

Baseline Port Structure and Heterogeneous Responses to External Disruptions: Evidence from Major West African Ports

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Abstract

Maritime ports occupying different functional positions within a regional transport system may respond differently to major external disruptions, yet it remains unclear whether simple baseline structural indicators capture this heterogeneity. Using daily International Monetary Fund (IMF) PortWatch observations for ten major conventional West African ports, this study measures cargo diversification and absolute import–export maritime-activity imbalance from a common 2019 baseline and examines responses to COVID-19, the onset of the Russia–Ukraine war, and the December 2023 Red Sea disruption. A stacked event-time model combines port-by-event and event-by-date fixed effects with small-cluster inference. Cargo diversification is associated with a higher day-30 estimated maritime shipment-activity response in the primary specification, but the association disappears after event-specific structural-trend adjustment and does not extend to cargo-call or total-call frequency. Trade imbalance shows no systematic principal endpoint association. The findings therefore indicate that cargo mix and directional orientation describe ports’ baseline functional position but should not be interpreted as stand-alone resilience indicators. Structural indicators are most informative when considered alongside operational capability, network and hinterland context, disruption type, and the specific performance dimension being assessed.

Keywords: Port resilience; port geography; cargo diversification; maritime-flow imbalance; external disruptions; West Africa

1. Introduction

Maritime ports operate within interconnected global supply chains in which externally generated disruptions can produce substantial operational uncertainty. Recent pandemic, geopolitical, and maritime-route disruptions have shown that common external shocks do not necessarily generate identical consequences across port systems (Crotti et al., 2022; Daudet et al., 2026). Ports exposed to similar disruption environments may exhibit different operational trajectories, raising an important question: which observable baseline structural conditions are associated with those heterogeneous responses (Chen et al., 2025; Kuai et al., 2026; Liu et al., 2026)?

Existing research has substantially advanced understanding of port disruption impacts, vulnerability, recovery, and adaptation. Maritime studies examine disruption exposure and operational recovery, while supply-chain resilience research emphasises flexibility, redundancy and adaptive capacity (Russell et al., 2022; López et al., 2025; Tsoufas, 2026). Yet evidence remains limited on whether fixed ex-ante structural characteristics systematically differentiate dynamic response across multiple ports exposed to common externally dated disruptions, and whether any observed relationship survives reasonable trend adjustments, alternative operational outcomes, and directional tests (Sun et al., 2026; Zhang et al., 2026).

Regional port systems are functionally differentiated before disruptions occur. Cargo composition and directional maritime-flow orientation are observable expressions of that division of functions: some ports occupy specialised commodity-export roles, while others operate as more diversified gateways linking hinterlands to regional and extra-regional shipping systems (Ducruet, 2013; Pérez et al., 2020; Liu et al., 2026). Diversification may distribute exposure across activities, but specialisation can also provide advantages through dedicated infrastructure, accumulated expertise and established operating routines. Import-export maritime-activity imbalance may represent coordination exposure arising from directional flows, yet it may also reflect commodity geography and a port's stable commercial role (Castrellon et al., 2023; Xiang et al., 2024). These characteristics describe functional position. They are not resilience capabilities in themselves.

This study therefore examines whether baseline cargo diversification and import-export maritime-activity imbalance, hereafter trade imbalance, are associated with heterogeneous operational responses across major West African ports during externally dated disruptions. These characteristics capture different dimensions of port function: cargo diversification describes the breadth of activity across cargo categories, whereas directional imbalance describes the concentration of maritime activity between imports and exports. Neither is treated as a resilience capability in itself (Ducruet, 2013; Pérez et al., 2020, Li et al., 2026). The central empirical question is whether major ports that enter a common disruption environment with different baseline functional structures exhibit systematically different response trajectories. The analysis covers ten major conventional ports across eight countries and three primary disruption events and maintains an associational interpretation throughout.

The study advances the literature by separating observable port structure from realised resilience performance and testing that distinction in a multi-port, multi-disruption setting. Empirically, it examines a West African regional port system in which major ports differ sharply in cargo composition and directional orientation. The stacked event-time design further combines port-by-event and event-by-date fixed effects with small-cluster inference and prespecified trend, outcome, and directional checks, allowing clearly favourable structural associations to be evaluated against important empirical boundaries. The contribution is therefore evidential rather than estimator-driven, as it clarifies when observable baseline port structure is, and is not, informative about realised disruption response.

The remainder of the paper is organised as follows. Section 2 reviews the literature; Section 3 presents the study design and estimation strategy; Section 4 reports the results; Section 5 interprets the evidence, compares it with recent work, and sets out policy implications and limits; and Section 6 concludes.

2. Literature review

2.1. External disruptions and baseline functional structure

Maritime ports operate within interconnected transport and production systems in which externally generated disruptions can produce heterogeneous operational consequences across locations exposed to similar shocks. Recent disruption research shows that exposure alone does not explain differences in port performance trajectories; observed responses also reflect pre-existing structural and network conditions (Notteboom et al., 2021; Chen et al., 2025; Daudet et al., 2026; Kuai et al., 2026; Liu et al., 2026). Resilience research has therefore moved beyond documenting disruption impacts toward identifying the factors associated with differential response capacity (Kuai et al., 2026; Sun et al., 2026; Tsoufas, 2026; Zhang et al., 2026). Those pre-existing conditions include a regional division of port functions.

Cargo composition and directional maritime-flow orientation are not generic attributes that happen to vary across space, as they record how ports fit into commodity geographies and shipping systems. Specialised commodity-export ports concentrate activity in a narrow cargo stream, often tied to a particular hinterland resource. Diversified gateways handle a broader mix of container, bulk, general cargo and tanker activity and mediate a wider set of hinterland and extra-regional

connections (Ducruet, 2013; Pérez et al., 2020; Li et al., 2026). Directional orientation likewise reflects whether a port's estimated maritime activity is predominantly inbound, outbound, or more balanced, a pattern that is often linked to commodity geography rather than to operational failure (Castrellon et al., 2023; Xiang et al., 2024). Baseline structural characteristics should therefore be distinguished from resilience capabilities. Cargo composition, trade orientation, network position, and operational configuration describe the setting in which a port encounters disruption, but they do not establish whether the port can resist, absorb, or recover from that disruption (Liu et al., 2026; Sun et al., 2026; Zhang et al., 2026). This study therefore treats functional structure as a potential conditioning environment and tests whether that structure is associated with systematically different disruption responses. Cargo diversification and trade imbalance provide two complementary structural dimensions for that test. Diversification considers the distribution of activity across cargo categories; trade imbalance, on the other hand, captures directional concentration in estimated maritime activity. Their value lies in providing observable baseline characteristics whose associations with dynamic response can be evaluated directly.

2.2. Cargo diversification and dynamic port response

Cargo diversification may reduce concentration exposure because a port with a broader cargo portfolio is less dependent on a single commodity or market segment (Ducruet, 2013; Li et al., 2026). If disruption is concentrated in particular cargo streams, alternative activity segments may partially offset losses. This logic is consistent with a risk-distribution interpretation of diversification. The competing mechanism is specialisation. Specialised ports may benefit from dedicated infrastructure, technical expertise, established handling procedures and strong alignment between terminal capabilities and dominant cargo requirements (Pérez et al., 2020). Such operational depth may support reliability even when the activity mix is narrow.

