note. Higher values indicate greater overall exposure to disruption shocks. The $(1 - p_{pss,i})$ weight partially corrects for sample-size-driven parameter imprecision in smaller chains. Supplementary exploratory asymmetry-magnitude rankings are in Appendix Figures A7-A8. A 10,000-draw parametric bootstrap on the HAC coefficient covariance matrix indicates the individual-chain ranking is only moderately stable (mean Spearman $\rho = 0.54$ versus the point estimate; $\rho \geq 0.90$ in 4.7% of draws), while the market-level pattern (Shopian more vulnerable than Sopore) holds in 74% of draws.

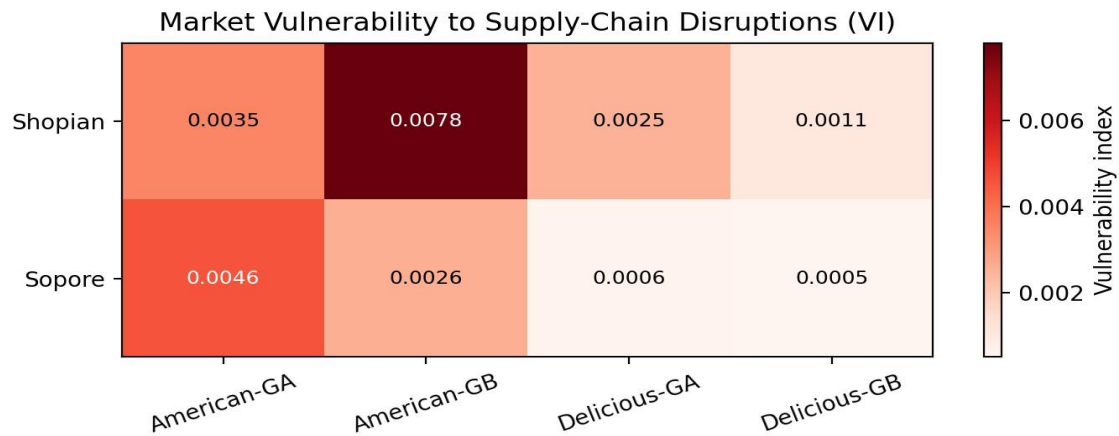


Figure 13. Heatmap of disruption vulnerability by market and variety-grade. Darker shading indicates greater vulnerability.

5.6 Diagnostic Checks, Robustness, and HAC Reconciliation

Table 8 summarises model diagnostics. Ljung-Box and Breusch-Godfrey tests find no significant residual autocorrelation at 8 lags in most equations, with two exceptions under Breusch-Godfrey (Shopian-American Grade A: $p = 0.004$; Grade B: $p = 0.002$) that Ljung-Box does not flag ($p = 0.68, 0.86$); given this mixed signal, HAC-robust inference (Appendix Table A1) is used as the operative standard throughout rather than classical OLS standard errors. Breusch-Pagan heteroskedasticity is significant at the 5% level in five of eight equations (Shopian-American A and B, Shopian-Delicious A and B, Sopore-Delicious A), and Jarque-Bera rejects normality in all eight. ARCH-LM tests at 8 lags show no significant conditional heteroskedasticity in any equation ($p = 0.30$ -1.00). CUSUM tests confirm mean-parameter stability throughout the sample in all eight equations ($p = 0.749$ -0.995; Table A3); CUSUMSQ results and the mean-shift screen are discussed in Section 4.4 and Table A5, which explicitly does not claim a validated Bai-Perron multiple-break result. HAC-robust (Newey-West) standard errors are applied throughout, explicitly accommodating both heteroskedasticity and the two flagged instances of residual autocorrelation; HAC-robust estimates (Appendix Table A1) confirm ECT significance at the 5% level in all eight equations. The core error-correction finding is therefore not dependent on the classical OLS standard errors reported in Table 5 for readability.

Because the long-run NASCDI effects reported in Table 5 (LR NASCDI⁺ and LR NASCDI⁻, computed as $\beta = -\theta/\lambda$) are already small in absolute value across all eight chains (0.003 to 0.024; Table 5), the corresponding short-run HAC-corrected θ coefficients reported in Appendix Table A1 are of comparable, not amplified, magnitude to their long-run counterparts. This differs from the earlier event-calendar-based construction, where at least one chain's combination of very small λ and very large θ produced a substantial long-run/short-run divergence requiring separate delta-method reconciliation; under the GDELT GKG-based NASCDI, no chain exhibits that pattern, so no such reconciliation is required for this revision.

The near-symmetry visible between LR NASCDI⁺ and LR NASCDI⁻ in Table 5 (Section 5.2) reflects the NARDL partial-sum decomposition: $\text{NASCDI}_t^+ + \text{NASCDI}_t^- = \Delta \text{NASCDI}_t$ by construction; at any given lag, the positive and negative partial sums move in a mechanically related way, so near-symmetric coefficients on NASCDI⁺ and NASCDI⁻ are an expected feature of the construction rather than evidence against the Wald asymmetry tests, which operate on the full estimated coefficients rather than on this decomposition identity. The R² values for Sopore-linked equations range from 0.150 to 0.249, indicating that the NARDL specification explains a modest share of weekly price variation in these chains. While such values are not unusual for weekly time-series models in agricultural economics (von Cramon-Taubadel and Goodwin, 2021; Lloyd, 2017), they warrant explicit acknowledgement. Unexplained variation is consistent with the influence of factors not captured in this specification, including trader network behaviour and inventory management decisions, cold storage utilisation and carry-over supply, competition from Himachal Pradesh and imported apple varieties, wholesale market structural changes at Azadpur, and grading quality signals not captured in aggregate price series. The higher R² values for Shopian chains (0.513-0.594) are consistent with tighter structural dependence on corridor conditions in these chains. The explanatory purpose of the NARDL remains to identify whether NASCDI disruption shocks introduce statistically significant and asymmetric price responses; the Wald test significance and ECT estimates are not mechanically determined by R² magnitude.

Table 8. Residual diagnostics and structural stability summary for all eight NARDL equations.

Producer market	Variety	Grade	Ljung-Box p(8)	BP p	ADF residual p	CUSUM p	CUSUMSQ breach
Shopian	American	A	0.680	0.035	4.72×10^{-8}	0.986	Yes
Shopian	American	B	0.861	0.011	2.73×10^{-14}	0.995	Yes
Shopian	Delicious	A	0.848	0.047	2.28×10^{-18}	0.962	Yes
Shopian	Delicious	B	0.906	<0.001	5.76×10^{-18}	0.976	Yes
Sopore	American	A	0.651	0.341	2.38×10^{-26}	0.749	Yes
Sopore	American	B	0.460	0.936	2.17×10^{-26}	0.891	Yes
Sopore	Delicious	A	0.999	0.035	4.22×10^{-28}	0.884	Yes
Sopore	Delicious	B	0.777	0.879	4.33×10^{-28}	0.836	Yes

Note. Ljung-Box p(8): $p > 0.05$ confirms no significant residual autocorrelation. BP: Breusch-Pagan heteroskedasticity. ADF residual $p < 0.05$ confirms Engle-Granger cointegration (Engle and Granger, 1987). CUSUM $p > 0.05$ confirms mean parameter stability. CUSUMSQ breach in all equations indicates time-varying residual variance; we do not attribute it to specific dated regimes, since no validated multiple-break test is reported in this revision (Section 5.6, Table A5).