The relationship between diversification and disruption response is therefore theoretically ambiguous as diversification may distribute exposure, while specialisation may create efficiency and capability advantages (Li et al., 2026; Liu et al., 2026). This ambiguity also limits what can be inferred from a diversification index. Cargo variety does not, by itself, establish spare capacity, substitutable equipment, alternative hinterland routes or adaptive operating arrangements (Russell et al., 2022; Tsoulfas, 2026). It is consequently treated as a structural characteristic rather than a direct resilience measure. Measurement choice remains relevant because entropy and

concentration indices emphasise related but not identical features of the cargo distribution (Shannon, 1948; Hirschman, 1964). Agreement between normalised Shannon entropy and one minus the Herfindahl–Hirschman Index (1-HHI) can therefore establish measurement robustness, but not independent replication, because both measures are constructed from the same underlying cargo classes.

2.3. Trade imbalance and dynamic port response

Trade imbalance represents a second dimension of baseline structure. Strong asymmetry between inbound and outbound maritime activity can affect coordination, equipment utilisation, storage requirements, and service planning when disruptions alter established flows (Castrellon et al., 2023; Xiang et al., 2024; Liu et al., 2026). In container systems, empty-equipment repositioning is a prominent mechanism through which directional imbalance can create operational costs and coordination demands (Castrellon et al., 2023; Xiang et al., 2024). However, directional concentration should not automatically be interpreted as operational weakness. Imbalance may reflect a stable commercial role, specialised infrastructure or commodity geography to which port operations are already adapted (Li et al., 2026). Moreover, mechanisms derived from container shipping do not necessarily transfer to mixed-cargo systems containing bulk, tanker, general cargo, roll-on/roll-off (ro-ro) and container activity. Trade imbalance is therefore treated as a measurable structural exposure whose relationship with disruption response is context-dependent rather than predetermined.

Structural-response relationships also depend on how disruption performance is measured. Port resilience studies use throughput, congestion, service reliability, recovery duration, connectivity and network performance, among other outcomes (Chen et al., 2025; Kuai et al., 2026; Tsoulfas, 2026). These quantities capture different operational dimensions and need not produce identical conclusions. Maintaining estimated maritime shipment activity, for example, does not imply unchanged vessel-call frequency or equivalent recovery behaviour.

Directional decomposition creates a second boundary. Aggregate maritime activity combines inbound and outbound flows that can respond differently to external disruption (Liu et al., 2026). Yet a significant coefficient in one directional model and an insignificant coefficient in another does not establish that the two associations differ (Gelman & Stern, 2006). Evidence of asymmetry requires a formal comparison that accounts for covariance between the estimates. Accordingly, the

empirical framework treats cargo diversification and trade imbalance as potential conditioning factors of heterogeneous port response and evaluates whether their associations persist across response horizons, structural-trend sensitivity, alternative operational outcomes, and formal directional comparisons. This conditional structural-response perspective provides the conceptual bridge between observable baseline structure and realised disruption performance without equating the two.

3. Methods

3.1. Study area and regional port system

The study area is the Atlantic maritime facade of West Africa, treated here as one regional port system rather than as a set of isolated national terminals. Ten major conventional ports in eight countries, Benin, Côte d'Ivoire, Ghana, Guinea, Mauritania, Nigeria, Senegal and Togo, are located from Nouadhibou on the north-west Atlantic coast to Bonny in the eastern Gulf of Guinea (**Fig. 1**). These ports share exposure to common extra-regional shipping disruptions while occupying sharply different functional positions; specialised commodity-export nodes, notably tanker-specialised Bonny and dry-bulk Kamsar, sit alongside more diversified gateways such as Lagos and Dakar (Ducruet, 2013; Pérez et al., 2020; Li et al., 2026) (Table 1). Cargo composition and directional maritime-activity orientation therefore record a regional division of functions rather than a uniform port type. Comparison within this common regional system is analytically useful because it holds the disruption calendar fixed while allowing baseline functional structure to vary across ports.

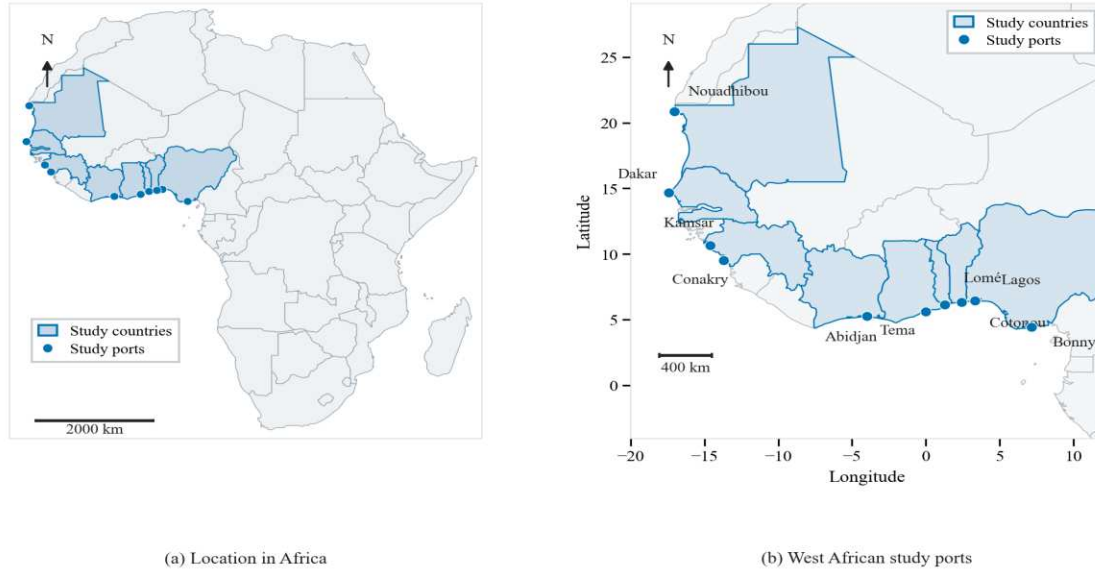


Fig. 1. Study area and selected major West African ports

3.2. Data and sample construction

The study uses a high-frequency observational panel to examine whether baseline port structure is associated with differential operational response to common external disruptions affecting maritime systems. The underlying observational unit is the port-day; the estimation unit is the port-event-day after disruption windows are stacked. Because the structural exposures are defined at port level, the sampling unit is the port rather than the country.

The source is the International Monetary Fund (IMF) PortWatch panel (Arslanalp et al., 2025) which covered 62 West African maritime nodes. Twenty-five nodes explicitly classified as offshore or floating storage/offloading facilities were excluded before sample selection, leaving 37 eligible conventional ports. Ports were ranked ex-ante by total 2019 estimated maritime shipment activity, and the top quartile, using the ceiling rule, yielded 10 major conventional ports across eight countries. The resulting sample represents 78.39% of 2019 estimated maritime shipment activity among the 37 eligible conventional ports (**Table 1, TableS1**). The daily panel spans 1 January 2019 to 17 July 2026 and contains 27,550 port-days. Sample membership was fixed before the disruption-response models were estimated and was not altered on the basis of estimated coefficients or statistical significance. The target population for inference is therefore major conventional West African ports as operationalised by the prespecified upper-quartile activity rule, rather than the universe of West African ports.