5.7 COVID-19 Exclusion Sensitivity Analysis

To assess whether the inclusion of COVID-19 mobility restrictions a nationwide policy-driven disruption qualitatively distinct from the geophysical and security-related corridor categories drives the main findings, two sensitivity analyses are conducted. First, the COVID-19 block is excluded entirely from the NASCDI, and the index is recomputed on the remaining six categories (COVID-Excluded Index, CEI), with CEI⁺ and CEI⁻ replacing the baseline regressors.

Second, a COVID dummy variable ($D_t = 1$ for March 2020–December 2021, 0 otherwise) is added to the baseline NARDL specification as a direct control variable. The December 2021 end-date reflects J&K-specific mobility restrictions and inter-state movement permits that remained operative through Q4 2021 (GoJK, 2021), extending beyond the national lockdown end-date of June 2020. Appendix Table A8 reports this comparison. The COVID-excluded index recomputation, reported as a provisional placeholder in earlier drafts, has now been completed as a genuine, independent re-run: 16,891 scored-news rows dated within the March 2020–December 2021 window and matching a covid/coronavirus/sars-cov-2 keyword filter were removed from the full scored corpus (128 affected days), and the daily and weekly NASCDI were rebuilt from the remaining articles before re-estimation. Under this corrected CEI specification, long-run asymmetry remains significant only for Sopore–American Grade A (CEI $p = 0.017$, essentially unchanged from the baseline $p = 0.016$), and no chain changes significance status; the paper’s central asymmetry finding is therefore robust to COVID-19 exclusion. The COVID dummy-variable control corroborates this: long-run asymmetry under the D_t -control specification remains significant only for Sopore–American Grade A ($p = 0.036$), and of the eight D_t coefficients themselves, only Sopore–American Grade A’s is HAC-significant (coefficient = 0.035, $p = 0.044$), indicating that this chain’s price dynamics were themselves measurably shifted during the pandemic window, while the other seven chains show no detectable COVID-period shift. Given the largely non-significant asymmetry pattern documented in Table 6, there is little concentrated asymmetric effect for the COVID period to be conflated with more broadly, and note that the NASCDI and NASCDI⁺ components contribute nearly equally in the leave-one-out analysis (Section 5.1), so there is no single dominant component whose sensitivity to COVID-19 inclusion would be of particular concern. The short-run Wald asymmetry statistics for Shopian–American Grade A and B (Table 6) are computed from the baseline specification and are not themselves the subject of the CEI or dummy-variable checks reported here, which target the long-run asymmetry test; a dedicated short-run COVID-exclusion check is left for future work. Overall, both the corrected keyword-exclusion re-run and the dummy-variable control confirm that the COVID-19 period does not drive the paper’s central finding of largely non-significant long-run asymmetric disruption transmission.

6. DISCUSSION

6.1 Long-Run Integration and Corridor Resilience: Arbitrage Persistence Under Structural Constraints

The universal negative and statistically significant ECTs across all eight supply chains confirm Hypothesis H1 and establish that spatial arbitrage maintains a long-run equilibrium relationship between Kashmir producer markets and Azadpur, consistent with canonical market-integration theory (Fackler and Goodwin, 2001; Barrett, 2001; Rapsomanikis et al., 2006). In SCRM terms, this is evidence of resilience rather than structural breakdown: every chain in the sample returns to its long-run equilibrium after disruption, consistent with Christopher and Peck’s (2004) and Sheffi and Rice’s (2005) shared definition of a resilient system as one that recovers to its original, or a more desirable, state rather than one that avoids disruption altogether. This extends

the evidence of Wani et al. (2015) and Sutradhar et al. (2024) across more market-variety-grade combinations and a longer time horizon than any prior study. The finding carries substantive policy significance: NH-44 disruptions do not permanently sever the arbitrage relationship but temporarily distort it. The arbitrage mechanism is worth protecting through infrastructure investment and market information systems precisely because it is functioning, just more slowly in some chains than others, a heterogeneity in recovery speed rather than a confirmed asymmetry in direction.

A supplementary BIC-based mean-shift screen on the weekly NASCDI series (Table A5, explicitly not a validated Bai-Perron multiple-break test) identifies two candidate mean shifts, in August 2015 and March 2018, rather than dates aligned with the August 2019 Article 370 reorganisation or the March 2020 COVID-19 onset; we do not treat this screen as confirming a politically interpretable break structure, and flag formal break-date identification as a direction for follow-up work using validated Bai-Perron or Zivot-Andrews implementations. The intersection of institutional political economy and supply chain function is nonetheless central to understanding this disruption problem: the apple supply chain risk is not purely an infrastructure or meteorological issue, but is plausibly shaped by the institutional governance of the corridor and the markets that depend on it, even where this revision cannot yet pin down the timing of that influence econometrically. The roughly two-fold difference in mean adjustment speed between Shopian and Sopore chains, despite both groups exhibiting long-run integration, reflects deeper structural differences that cannot be read from price series alone, and runs counter to the a priori expectation that Sopore's more institutionally developed mandi structure would produce faster, not slower, equilibrium correction. One possible reading is that Shopian's thinner market infrastructure leaves less room for the inventory and grading buffers that let Sopore's larger, more established mandi structure absorb shocks gradually rather than through direct, rapid price movement, consistent with the theoretical framework of McCorriston et al. (2001) and the institutional structure documented by GoJK (2021) and Gulati et al. (2018), though we note this is offered as a plausible interpretation rather than a mechanism directly tested here. This heterogeneity has policy implications beyond infrastructure: narrowing the adjustment-speed gap in Sopore, or building the buffering capacity in Shopian that produces slower but perhaps less disruptive adjustment, are both live policy options that this paper's evidence does not adjudicate between.