Table 1

Prespecified study sample, 2019 port structure, and primary disruption events

A. Prespecified major-port sample and 2019 structural characteristics						
Rank	Port	Country	Shannon diversification	Trade imbalance	Dominant cargo (share)	
1	Lagos	Nigeria	0.757	0.906	Dry (39.7%)	bulk
2	Dakar	Senegal	0.756	0.687	Dry (47.7%)	bulk
3	Abidjan	Côte d'Ivoire	0.677	0.550	Dry (61.5%)	bulk
4	Kamsar	Guinea	0.096	0.950	Dry (97.2%)	bulk
5	Lomé	Togo	0.654	0.555	Container (60.3%)	
6	Bonny	Nigeria	0.001	1.000	Tanker (100.0%)	
7	Tema	Ghana	0.683	0.833	Dry (44.1%)	bulk
8	Nouadhibou	Mauritania	0.389	0.631	Dry (78.1%)	bulk
9	Conakry	Guinea	0.648	0.259	Dry (62.6%)	bulk
10	Cotonou	Benin	0.711	0.709	Container (45.1%)	
B. Primary externally dated disruptions						
Disruption		Onset date		Disruption class		
COVID-19		11 Mar 2020		Pandemic / supply-demand-logistics disruption		
Russia–Ukraine war onset		24 Feb 2022		Geopolitical / commodity-shipping disruption		
Red Sea operational disruption		15 Dec 2023		Geopolitical / chokepoint-security disruption		

Shannon diversification is normalised across five fixed cargo classes; larger values indicate a more diversified cargo mix. Trade imbalance is the absolute import–export imbalance and ranges from 0 (balanced) to 1 (one-directional). Dominant-cargo shares are descriptive 2019 baseline

characteristics. The alternative 1-HHI diversification measure, signed trade orientation, and the complete variable dictionary are reported in Table S2. PortWatch import and export quantities are interpreted throughout as estimated maritime shipment activity rather than official customs or merchandise-trade statistics. The primary outcome is $\ln(1 + \text{estimated maritime shipment activity})$. Two operational-outcome robustness measures use $\ln(1 + \text{cargo-port-call frequency})$ and $\ln(1 + \text{total-port-call frequency})$, while directional component analyses use $\ln(1 + \text{estimated import activity})$ and $\ln(1 + \text{estimated export activity})$. The log-one-plus transformation retains observations with zero activity and reduces the leverage of very large daily values.

The panel was assembled on a common calendar-date key, with one observation for each of the ten ports on every day in the study period. Baseline structural attributes were merged by port and weather controls by port-date before event stacking. The resulting daily base contains no duplicate port-dates and provides complete values for the primary outcome and the weather controls used in estimation. Activity outcomes were not winsorized, and no composite resilience score was constructed; the dynamic response of each observed operational quantity is modelled directly.

Daily meteorological controls were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis (Hersbach et al., 2020) through the Open-Meteo Historical Weather API (Zippenfenig, 2024), with ERA5 explicitly selected and sea-cell preference applied to the port coordinates. The weather panel is complete for all 27,550 port-days. The primary specification includes daily mean 10-metre wind speed and precipitation. Mean and maximum wind speed were highly correlated ($r = 0.924$), so they were not entered jointly in the primary specification. Dominant wind direction was not entered linearly: compass bearing is circular, so 0° and 360° denote the same direction, and a linear coefficient on degrees is not identified.

3.3. Baseline structural variables

All structural variables were constructed exclusively from 2019 activity and held time-invariant during the event analyses. Cargo composition was measured using five fixed classes: container, dry bulk, general cargo, ro-ro, and tanker. Let s_{ik} denote the 2019 share of cargo class k at port i , with $\sum_{k=1}^5 s_{ik} = 1$. The primary diversification measure is normalised Shannon entropy (Shannon, 1948); one minus the Herfindahl–Hirschman Index (1-HHI) (Hirschman, 1964) provides an

alternative operationalization of the same construct; and absolute import-export imbalance measures directional concentration:

$$D_i^E = -\frac{\sum_{k=1}^5 s_{ik} \ln(s_{ik})}{\ln(5)} \quad (1a)$$

$$D_i^{HHI} = 1 - \sum_{k=1}^5 s_{ik}^2 \quad (1b)$$

$$I_i = \frac{|M_i - X_i|}{M_i + X_i} \quad (1c)$$

where M_i and X_i are the total estimated 2019 import and export maritime shipment activity, respectively, and $0 \ln 0$ is defined as zero. D_i^E ranges from 0 to 1, with larger values denoting a more even cargo composition. With five cargo classes, D_i^{HHI} ranges from 0 under complete specialisation to a maximum of 0.8 under equal shares. I_i ranges from 0 for balanced import-export activity to 1 for complete one-directional activity. Diversification was calculated from the five explicit annual cargo-class totals, whereas trade imbalance was calculated from aggregate import and export activity.

Normalised Shannon entropy is the primary diversification exposure. The 1-HHI measure substitutes for Shannon entropy only in measurement-robustness analyses; the two measures are not entered jointly and are not treated as independent replications. A signed orientation measure $(M_i - X_i)/(M_i + X_i)$, is retained for descriptive context, with positive values denoting net-import orientation and negative values net-export orientation, but it is not a principal structural interaction. For estimation, diversification and absolute imbalance are standardized using the full 10-port 2019 means and sample standard deviations. These standardization constants are held fixed in leave-one-port-out analyses rather than being recomputed after each omission. The two diversification measures are themselves highly correlated because they summarize the same five-class cargo composition; substitution rather than joint inclusion therefore preserves the intended interpretation of the diversification construct.

3.4. Disruption events and event-time construction

Disruption onset dates were specified externally rather than inferred from observed port outcomes. Three events form the primary pooled analysis: COVID-19 on 11 March 2020, when WHO characterised the outbreak as a pandemic, the onset of the Russia–Ukraine war on 24 February 2022, as recorded in contemporaneous United Nations reporting of the Russian military offensive

and the Red Sea operational disruption on 15 December 2023, the date on which MSC recorded the attack on MSC Palatium III and announced the rerouting of Suez traffic around the Cape of Good Hope, The Suez Canal obstruction on 23 March 2021, the date of the MV Ever Given grounding recorded by the International Maritime Organization, was designated a secondary event because of its short acute duration and its occurrence within the broader COVID-era operating environment; it is retained in the four-event data architecture but excluded from the three-event primary pooled estimation. Event dates, primary/secondary status, and sample membership were not moved, added, removed, or reclassified in response to model results (**Table S1**).

For every port-event pair, the event time h runs from -90 to +180 days. Days -90 to -31 form the reference baseline, days -30 to -1 form an anticipation interval, and days 0 to +180 form the post-event period. Each port-event window therefore contains 271 observations. The four-event stacked panel contains 10,840 observations; the three primary events yield 30 port-event cells and 8,130 balanced port-event-day observations. **Fig. 2** summarises the chronology, windows and response basis.