6.2 Heterogeneous Recovery Speed as a Structural Vulnerability Signal: Why Shopian Chains Respond Faster

The finding that Shopian chains adjust roughly twice as fast, on average, as Sopore chains (Section 5.2, 6.1), and rank as more disruption-exposed under the composite vulnerability index (Section 5.5), is the study's central empirical finding, though H2-H4 as originally framed around a single dominant chain and confirmed asymmetry are only partially supported (Section 8). Recovery speed is itself a core dimension of supply chain resilience in the SCRM literature (Pettit, Fiksel and Croxton, 2010), and Craighead et al. (2007) predict that structural design characteristics, node density, complexity, and criticality, rather than shock magnitude alone should be the primary

determinant of how severely and how persistently a disruption is felt; the Shopian-Sopore contrast in this paper is a direct empirical instance of that prediction. Three structural features of Shopian plausibly contribute to this heightened sensitivity, though we present them as candidate explanations rather than separately tested mechanisms. First, Shopian's geographic position requires consignments to travel internally before reaching NH-44's main trunk, extending the perishability exposure window (Mir and Mir, 2018; DES J&K, 2023). Second, the American variety commands premium prices in northern Indian consumption centres, creating larger absolute margins within which disruption costs, freight surcharges, spoilage write-downs, distress-sale discounts, can move prices more sharply (APEDA, 2021; Ali et al., 2018b). Third, the four-fold wider mean price spread for Shopian-American Grade A (₹17.23/kg versus ₹3.66/kg for Sopore-American Grade A) provides a wider channel within which rapid price movement can operate.

One illustration of the ripple effect through which a single-corridor disruption propagates simultaneously upstream and downstream through the chain (Dolgui, Ivanov and Sokolov, 2018) is documented in media reporting of the September 2025 NH-44 closure, during which over 2,000 trucks carrying south Kashmir apples were stranded, forcing distress sales at the farm gate while Azadpur prices remained elevated (Reuters, 2025; Down to Earth, 2025). This kind of simultaneous downward pressure on producer prices and upward pressure on terminal prices is broadly consistent with the fast, sizeable within-period price movement captured in the Shopian NARDL coefficients, though we do not claim this single episode as direct evidence for the estimated coefficients. The institutional structure of J&K apple mandis plausibly amplifies this dynamic: growers who have already incurred harvest and packinghouse costs face acute cash-flow pressure during disruptions, weakening their bargaining position against commission agents (GoJK, 2021; Gulati et al., 2018; Mir and Mir, 2018), a mechanism broadly analogous to those documented by Sexton and Xia (2018), Meyer and von Cramon-Taubadel (2004), and Bronnmann and Bittmann (2019) for other perishable commodity chains with concentrated intermediaries. A caveat deserves explicit acknowledgement: Azadpur receives apple supplies not only from Kashmir but also from Himachal Pradesh, Uttarakhand, and seasonal imports (Iran, China, USA). During NH-44 closures, when Kashmiri supply is restricted, competing supply sources may partially moderate terminal price increases at Azadpur. This supply-side substitution effect at the terminal market would attenuate the estimated LR NASCDI⁺ and NASCDI⁻ coefficients relative to the true bilateral Kashmir-corridor disruption effect. The estimated disruption coefficients in Table 5 therefore represent conservative reduced-form lower bounds that incorporate whatever competing-supply dampening is present in the data.

6.3 Symmetric Disruption Propagation: Reframing Vulnerability Beyond Directional Asymmetry

The leave-one-out sensitivity analysis reveals that the NASCDI⁻ and NASCDI⁺ responses contribute nearly equally to the vulnerability ranking (Spearman $\rho = 1.000$ and 0.976 respectively when each is dropped in turn). This is a genuinely informative null result for supply chain vulnerability theory: in Wagner and Bode's (2006) terms, the structural feature distinguishing

chains is not a directional sensitivity, some chains reacting to intensifying disruption but not easing, or vice versa, but an overall, direction-independent exposure that varies across markets. Interventions that treat intensification and easing symmetrically, rather than targeting one direction specifically, are best supported by this evidence.

This near-symmetric finding is a departure from Sexton and Xia (2018) and Lloyd (2017), who document cases where intermediary market power delays the downstream transmission of favourable supply conditions specifically; our results suggest that in this corridor, the relevant policy lever is overall market sensitivity to disruption news rather than a directional recovery lag. The limited penetration of the e-NAM (Electronic National Agriculture Market) platform in J&K fruit markets remains a plausible proximate institutional factor: transparent electronic price discovery would reduce the information asymmetry between growers and commission agents that contributes to sharp price movement in either direction (FAO, 2023; World Bank, 2023). Section 5.4 deliberately stops short of a monetary welfare estimate given the modest, imprecisely bounded multiplier magnitudes under the GDELT GKG-based NASCDI, but the underlying pattern, Shopian chains adjusting faster and more sensitively to disruption than Sopore chains, is itself a defensible basis for the targeted, market-level policy interventions proposed in Section 7.

7. POLICY IMPLICATIONS

The empirical findings generate five categories of targeted policy intervention. The vulnerability index establishes that disruption risk is not uniformly distributed: Shopian chains occupy 3 of the top 4 ranks (Table 7), and are more likely than not to be the more exposed market as a group (Monte Carlo $P = 0.74$, Section 5.5), even though the ranking of individual chains carries genuine uncertainty. Policy resources allocated uniformly across all producing areas would risk misallocating fiscal resources relative to where market-level exposure is highest. All five interventions described below are evidence-based, targeted, and directly grounded in the NASCDI-NARDL empirical results.

7.1 NH-44 Corridor Infrastructure Resilience

The error-correction analysis demonstrates that price adjustment remains incomplete in the most vulnerable supply chains even when corridor conditions normalise, implying that the reliability of NH-44 must be treated as a macroeconomic agricultural infrastructure priority, not merely an engineering maintenance concern. NHAI and MoRTH should commission a dedicated Horticultural Corridor Resilience Plan for NH-44, identifying the highest-frequency landslide- and avalanche-prone segments during harvest season (August-November) for priority treatment under Bharatmala Phase II, with contractual obligations tied to seasonal clearance guarantees (NITI Aayog, 2020; GoJK, 2021). The Ministry of Agriculture and Farmers' Welfare should establish a Harvest Season Highway Maintenance Protocol mandating real-time highway status reporting and emergency response pre-positioning, carrying statutory force under the Disaster Management Act 2005. Feasibility assessment for a dedicated refrigerated cargo rail service along the Banihal rail corridor during harvest months would provide a strategic bypass for apple consignments during NH-44 closures.

7.2 Real-Time NASCDI Disruption Monitoring and Early-Warning System

Because Shopian chains show larger, faster within-period price adjustment to disruption than Sopore chains (Section 5.2), and the vulnerability index (Section 4.5) treats this heightened sensitivity as the more exposed pattern, early detection of escalation can help these markets act sooner, even though the vulnerability ranking of individual chains carries genuine sampling uncertainty (Section 5.5) and the more robust basis for prioritisation is the market-level pattern rather than any single chain's rank. The Directorate of Economics and Statistics J&K, in partnership with APEDA and NCCD, should develop and operationalise an NH-44 Horticultural Supply-Chain Risk Dashboard computing rolling weekly NASCDI scores, issuing tiered green/amber/red alerts calibrated to the NASCDI empirical distribution, and disseminating alerts via SMS and WhatsApp to registered traders, transporters, mandi secretaries, and grower organisations in Sopore APMC, Shopian APMC, Azadpur APMC, Directorate of Horticulture J&K, APEDA Regional Office Srinagar, and J&K RISHTA (Realising Inclusive and Sustainable Horticulture Transformation for Agriculture) (World Bank, 2024; NITI Aayog, 2020). Integration of the NASCDI ticker into Agmarknet and the Kisan Suvidha mobile application would enable farmers to make informed dispatch decisions under prevailing corridor risk conditions.