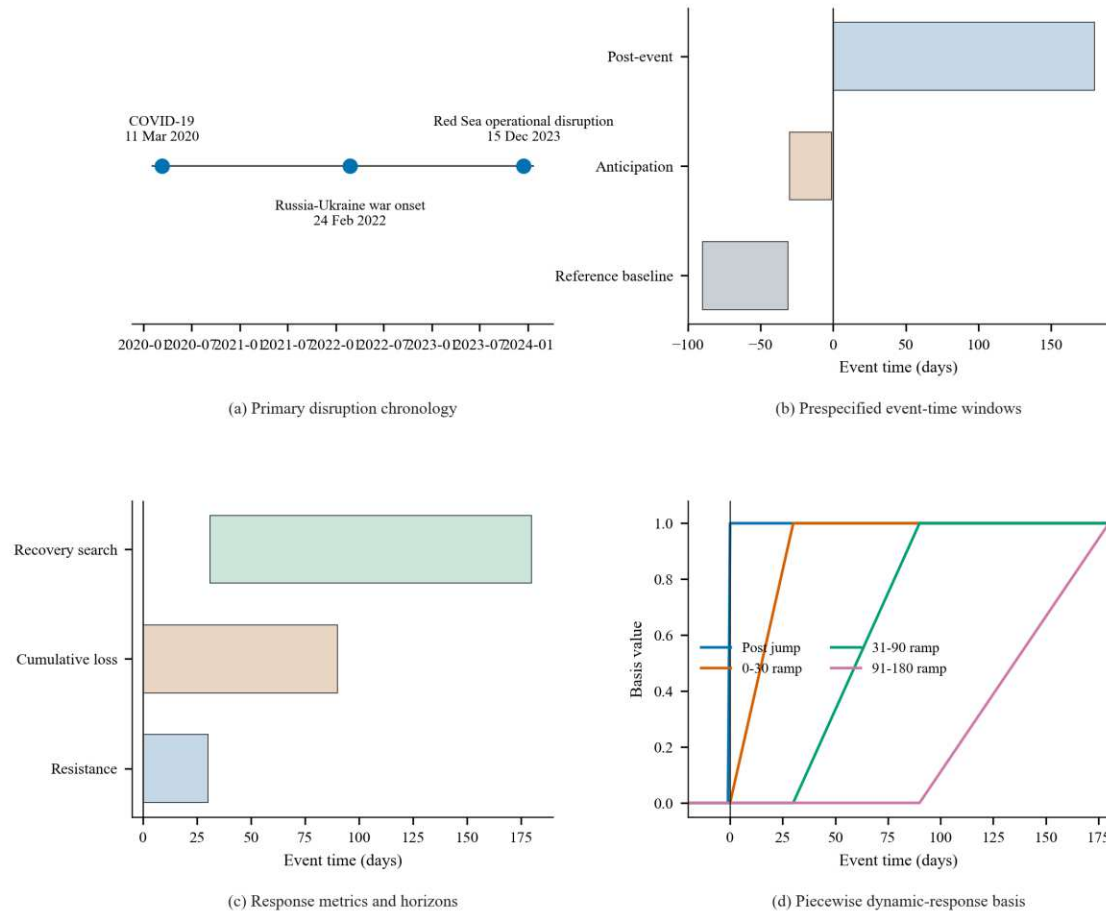


Fig. 2. Disruption chronology and event-time construction

The reference period ends 30 days before each event so that the -30 to -1 anticipation interval is not included in the omitted reference interval. This separation permits pre-event changes close to the externally dated onset to be represented by a dedicated anticipation term rather than absorbed into the baseline. The four 271-day event windows were also checked for overlap and do not overlap. **Fig. 2** also records three descriptive response windows defined before estimation: resistance over days 0-30, cumulative activity loss over days 0-90, and recovery search over days +31 to +180. Recovery requires restoration of at least 90% of the trough loss for 14 consecutive days; non-recovery by +180 is right-censored, and recovery time is undefined when no negative response occurs. These summaries describe the response architecture, whereas primary inference uses the dynamic structural endpoint contrasts.

Dynamic response is represented parsimoniously using an anticipation indicator, an immediate post-event jump, and three piecewise-linear ramps. Define

$$\mathbf{B}(h) = \begin{bmatrix} A(h) \\ \mathbb{1}(h \geq 0) \\ R_1(h) \\ R_2(h) \\ R_3(h) \end{bmatrix}, \quad A(h) = \mathbb{1}(-30 \leq h \leq -1), \quad R_1(h) = \frac{\text{clip}(h, 0, 30)}{30}, \quad R_2(h) = \frac{\text{clip}(h-30, 0, 60)}{60}, \quad R_3(h) = \frac{\text{clip}(h-90, 0, 90)}{90} \quad (2)$$

The post-jump coefficient captures the discontinuity at event onset, while the three ramp coefficients capture incremental changes over days 0-30, 31-90, and 91-180. Because a spline increment describes a change in trajectory rather than the level of the cumulative response, inference on individual ramp coefficients is kept distinct from inference on endpoint contrasts.

3.5. Identification and estimation

The estimand is the association between ex-ante port structure and differential operational response to externally dated common disruptions. It is not a causal effect of cargo diversification or trade imbalance. All sampled ports are exposed to the same dated events, and there is no untreated comparison group. The association is therefore estimated from cross-port differences in event-time response related to baseline structural characteristics after absorbing common event-specific daily conditions and time-invariant port-event heterogeneity. The predetermined inputs, stacked event panel and small- G inference framework are summarised in Fig. S1.

Let y_{iet} denote the transformed outcome for port i , disruption e and calendar date t ; let h_{iet} denote event time; D_i^* and I_i^* denote standardized Shannon diversification and absolute trade imbalance; and W_{it} contain the ERA5 weather controls. The primary model is

$$y_{iet} = \alpha_{ie} + \lambda_{et} + D_i^* B(h_{iet})' \beta_D + I_i^* B(h_{iet})' \beta_I + W_{it}' \gamma + \varepsilon_{iet} \quad (3)$$

where α_{ie} are port-by-event fixed effects and λ_{et} are event-by-calendar-date fixed effects. The first absorb time-invariant characteristics specific to a given port-event pairing; the second absorb day-specific conditions common to ports within each disruption, including the unrestricted common event-time path. The two high-dimensional fixed-effect sets are absorbed computationally rather than represented as dense dummy matrices, consistent with standard high-dimensional fixed-effect estimation (Guimarães & Portugal, 2010). These fixed effects remove common event-date factors and time-invariant port-event heterogeneity, but they cannot eliminate unobserved port-specific time-varying confounding; interpretation therefore remains associational.

Because diversification and imbalance are time-invariant within port, their level effects are absorbed by the port-event fixed effects. The coefficients of interest are therefore their interactions with the event-time basis. Event-by-calendar-date fixed effects allow each disruption to have an unrestricted common daily path shared by the ten ports, so the estimation does not impose a common parametric shock trajectory across COVID-19, the Russia–Ukraine war, and the Red Sea disruption.

Equation (3) contains Shannon diversification and absolute trade imbalance jointly. The 1-HHI measure replaces, rather than accompanies, Shannon diversification in the corresponding robustness specification. Primary weather controls are mean wind speed and precipitation. No universal diversification-by-time or imbalance-by-time trend is added to the primary model because pre-event diagnostics did not support a stable common structural trend across disruptions. Pre-event diagnostics were used to characterize possible differential trends rather than as significance filters for removing ports or events. Event-specific structural linear trends therefore constitute a prespecified sensitivity specification and are evaluated alongside, not in place of, the primary model.

For a given structural variable, endpoint contrasts are linear combinations of the estimated basis coefficients. The day-30 contrast combines the immediate post-event jump with the complete 0-30-day ramp; the day-90 contrast additionally incorporates the 31-90-day ramp; and the day-180 contrast additionally incorporates the 91-180-day ramp. This construction is why statistical support for an individual ramp coefficient is not interpreted as statistical support for the corresponding endpoint level. Results are reported for the anticipation period, event onset, and the designated post-event horizons. Because the dependent variable is $\ln(1 + y)$, a log-response contrast $g(h)$ converted as $100[\exp\{g(h)\} - 1]$ is the proportional contrast in $1 + y$, not exactly in raw activity y . When y is large, the two interpretations are numerically close; the distinction is retained because zeros are one reason the log-one-plus transformation was used. Because the structural exposures are standardized, reported contrasts correspond to a one-standard-deviation increase in the relevant 2019 structural characteristic.