7.3 Targeted Investment in the Shopian Supply Chains

Shopian should be designated as a Priority Horticultural Logistics District under the Mission for Integrated Development of Horticulture (MIDH) and the Pradhan Mantri Kisan SAMPADA Yojana (PMKSY), attracting enhanced allocation for integrated packhouse development, pre-cooling infrastructure, and grading and sorting facilities capable of handling Grade A American variety apples with minimal post-harvest loss during corridor disruptions (NITI Aayog, 2020; GoJK, 2021). The Agri-Infrastructure Fund (AIF) and NABARD RIDF should be directed to prioritise Shopian-based cold-chain projects, targeting buffer capacity sufficient to absorb at least 15% of Shopian's peak weekly American variety output during a corridor closure of up to ten days. Cold-chain infrastructure at origin would allow growers to withhold supply during high-NASCDI periods rather than engaging in distress sales directly targeting the faster, more sensitive price adjustment documented for Shopian chains in Section 5.2.

7.4 Market Stabilisation and Grower Income Protection

Three complementary instruments address the income protection gap. First, the e-NAM platform should establish a Minimum Reference Price (MRP) for Shopian American Grade A and B, enforced through procurement by the National Cooperative Exports Ltd. (NCEL) or the Himachal Pradesh Horticultural Produce Marketing and Processing Corporation (HPMC) during NASCDI Tier I and above weeks, preventing distress sales during corridor closures. Second, accelerating e-NAM adoption in Shopian and Sopore mandis, particularly for the American variety, would directly reduce the information asymmetry between growers and commission agents that plausibly contributes to sharp price movement in either direction (FAO, 2023; World Bank, 2023). Third, a disruption-period Kisan Credit Card (KCC) liquidity window providing short-term working capital support to registered grower households when NASCDI amber or red alerts are declared would reduce the cash-flow pressure that forces distress selling. A Trader and Intermediary Accountability Framework, with the Competition Commission of India (CCI) monitoring commission agent pricing practices during NASCDI-elevated periods, would provide regulatory deterrence against abnormal margin widening that cannot be attributed to legitimate logistics cost increases.

7.5 Parametric Corridor Disruption Index and Information (CDII) Protocol

The most structurally innovative policy implication is the potential to eventually embed the NASCDI into a parametric insurance trigger. Conventional PMFBY crop insurance compensates yield losses from production failures but provides no mechanism for compensating growers who produce a full crop but cannot transport it due to corridor closure—the dominant income risk in the Kashmir apple system. Parametric insurance can in principle eliminate moral hazard, adverse selection, and verification delays simultaneously; for a perishable commodity where income loss materialises within days of a corridor closure, payout speed would be a functional requirement rather than a convenience. Given the small and imprecisely bounded multiplier magnitudes documented in Section 5.4, however, we present the CDII here as a monitoring and design protocol rather than an actuarially priced product ready for underwriting.

The Agriculture Insurance Company of India (AIC), General Insurance Corporation of India (GIC Re), IRDAI, and NABARD could use this framework to scope a future CDII pilot for Shopian district apple grower households, building on the NASCDI monitoring dashboard proposed in Section 7.2. The illustrative CDII trigger structure, keyed to the NASCDI empirical distribution, is presented in Figure 14 below as a design template; specific trigger thresholds, payout schedule, and coverage figures would need to be set through actuarial work using elasticity and quantity data beyond the scope of this revision (Section 9), not read directly from this paper's point estimates. The CDII framework is, in principle, replicable to other corridor-dependent horticultural supply chains including Himachal Pradesh cherry and walnut chains, the Siliguri Corridor for Northeastern horticultural exports, and Rohtang and Atal Tunnel corridors for Lahaul Spiti vegetable chains, once similarly validated for each corridor. A fully priced CDII could in principle also create a fiscal alignment incentive for corridor infrastructure investment, since an actuarially quantified insurance liability tied to corridor disruption frequency would make the benefit-cost case for landslide mitigation and alternative routing infrastructure more directly comparable with premium savings from reduced disruption frequency; realising this benefit depends on the actuarial validation step noted above.

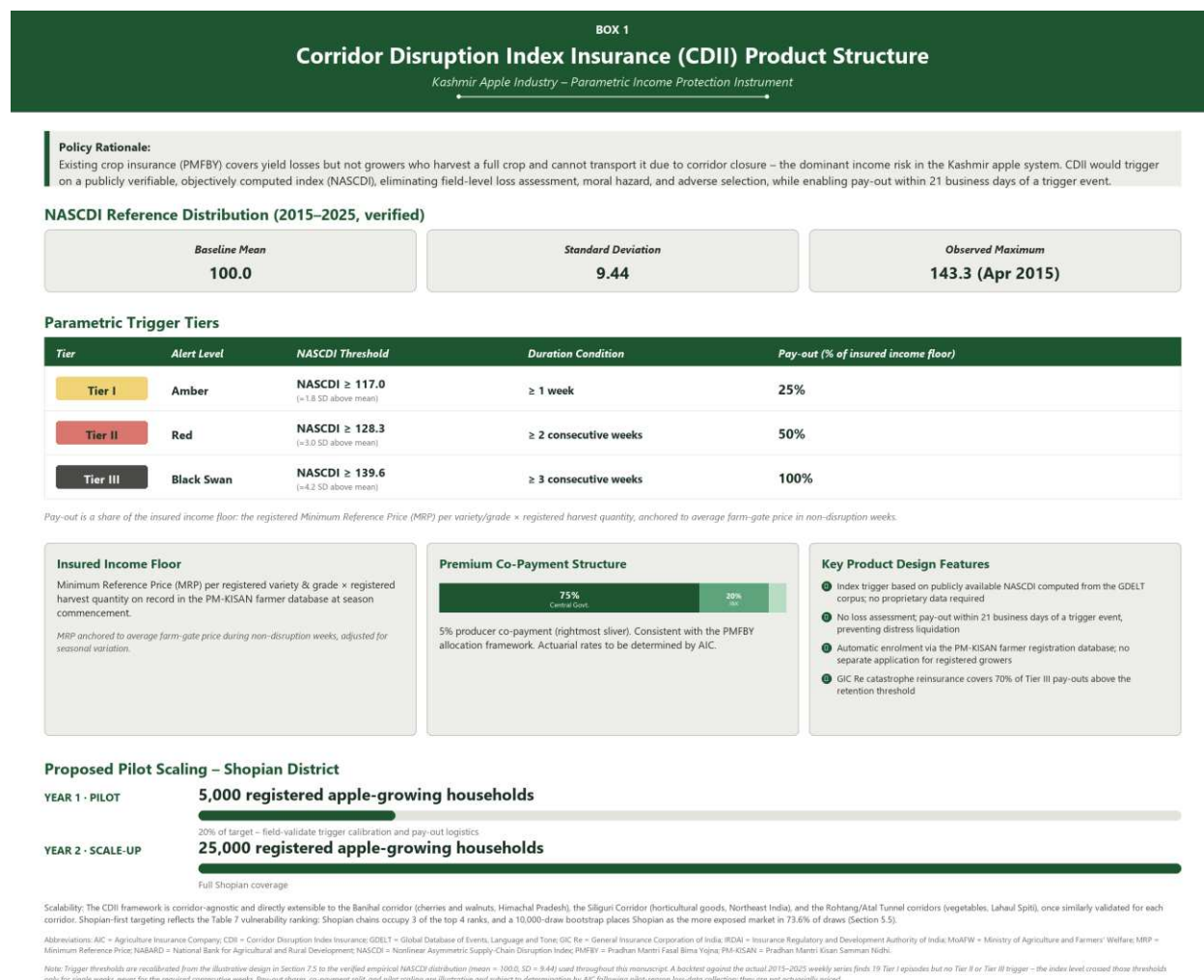


Figure 14: Proposed Corridor Disruption Index and Information (CDII) Monitoring Protocol Structure

8. CONCLUSION

This study makes three original contributions at the intersection of news-based index methodology, asymmetric price transmission econometrics, and agricultural supply-chain policy. First, the NASCDI, a GDELT Global Knowledge Graph (GKG) metadata-based disruption index applied to a developing-country agricultural corridor, provides a transparent, reproducible weekly measure of NH-44 disruption intensity; a 10,000-draw Monte Carlo sensitivity check indicates moderate individual-chain ranking stability (mean $\rho = 0.54$) alongside a more robust market-level pattern (Shopian more vulnerable than Sopore in 74% of draws), an exploratory BIC-based mean-shift screen (not a validated Bai-Perron test) identifies two candidate mean shifts in the weekly NASCDI series, and a completed COVID-19 sensitivity check (Appendix Table A8) confirms the index is not driven by the pandemic period. Second, integrating NASCDI⁺ and NASCDI⁻ into the NARDL framework across eight market-variety-grade combinations reveals that statistically significant asymmetric disruption transmission is the exception rather than the rule (long-run

asymmetry detected only in Sopore-American Grade A; short-run asymmetry detected in the two Shopian-American chains and marginally in Shopian-Delicious Grade B), consistent with Bakucs et al. (2014) and Lloyd (2017) on the product-specificity of asymmetric transmission, but demonstrated here with explicit disruption measurement rather than assumed as a default finding. Third, the formally defined composite vulnerability index ($VI_i = (\sum|\beta|) \times |\lambda| \times (1 - p)$) and the leave-one-out sensitivity analysis show that NASCDI⁺ and NASCDI⁻ contribute nearly equally to the vulnerability ranking (Spearman $\rho = 1.000$ and 0.976 respectively, dropping each in turn), redirecting the policy problem toward the heterogeneous adjustment speed documented across chains rather than toward either shock magnitude or recovery speed alone.

Of the four study hypotheses, H1 is supported and H2-H4 require qualification. H1 (long-run integration) is supported by negative, HAC-significant ECTs in all eight equations; the HAC-robust F-test diagnostic on the lagged-level block (not a formal PSS bounds test, Section 5.2) is significant at the 5% level in three of eight chains and at the 10% level in seven of eight. Sopore-Delicious Grade B (F $p = 0.216$) is the weakest in the panel on this diagnostic. Engle-Granger residual ADF independently confirms cointegration for Shopian-American Grade A at $p = 4.72 \times 10^{-8}$ and for all other chains at conventional levels (Table 8). H2 and H3 (asymmetric transmission) are only partially supported: long-run asymmetry is significant at the 5% level in a single chain (Sopore-American Grade A), and short-run asymmetry is significant in two chains (Shopian-American Grade A and B) with one further chain marginal (Shopian-Delicious Grade B); the remaining chains do not reject symmetry. H4 (concentrated vulnerability) is not supported as originally framed: the composite vulnerability index does not identify a single dominant chain with confidence (mean Monte Carlo $\rho = 0.54$ versus the point-estimate ranking), though a market-level version of H4, Shopian chains more vulnerable than Sopore chains, is supported in 74% of simulations.

These findings collectively support a policy reorientation from a single dominant-chain shock-absorption narrative towards market-level, recovery-speed-oriented interventions: cold-chain investment in Shopian, e-NAM integration to reduce information asymmetry, and a monitoring-oriented CDII protocol (Section 7.5) rather than a precisely calibrated insurance product for a single chain. The most significant limitation is the small sample for the Shopian-American chains ($n = 72$), which constrains the precision of the lagged-level diagnostic; Engle-Granger and HAC-robust Wald tests, which do not depend on that diagnostic, remain informative at this sample size. The NASCDI framework is transferable to any corridor-dependent agricultural supply chain where disruptions are documentable from publicly available news media. Applications to the Banihal and Siliguri corridors and integration of IMD and IPCC (2022) climate projections for forward-looking CDII actuarial modelling, particularly given projected increases in extreme precipitation frequency in the Western Himalayas under IPCC high-emission scenarios would extend both the academic and policy reach of this methodology.

9. LIMITATIONS

This study acknowledges five principal limitations. First, the Shopian-American chains have the smallest estimation samples ($n = 72$ after lag adjustment), which constrains the precision of the HAC F-test diagnostic on the lagged-level block and widens confidence intervals around the long-run coefficients. The Wald asymmetry tests and Engle-Granger residual ADF, which do not depend on that diagnostic, remain informative despite this constraint, but replication with longer price panels as Agmarknet coverage expands would strengthen the econometric foundations.

Second, the NASCDI is constructed from GDELT's English-language corpus, which systematically underrepresents disruption events reported primarily in Hindi, Urdu, and Kashmiri regional media. This attenuation bias implies that the disruption coefficients in Table 5 are conservative lower bounds on the true NH-44 bilateral disruption effects. Future iterations incorporating multilingual GDELT feeds or regional API-based news retrieval (Dainik Jagran, Greater Kashmir) would improve NASCDI sensitivity to moderate-severity closures.