3.6. Inference and prespecified robustness analyses

Inference must accommodate the small number of independent port clusters. Standard errors and bootstrap procedures therefore cluster by port, giving $G = 10$. The principal auxiliary variance

estimator is the cluster jackknife / CV3 variance of (MacKinnon et al., 2023a, 2023b) labelled CRV3 (CV3) in that literature. Primary p -values are obtained from the corresponding restricted wild-cluster bootstrap for a few clusters, labelled WCR31 (WCR-S), which imposes the null (MacKinnon et al., 2023a, 2023b). The bootstrap uses Webb's six-point weights (Webb, 2023), 9,999 replications, seed 20260823, and two-tailed p -values. For reproducibility, the full-sample bootstrap design is held fixed across reported tests: the same port-cluster definition, Webb weight distribution, null-imposed restricted bootstrap, replication count, and seed are used for each term or linear contrast. CRV3 provides an auxiliary small- G variance benchmark, whereas WCR31 p -values provide the primary inferential statements.

Robustness analyses follow an analysis hierarchy fixed before interpretation of the corresponding results rather than being selected by statistical significance. First, the primary model is re-estimated with event-specific structural linear trends. Second, normalized Shannon entropy is replaced by 1-HHI to test sensitivity to the diversification measurement. Third, the outcome is replaced by cargo-port-call frequency and total-port-call frequency to test whether the structural-response pattern transfers from estimated maritime shipment activity to call-frequency measures. These alternatives are treated as distinct operational outcomes, not as throughput measures. All robustness models retain the same sample, event dates, dynamic basis, fixed-effect structure, clustering level, and primary weather controls unless the robustness exercise explicitly changes the structural measure or operational outcome. This keeps each comparison focused on one prespecified dimension. Maximum wind speed is not added jointly to the primary mean-wind specification.

Fourth, import and export activity are modelled separately as directional components. Statistical significance in one component and not the other is not treated as evidence that the two responses differ. Directional differences are tested using covariance-aware formal export-minus-import contrasts. The family contains 20 prespecified formal directional contrasts across diversification and trade imbalance, the primary and structural-trend specifications, and the designated horizons. Raw bootstrap p -values are supplemented with Holm familywise-error adjustment (Holm, 1979) and Benjamini–Hochberg (BH) false-discovery-rate adjustment (Benjamini & Hochberg, 1995). These multiplicity adjustments qualify the directional family; they do not replace the prespecified primary WCR31 inference. A parallel transparency check applies Holm, Bonferroni, and BH

adjustments to the five primary diversification endpoints and, separately, to the ten primary structural endpoints (Table S10). Those adjustments are reported as a boundary check only.

Finally, leave-one-port-out (LOO) estimation assesses whether coefficient direction is driven by a single port. Structural standardization remains fixed at the full-sample values. Reducing the analysis to nine clusters produced numerically unstable wild-bootstrap inference during validation; leave-one-port-out p-values are therefore withheld. Only coefficient direction and stability are used, while full-sample WCR31 inference remains the basis for inferential reporting. The robustness hierarchy is interpreted symmetrically. A change in significance is not itself a reason to prefer one specification, redefine a disruption, remove a port, or promote a secondary outcome. Likewise, a supported spline increment is not substituted for an unsupported endpoint level, and alternative diversification indices are treated as measurement robustness rather than independent replication. These restrictions preserve the associational estimand and prevent specification choice from being driven by the realized results.

4. Results

4.1. External disruptions and baseline structural heterogeneity

The analysis sample comprises 10 major conventional West African ports across eight countries, representing 27,550 daily port observations and 78.39% of 2019 estimated maritime shipment activity among the 37 eligible conventional ports (Table S1; Fig. 1). Baseline structure varies markedly across these ports and records a regional division of functions. Bonny is almost entirely tanker-specialised (Shannon diversification 0.001; tanker share 100.0%) and Kamsar is a dry-bulk export node (0.096; 97.2% dry bulk), whereas Lagos (0.757) and Dakar (0.756) occupy much more diversified gateway positions. Absolute trade imbalance ranges from 0.259 at Conakry to 1.000 at Bonny, with Kamsar (0.950) and Lagos (0.906) also positioned toward the high-imbalance end of the distribution (Table 1).

The three primary externally dated disruptions are COVID-19 (11 March 2020), the onset of the Russia–Ukraine war (24 February 2022), and the Red Sea operational disruption (15 December 2023). The prespecified –90 to +180-day event window yields 30 port-event cells and a balanced primary analysis sample of 8,130 port-event-day observations, with 271 observations per port-event (Fig. 2). Fig. 3 reports the corresponding descriptive trajectories. Daily cross-port medians show pronounced high-frequency variation, while the seven-day rolling medians provide only a

visual guide to the event-specific temporal profiles; these descriptive series introduce no additional inference.