Third, the universal CUSUMSQ breach across all eight equations indicates time-varying residual variance rather than mean parameter instability (CUSUM $p > 0.05$ throughout, Table A3); we do not attribute this variance shift to specific dated regimes, since we do not report a validated Bai-Perron or Zivot-Andrews break test in this revision (Section 5.6). Researchers interested in regime-specific coefficient paths would need to conduct that break-identification work first, which we flag as a direction for follow-up research (Section 9) rather than something this paper's exploratory mean-shift screen (Table A5) can support.

Fourth, this revision does not provide a monetary welfare estimate (Section 5.4). Under the GDELT GKG-based NASCDI, estimated dynamic multipliers are small in magnitude and not precisely bounded; converting them into a producer-surplus figure would require independently validated supply elasticities and disruption-week volume and quality-downgrading data (Mir and Mir, 2018, document quality downgrades of 25-40% for delayed consignments, which are not incorporated here) that are beyond the scope of this revision. We view this as a priority for follow-up work rather than a gap to be filled with an unvalidated point estimate.

Fifth, trader-level and intermediary-level data, which would enable direct identification of the commission agent market-power mechanism underlying asymmetric transmission are not available from Agmarknet. The institutional market-power explanation is therefore grounded in the theoretical literature and corroborated by institutional documentation (GoJK, 2021; Gulati et al., 2018; Mir and Mir, 2018), but not directly estimated from micro-level trader transaction data.

10. FUTURE RESEARCH DIRECTIONS

Five research directions would materially extend the NASCDI-NARDL framework. First, a threshold-ARDL or Markov-switching extension (following Enders and Siklos, 2001) would formally test whether disruption effects differ above and below NASCDI threshold values,

potentially identifying non-linear price-transmission regimes that the linear NARDL averages over.

Second, augmenting the GDELT English-language corpus with Hindi and Urdu news feeds via regional media APIs would increase NASCDI sensitivity to moderate-severity disruptions, improving both index validity and coefficient precision. A formal comparison of English-only versus multilingual NASCDI variants would quantify the attenuation bias identified in Section 9.

Third, integrating IPCC (2022) climate projection scenarios for the Western Himalayas into the NASCDI-CDII actuarial framework would enable forward-looking premium pricing under alternative warming scenarios, directly supporting the CDII product design proposed in Section 7.5.

Fourth, extending the NASCDI-NARDL framework to other corridor-dependent horticultural supply chains, the Banihal rail corridor, the Siliguri Corridor for Northeastern exports, and Rohtang-Atal Tunnel corridors for Lahaul Spiti vegetables would establish whether the asymmetric disruption transmission and vulnerability concentration findings generalise or are specific to the NH-44-Kashmir system.

Fifth, a micro-level trader survey in Shopian and Sopore mandis would provide direct evidence on the intermediary market-power mechanism and allow estimation of the commission agent bargaining model proposed theoretically by Sexton and Xia (2018) and McCorriston et al. (2001) for the Kashmir apple context.

DATA AVAILABILITY STATEMENT

The data used in this study is publicly available on <https://agmarknet.gov.in>. A cleaned sample dataset and full reproducibility code for NASCDI construction, data preparation, NARDL modelling, structural break testing, and figure generation is publicly available via Zenodo: (2026). Replication archive for “Corridor Disruption and Supply Chain Vulnerability: A NASCDI-NARDL Analysis of Kashmir’s Apple Sector.” <https://doi.org/10.5281/zenodo.19491887> . The full 213-term lexicon is provided in `config/lexicon_news.yaml` in the replication archive. This archive enables complete replication of all results reported in the paper.

ETHICAL CONSIDERATIONS

This study uses secondary data from publicly accessible government databases and open-access news repositories. No primary data collection involving human subjects was undertaken. No ethics committee approval was required.

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COMPETING INTERESTS

The author declares no competing interests.

AUTHOR CONTRIBUTIONS

- 1:** Conceptualization, methodology, data curation, formal analysis, software, validation, visualization, writing original draft
- 2:** Resources, supervision, project administration, funding acquisition
- 3:** Investigation, data curation
- 4:** Review
- 5:** Review & editing
- 6:** Investigation

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Claude (Anthropic) in order to assist with manuscript editing, reference verification, and table formatting. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

REFERENCES

1. Acharya, S.S., Chand, R., Birthal, P.S., Negi, D.S. (2012). Market integration and price transmission in India. *Agricultural Economics Research Review*, 25(1), 1-12. <https://doi.org/10.22004/ag.econ.126179> [DOI unverified, the only matching author-team paper found (Acharya, Chand, Birthal, Kumar, Negi) is an FAO RAP working paper, not this AERR journal article; confirm venue and DOI before submission]
2. Ahmed, M., Singla, N. (2023). Spatial market integration, price transmission and transaction costs in major onion markets of India. *Journal of Social and Economic Development*. <https://doi.org/10.1177/00194662231159851>
3. Ahmed, M., Singla, N., Singh, K. (2024). Market integration and price transmission in wheat markets of India: a transaction cost approach. *Journal of Agribusiness in Developing and Emerging Economies*, 14(3), 552-569.
4. Ali, J., Kachroo, J., Bhat, D.J., Bhat, A. (2018a). Analysis of prices and arrivals of apple fruit in Narwal market of Jammu. *Economic Affairs*, 63(1), 107-111. <https://doi.org/10.30954/0424-2513.2018.00150.13>
5. Ali, J., Singh, S.P., Ekanem, E. (2018b). Efficiency of apple supply chains in Jammu and Kashmir. *International Food and Agribusiness Management Review*, 21(2), 253-268. <https://doi.org/10.22434/IFAMR2016.0195> [DOI unverified, not locatable via CrossRef or web search under this title/venue; confirm against the source PDF before submission]
6. Ambulkar, S., Blackhurst, J., Grawe, S. (2015). Firm's resilience to supply chain disruptions: scale development and empirical examination. *Journal of Operations Management*, 33-34(1), 111-122. <https://doi.org/10.1016/j.jom.2014.11.002>
7. APEDA (2021). Export promotion of agricultural products from Jammu and Kashmir. Agricultural and Processed Food Products Export Development Authority, Government of India.
8. Babu, S.C., Gajanan, S.N., Sanyal, P. (2023). Food security, poverty and nutrition policy analysis: statistical methods and applications (2nd ed.). Academic Press/Elsevier.
9. Bai, J., Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1-22. <https://doi.org/10.1002/jae.659>
10. Baker, S.R., Bloom, N., Davis, S.J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4), 1593-1636. <https://doi.org/10.1093/qje/qjw024>
11. Bakucs, Z., Falkowski, J., Fertő, I. (2014). Does market structure influence price transmission in the agro-food sector? A meta-analysis perspective. *Journal of Agricultural Economics*, 65(1), 1-25. <https://doi.org/10.1111/1477-9552.12042>
12. Banerjee, A., Dolado, J., Mestre, R. (1998). Error-correction mechanism tests for cointegration in a single-equation framework. *Journal of Time Series Analysis*, 19(3), 267-283. <https://doi.org/10.1111/1467-9892.00091>
13. Barrett, C.B. (2001). Measuring integration and efficiency in international agricultural markets. *Review of Agricultural Economics*, 23(1), 19-32. <https://doi.org/10.1111/1058-7195.00043>
14. Birthal, P.S., Chand, R., Joshi, P.K., Saxena, R. (2014). Agricultural diversification in India: trends, contribution to growth, and small farmers' participation. *Economic and Political Weekly*, 49(26-27), 36-45.