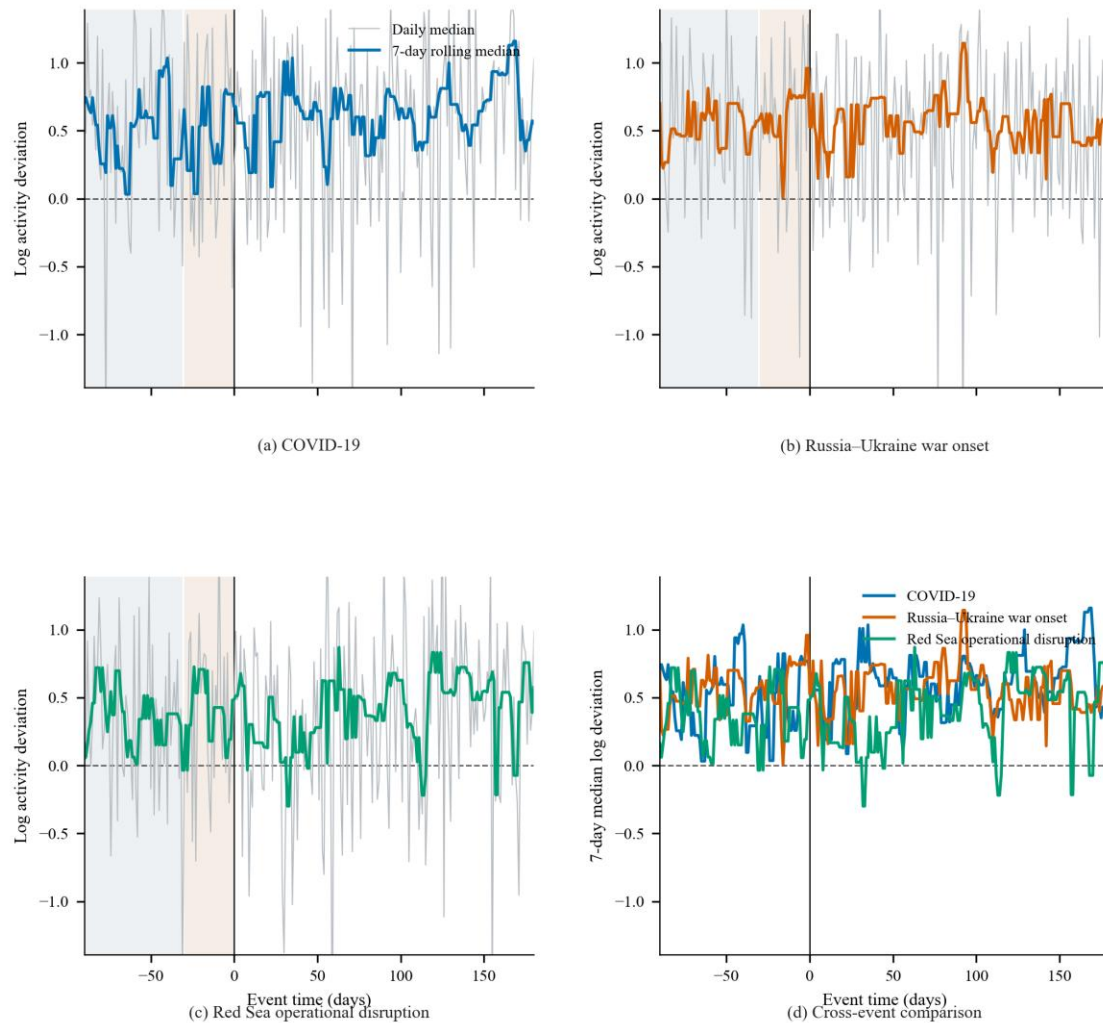


Fig. 3. Descriptive operational response across primary disruptions

4.2. Cargo diversification and dynamic port response

Among the five prespecified diversification endpoints in the primary specification, day 30 is the only endpoint supported at the 5% level. A one-standard-deviation increase in normalised Shannon diversification is associated with a 77.0% higher day-30 contrast in $1 +$ estimated maritime shipment activity (WCR31 $p = 0.009$). The association is not sustained at day 90, where the endpoint is -4.0% ($p = 0.790$), and the remaining non-day-30 primary endpoints are also unsupported (Fig. 4a,d). The primary profile therefore contains a concentrated early association rather than a uniformly positive post-disruption pattern.

A supplementary multiplicity check, calculated from the stored WCR31 p -values and not used as primary inference, leaves the day-30 result supported within the five-endpoint diversification family (Holm, Bonferroni and BH adjusted $p = 0.044$) but not within the broader ten-test family of primary diversification and trade-imbalance endpoints (adjusted $p = 0.087$; Table S10). The event-specific structural-trend sensitivity removes that day-30 support. The corresponding day-30 endpoint is +1.9% ($p = 0.959$), compared with +77.0% in the primary specification, while the day-90 endpoint is -61.6% ($p = 0.139$). None of the five structural-trend endpoints is supported at the 5% level (Fig. 4b–d). Thus, the primary day-30 diversification association is not robust to the event-specific structural-trend adjustment. Endpoint-level statements are based on the prespecified endpoint contrasts rather than on individual spline increments. A supported change in one segment of the fitted response path is not treated as evidence that the corresponding endpoint level is itself supported.

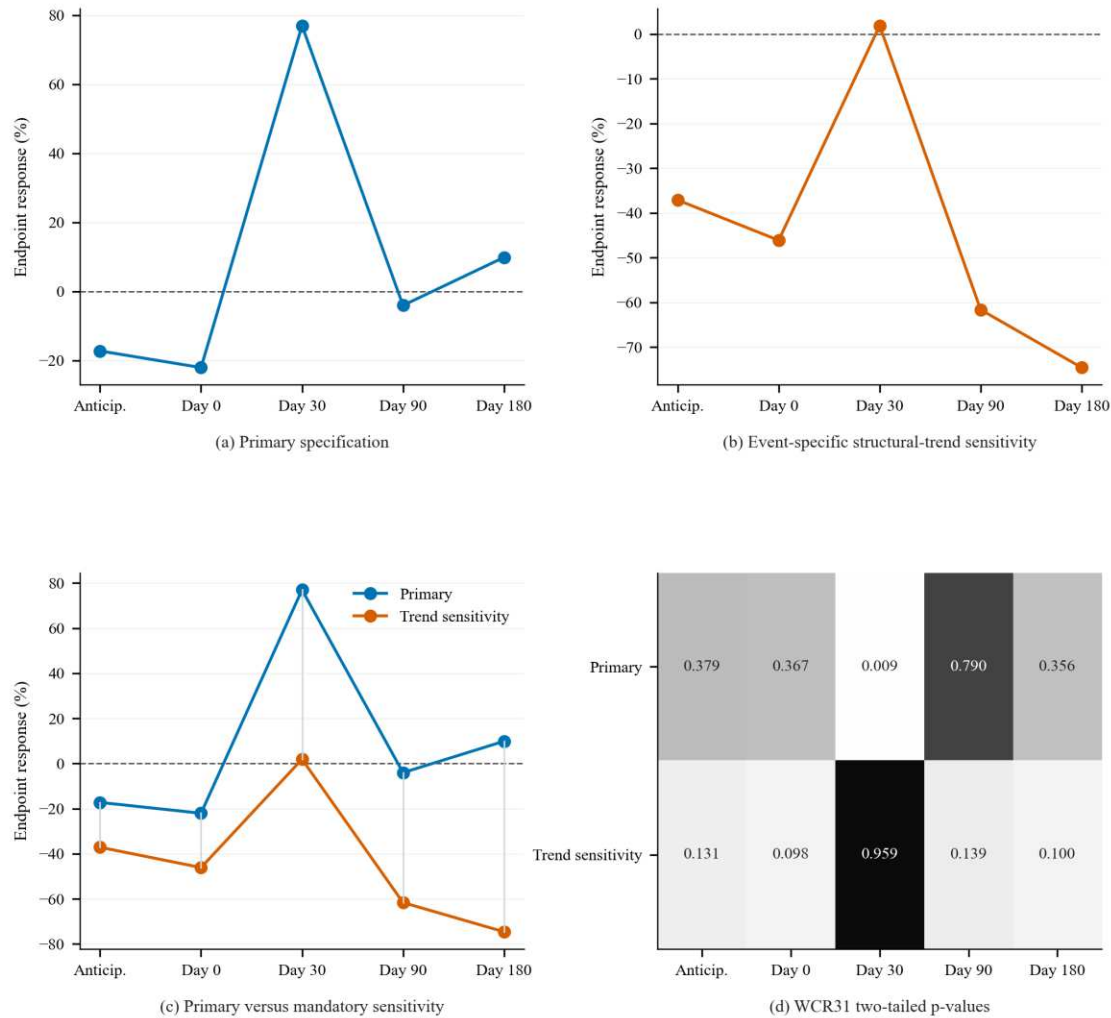


Fig. 4. Cargo diversification and dynamic port response

4.3. Trade imbalance and dynamic port response

Trade imbalance does not exhibit a comparable endpoint pattern. Across the five prespecified reporting endpoints under each of the primary and event-specific structural-trend specifications, none of the 10 trade-imbalance endpoint tests reaches the 5% level (Table 2; Fig. 5). The estimates vary in sign and magnitude across anticipation, event onset, and the post-event horizons, but the corresponding WCR31 p -values remain above 0.05 throughout the endpoint family. Fig. 5a–b reports the two endpoint profiles, Fig. 5c compares them directly, and Fig. 5d displays the associated WCR31 p -values. Although several structural-trend percentage estimates are numerically large, they remain statistically unsupported at the prespecified 5% level. The endpoint

evidence therefore provides no systematic association between baseline absolute trade imbalance and differential estimated maritime shipment-activity response across the tested horizons.