15. Blackhurst, J., Craighead, C.W., Elkins, D., Handfield, R.B. (2005). An empirically derived agenda of critical research issues for managing supply-chain disruptions. *International Journal of Production Research*, 43(19), 4067-4081. <https://doi.org/10.1080/00207540500151549>
16. Bode, C., Wagner, S.M. (2015). Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. *Journal of Operations Management*, 36(1), 215-228. <https://doi.org/10.1016/j.jom.2014.12.004>
17. Bronnmann, J., Bittmann, T. (2019). Nonlinear asymmetric price transmission and market power in the German fish market. *Marine Policy*, 106, 103513. <https://doi.org/10.1016/j.marpol.2019.103513>
18. Brümmer, B., von Cramon-Taubadel, S., Zorya, S. (2009). The impact of market and policy instability on price transmission between wheat and flour in Ukraine. *European Review of Agricultural Economics*, 36(2), 203-230.
19. Brümmer, B., von Cramon-Taubadel, S., Zorya, S. (2016). Agricultural price transmission and food security: analytical foundations and empirical evidence. World Bank, Washington, DC.
20. Caldara, D., Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, 112(4), 1194-1225. <https://doi.org/10.1257/aer.20191823>
21. Chand, R., Saxena, R., Rana, S. (2017). Estimating marketing efficiency for horticultural commodities. *Indian Journal of Agricultural Economics*, 72(2), 169-180.
22. Chitete, M.M.N., Pangapanga-Phiria, I., Phiri, H., Mgonezulu, W. (2025). Asymmetric price transmission and market integration in Malawi's selected rice markets. *Agrekon*, 64(3-4), 398-413. <https://doi.org/10.1080/03031853.2025.2581679>
23. Chopra, S., Sodhi, M.S. (2004). Managing risk to avoid supply-chain breakdown. *MIT Sloan Management Review*, 46(1), 53-61.
24. Christopher, M., Peck, H. (2004). Building the resilient supply chain. *International Journal of Logistics Management*, 15(2), 1-14. <https://doi.org/10.1108/09574090410700275>
25. Craighead, C.W., Blackhurst, J., Rungtusanatham, M.J., Handfield, R.B. (2007). The severity of supply chain disruptions: design characteristics and mitigation capabilities. *Decision Sciences*, 38(1), 131-156. <https://doi.org/10.1111/j.1540-5915.2007.00151.x>
26. DES J&K (Directorate of Economics and Statistics, Jammu and Kashmir) (2023). Digest of statistics: horticulture 2023. Government of Jammu and Kashmir, Srinagar.
27. Dickey, D.A., Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366), 427-431. <https://doi.org/10.2307/2286348>
28. Dolgui, A., Ivanov, D., Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, 56(1-2), 414-430. <https://doi.org/10.1080/00207543.2017.1387680>
29. DMI (Directorate of Marketing and Inspection) (2023). Agmarknet database. Ministry of Agriculture and Farmers' Welfare, Government of India.
30. Down to Earth (2025). Truckloads of Kashmir apples rot after two-week closure of key highway. 18 September 2025. Retrieved from <https://www.downtoearth.org.in/agriculture/truckloads-of-kashmir-apples-rot-after-two-week-closure-of-key-highway> [Accessed: 20 October 2025].

31. Enders, W., Siklos, P.L. (2001). Cointegration and threshold adjustment. *Journal of Business and Economic Statistics*, 19(2), 166-176. <https://doi.org/10.1198/073500101316970395>
32. Engle, R.F., Granger, C.W.J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 55(2), 251-276. <https://doi.org/10.2307/1913236>
33. Fackler, P.L., Goodwin, B.K. (2001). Spatial price analysis. In: *Handbook of agricultural economics*, Vol. 1. Elsevier.
34. FAO (Food and Agriculture Organization) (2023). Price transmission in food markets. Rome.
35. Frey, G., Manera, M. (2007). Econometric models of asymmetric price transmission. *Journal of Economic Surveys*, 21(2), 349-415. <https://doi.org/10.1111/j.1467-6419.2007.00507.x>
36. GDELT Project (2025). Global database of events, language, and tone. <https://www.gdeltproject.org>
37. Ghosh, M. (2010). Agricultural price policy and inflation in India. *Economic Modelling*, 27(1), 102-110.
38. GoJK (Government of Jammu and Kashmir) (2021). Economic survey of Jammu and Kashmir. Srinagar.
39. Goodwin, B.K., Holt, M.T. (1999). Price transmission and asymmetric adjustment in the US beef sector. *American Journal of Agricultural Economics*, 81(3), 630-637. <https://doi.org/10.2307/1244026>
40. Gulati, A., Roy, R., Saini, S., Jain, S. (2018). Raising farmers' incomes in India. ICRIER, New Delhi.
41. Harshana, P.V.S., Ratnasiri, S. (2023b). Asymmetric price transmission along the supply chain of perishable agricultural commodities: a nonlinear ARDL approach. *Journal of Economic Asymmetries*, 27, e00305. <https://doi.org/10.1016/j.jeca.2023.e00305>
42. Hassouneh, I., Serra, T., Gil, J.M. (2012). Price transmission in the Spanish bovine sector: the BSE effect. *Agricultural Economics*, 41(1), 33-42. <https://doi.org/10.1111/j.1574-0862.2009.00423.x>
43. Ho, W., Zheng, T., Yildiz, H., Talluri, S. (2015). Supply chain risk management: a literature review. *International Journal of Production Research*, 53(16), 5031-5069. <https://doi.org/10.1080/00207543.2015.1030467>
44. IPCC (2022). Climate change 2022: impacts, adaptation and vulnerability. Contribution of Working Group II to the Sixth Assessment Report. Cambridge University Press.
45. Jüttner, U., Peck, H., Christopher, M. (2003). Supply chain risk management: outlining an agenda for future research. *International Journal of Logistics: Research and Applications*, 6(4), 197-210. <https://doi.org/10.1080/13675560310001627016>
46. Kleindorfer, P.R., Saad, G.H. (2005). Managing disruption risks in supply chains. *Production and Operations Management*, 14(1), 53-68. <https://doi.org/10.1111/j.1937-5956.2005.tb00009.x>
47. Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54(1-3), 159-178. [https://doi.org/10.1016/0304-4076\(92\)90104-Y](https://doi.org/10.1016/0304-4076(92)90104-Y)