Table 2

Principal estimates, prespecified sensitivity analyses, and boundary-condition tests

Evidence domain	Primary evidence	Prespecified sensitivity/robustness	Inference status
Cargo diversification, estimated maritime shipment activity	Day 30: +77.0%, WCR31 $p = 0.009$	Event-specific structural-trend day 30: +1.9% $p = 0.959$	Primary-only association; not pretrend-robust. No general diversification-resilience association.
Trade imbalance, estimated maritime shipment activity	None of the 10 prespecified trade-imbalance endpoints have $p < 0.05$	Primary and event-specific structural-trend endpoint families both retained	No systematic trade-imbalance association identified.
Diversification measurement robustness	Normalised Shannon entropy is the primary measure	1-HHI reproduces the same 5% endpoint classification pattern	Measurement-robust pattern; not independent replication.
Outcome robustness	Primary day-30 association appears for estimated maritime shipment activity	Not reproduced for cargo-call or total-call frequency outcomes	Outcome-sensitive; no vessel-size, cargo-per-call, or intensity mechanism identified.
Import/export diversification boundary condition	Export day 30: +75.5% ($p = 0.021$); import day 180: +24.0% ($p = 0.049$)	Trend counterparts: export $p = 0.912$, import $p = 0.838$; formal diversification contrasts: 0/10 $p < 0.05$	Directional primary signals are pretrend-sensitive; no formal diversification asymmetry at 5%.
Import/export trade-imbalance boundary condition	Trend-adjusted day-90 export-minus-import log contrast = 1.313, raw WCR31 $p = 0.021$	Holm-adjusted $p = 0.412$; BH $q = 0.412$	Isolated secondary contrast; not multiplicity-robust.

Notes. Reported endpoint contrasts for estimated maritime shipment activity and the directional component outcomes are expressed as $100[\exp(\hat{\beta}) - 1]$, which is the proportional contrast in $1 + y$. Principal inference uses port-clustered WCR31/WCR-S wild cluster bootstrap with Webb six-point weights, 9,999 replications, the null imposed, and two-tailed p -values. Event-specific structural trends constitute a prespecified sensitivity analysis rather than an alternative preferred specification. Shannon entropy and 1-HHI operationalize the same diversification construct and are not independent replications. Formal import–export differences are covariance-aware contrasts; differences in separate-model significance are not interpreted as asymmetry. The isolated trade-imbalance directional contrast is explicitly reported as non-multiplicity-robust. The interpretive restriction is that evidence identifies associations between ex-ante port structure and differential operational response to externally dated common maritime disruptions; it does not identify causal effects of cargo diversification or trade imbalance.

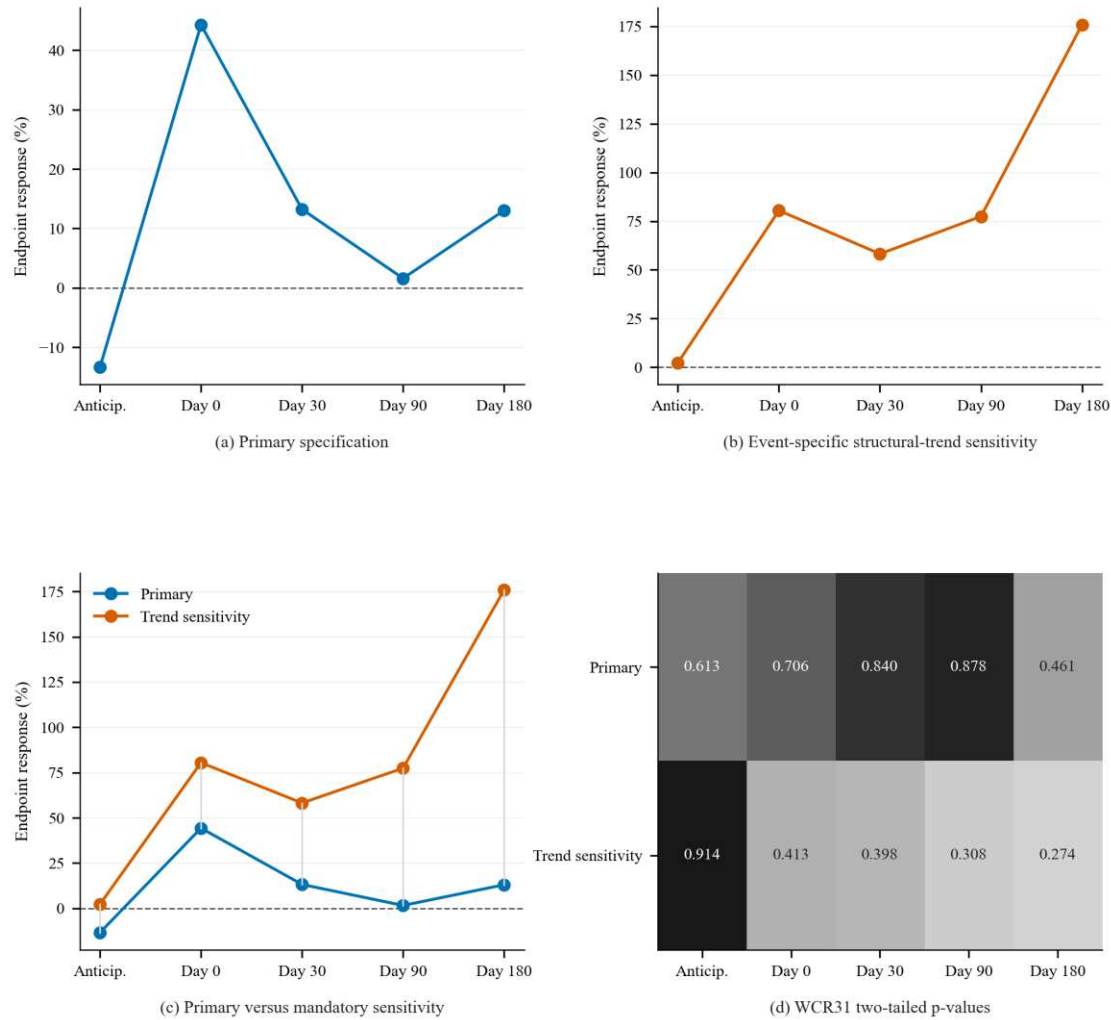


Fig. 5. Trade imbalance and dynamic port response

4.4. Outcome and directional boundary conditions

Replacing normalised Shannon entropy with 1-HHI reproduces the same 5% endpoint-classification pattern as the primary diversification measure (Table 2; Fig. 6a). This establishes robustness to the alternative operationalization of cargo diversification, but it is not an independent replication because both indices are constructed from the same five 2019 cargo classes. The diversification result is not reproduced for the two alternative port-call outcomes. The primary day-30 pattern for estimated maritime shipment activity does not appear when the dependent variable is cargo-call frequency or total-call frequency, and no diversification or trade-imbalance structural term reaches $p < 0.05$ across either alternative outcome family (Table 2; Fig. 6b). The diversification result is therefore outcome-sensitive within the tested operational measures.

The import and export component analyses show different primary timing, but the separate component estimates do not establish directional asymmetry. For export activity, the primary diversification day-30 endpoint is +75.5% ($p = 0.021$), whereas its event-specific structural-trend counterpart is unsupported ($p = 0.912$). For import activity, the primary diversification day-180 endpoint is +24.0% ($p = 0.049$), whereas the corresponding structural-trend result is unsupported ($p = 0.838$). Formal covariance-aware export-minus-import diversification contrasts yield no 5% directional difference across the 10 prespecified diversification contrasts (Fig. 6c–e). Accordingly, the component-specific signals do not constitute evidence of a general import–export diversification asymmetry.