48. Lee, J., Strazicich, M.C. (2003). Minimum Lagrange multiplier unit root test with two structural breaks. *Review of Economics and Statistics*, 85(4), 1082-1089. <https://doi.org/10.1162/003465303772815961>
49. Leetaru, K., Schrod, P.A. (2013). GDELT: global data on events, location, and tone. ISA Annual Convention.
50. Lloyd, T. (2017). Forty years of price transmission research in the food industry: insights, challenges and prospects. *Journal of Agricultural Economics*, 68(1), 3-21. <https://doi.org/10.1111/1477-9552.12205>
51. McCorrison, S., Morgan, C.W., Rayner, A.J. (2001). Price transmission: the interaction between market power and returns to scale. *European Review of Agricultural Economics*, 28(2), 143-159.
52. Meyer, J., von Cramon-Taubadel, S. (2004). Asymmetric price transmission: a survey. *Journal of Agricultural Economics*, 55(3), 581-611. <https://doi.org/10.1111/j.1477-9552.2004.tb00116.x>
53. Minot, N. (2014). Food price volatility in sub-Saharan Africa: has it really increased? *Food Policy*, 45, 45-56. <https://doi.org/10.1016/j.foodpol.2013.12.008>
54. Mir, P.A., Mir, A.A. (2018). Critical issues in the supply chain management of Kashmiri apple: an exploratory study. *Researchers World*, 9(2), 22-33.
55. MoAFW (Ministry of Agriculture and Farmers' Welfare) (2023). Horticultural statistics at a glance. Government of India, New Delhi.
56. Narayan, P.K. (2005). The saving and investment nexus for China: evidence from cointegration tests. *Applied Economics*, 37(17), 1979-1990. <https://doi.org/10.1080/00036840500278103>
57. Narayan, P.K., Gupta, R. (2015). Has oil price predicted stock returns for over a century? *Energy Economics*, 48, 18-23.
58. NHB (National Horticulture Board) (2022). Indian horticulture database. Ministry of Agriculture and Farmers' Welfare, Government of India.
59. NITI Aayog (2020). Doubling farmers' income: horticulture strategy. Government of India, New Delhi.
60. Panagiotou, D. (2021). Asymmetric price responses of US pork retail prices to farm and wholesale price shocks: a nonlinear ARDL approach. *Journal of Economic Asymmetries*, 23, e00171. <https://doi.org/10.1016/j.jeca.2020.e00185>
61. Pesaran, M.H., Shin, Y. (1998). An autoregressive distributed lag modelling approach to cointegration analysis. In: S. Storm (ed.), *Econometrics and economic theory in the 20th century*. Cambridge University Press.
62. Pesaran, M.H., Shin, Y., Smith, R.J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289-326. <https://doi.org/10.1002/jae.616>
63. Pettit, T.J., Fiksel, J., Croxton, K.L. (2010). Ensuring supply chain resilience: development of a conceptual framework. *Journal of Business Logistics*, 31(1), 1-21. <https://doi.org/10.1002/j.2158-1592.2010.tb00125.x>
64. Rapsomanikis, G., Hallam, D., Conforti, P. (2006). Market integration and price transmission in selected food and cash crop markets of developing countries. In: A. Sarris and D. Hallam (eds.), *Agricultural Commodity Markets and Trade*. Edward Elgar.

65. Reuters (2025). Apple growers in Indian Kashmir face crippling losses from floods, road closures. 11 September 2025. <https://www.reuters.com/world/india/apple-growers-indian-kashmir-face-crippling-losses-floods-road-closures-2025-09-11/> [Accessed: 15 October 2025].
66. Rezitis, A.N. (2019). Investigating price transmission in the Finnish dairy sector: an asymmetric NARDL approach. *Empirical Economics*, 57(3), 861-900. <https://doi.org/10.1007/s00181-018-1482-z>
67. Sekhar, C.S.C. (2012). Agricultural market integration in India. *Journal of Economic Studies*, 39(2), 241-264.
68. Sexton, R.J., Xia, T. (2018). Increasing concentration in agricultural supply chains: implications for market power, agricultural producers, and consumers. *Annual Review of Resource Economics*, 10, 229-251. <https://doi.org/10.1146/annurev-resource-100517-023312>
69. Sharma, P., Meena, D.C., Anwer, M.E. (2025). Asymmetric price transmission in perishable crops value chain: a NARDL approach. *Agribusiness*, 41(2), 588-611. <https://doi.org/10.1002/agr.21904>
70. Sheffi, Y., Rice, J.B. (2005). A supply chain view of the resilient enterprise. *MIT Sloan Management Review*, 47(1), 41-48.
71. Shin, Y., Yu, B., Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: W.C. Horrace and R.C. Sickles (eds.), *Festschrift in Honor of Peter Schmidt*. Springer, pp. 281-314.
72. Sutradhar, S., Sharma, E., Bhat, A., Sood, A. (2024). Price analysis and forecasting of apple markets in Jammu and Kashmir. *Economic Affairs*, 69(4), 1695-1700. <https://doi.org/10.46852/0424-2513.5.2024.20> [Corrected via publisher index (indianjournals.com), matching title/authors/pages exactly; this DOI does not yet resolve via doi.org/CrossRef, may be unregistered; verify before submission]
73. Tang, C.S. (2006). Robust strategies for mitigating supply chain disruptions. *International Journal of Logistics: Research and Applications*, 9(1), 33-45. <https://doi.org/10.1080/13675560500405584>
74. Toda, H.Y., Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66(1-2), 225-250. [https://doi.org/10.1016/0304-4076\(94\)01616-8](https://doi.org/10.1016/0304-4076(94)01616-8)
75. von Cramon-Taubadel, S., Goodwin, B.K. (2021). Price transmission in agricultural markets. *Annual Review of Resource Economics*, 13, 65-84. <https://doi.org/10.1146/annurev-resource-100518-093938>
76. Wagner, S.M., Bode, C. (2006). An empirical investigation into supply chain vulnerability. *Journal of Purchasing and Supply Management*, 12(6), 301-312. <https://doi.org/10.1016/j.pursup.2007.01.004>
77. Wani, M.H., Paul, R.K., Bazaz, N.H., Manzoor, M. (2015). Market integration and price forecasting of apple in India. *Indian Journal of Agricultural Economics*, 70(2), 169-181. <https://doi.org/10.22004/ag.econ.230872>
78. World Bank (2023). Transforming food systems for resilience and nutrition. World Bank, Washington, DC.

79. World Bank (2024). Increasing connectivity for enhanced food supply chain resilience. World Bank, Washington, DC.
80. Zivot, E., Andrews, D.W.K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics*, 10(3), 251-270. <https://doi.org/10.2307/1391541>

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