One isolated raw 5% trade-imbalance directional contrast occurs at day 90 under the event-specific structural-trend specification. The formal export-minus-import log contrast is 1.313 (WCR31 $p = 0.021$). Across the family of 20 formal directional contrasts, however, the Holm-adjusted p -value and Benjamini–Hochberg q -value are both 0.412 (Table 2; Fig. 6f). The contrast is therefore retained as endpoint-specific secondary evidence but is not multiplicity-robust. Across these robustness and boundary-condition analyses, the day-30 diversification association is reproduced under the alternative diversification measure but not under the event-specific structural-trend sensitivity or the tested port-call outcomes. Trade imbalance has no systematic principal endpoint support, and the formal directional tests do not identify a 5% diversification asymmetry.

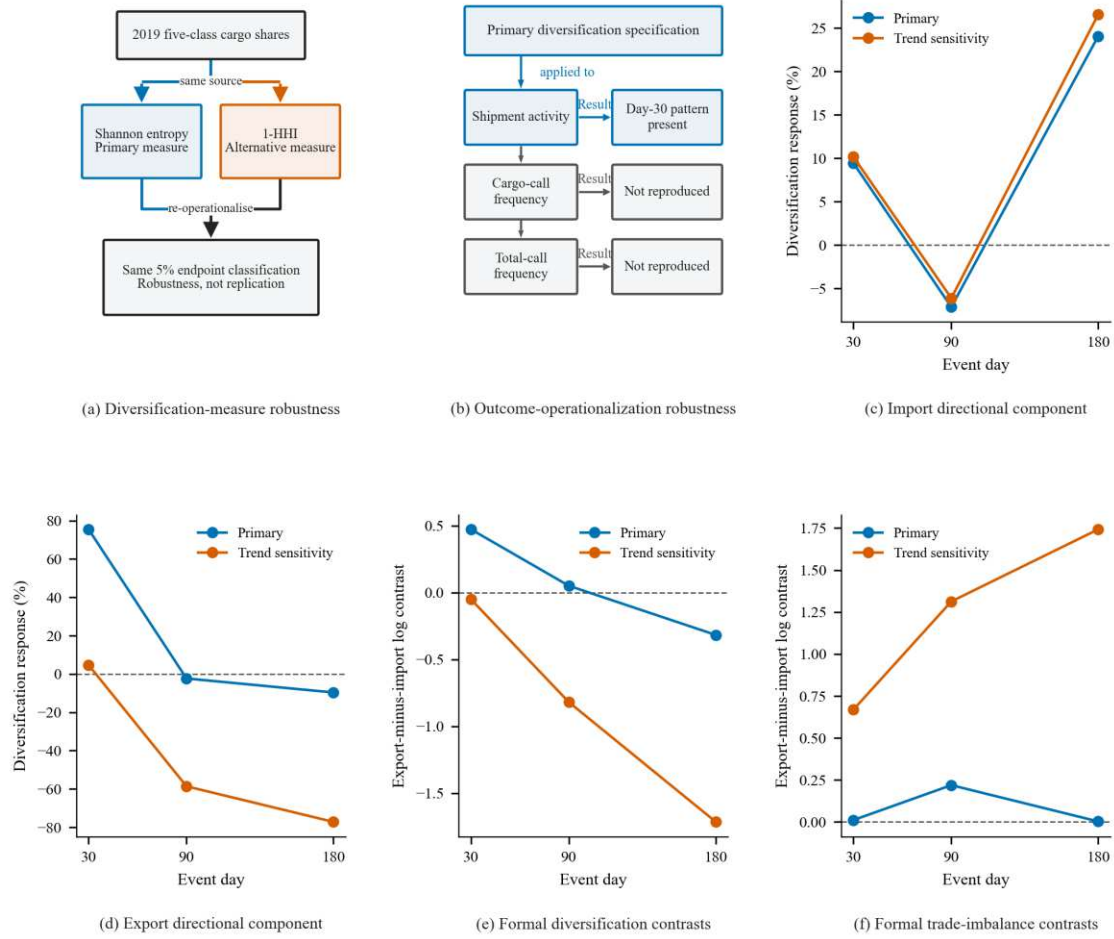


Fig. 6. Robustness and directional boundary conditions

5. Discussion

The central finding is that baseline port structure should not be treated as a direct measure of resilience. Across the ten major West African ports, cargo diversification is associated with a higher day-30 estimated maritime shipment-activity response in the primary specification, and the same endpoint classification is reproduced when diversification is measured with 1-HHI. That result is nevertheless narrow. It disappears after event-specific structural-trend adjustment and does not carry over to cargo-call or total-call frequency. Trade imbalance is even less consistent: none of its principal endpoints shows a systematic association with short-horizon response. Together, the evidence indicates that cargo mix and directional orientation describe a port's functional position, but their relationship with disruption performance depends on the specification, response horizon, and operational outcome considered.

This distinction matters because structural variety is not the same as the operational capability through which resilience is realised. A diversified cargo base does not by itself reveal spare capacity, substitutable infrastructure, alternative hinterland routes, or the ability to reconfigure operations when a disruption occurs. Conversely, a specialised port may have dedicated infrastructure, established routines, or service relationships that support a strong response within its particular operating environment. Russell et al. (2022) for example, show that flexibility in container-port capacity depends on multiple seaside, platform, landside, and system-wide elements rather than on a single structural characteristic, while Tsoulfas (2026) describes port resilience as a multidimensional concept spanning organisational, technical, and operational dimensions. The present results therefore qualify any simple portfolio interpretation of diversification: a broad cargo mix may spread exposure across cargo segments, but it does not automatically create the capabilities needed to absorb or recover from disruption.

The robustness results reinforce this boundary. Replacing the diversification index tests whether the result depends on how the same structural construct is measured; replacing shipment activity with port-call outcomes asks whether the relationship transfers to another dimension of performance. Those are different tests, and they yield different conclusions. This is consistent with recent empirical work showing that port resilience varies with the performance quantity being observed. Liu et al. (2026) identify substantial heterogeneity in congestion-based resilience during the Red Sea crisis; Kuai et al. (2026) find that operational impact, recovery duration, and freight-network impact are associated with different drivers; and Bedoya-Maya et al. (2025) show uneven changes in connectivity and transport-chain costs under Red Sea rerouting. Chen et al. (2025) and Sun et al. (2026) likewise evaluate resilience through evolving network position, congestion, adaptation, and recovery rather than through a single interchangeable indicator. The implication is methodological as well as substantive: conclusions about port resilience should be tied explicitly to the outcome being protected.

The West African evidence also supports a conditional interpretation of disruption response. UNCTAD (2025) reports that Africa's liner-shipping connectivity improved between June 2024 and June 2025 even as global shipping remained affected by route reconfiguration and operational uncertainty. Verschuur & Tavasszy (2026) further show that African port-hinterland accessibility and redundancy can move together or trade off, depending on the infrastructure investment

considered. These findings help explain why a structurally attractive port characteristic need not translate into uniformly stronger short-horizon performance. Disruption type matters as well. Li et al. (2026) show that COVID-19 and the war in Ukraine affected coal, grain, and iron-ore shipping networks differently, while López et al. (2025) identify distinct geopolitical disruption types with different supply-chain effects and managerial responses. A diversified port can therefore be exposed simultaneously to several commodity, routing, and demand processes rather than being generically insulated from disruption.

The practical implication is not that diversification or trade balance is uninformative, but that neither should be used as a stand-alone resilience score or investment rule. Port authorities and terminal operators can use these indicators to describe commercial structure, benchmark exposure, and support scenario design, but operational decisions require complementary information on capacity flexibility, network connectivity, hinterland alternatives, infrastructure substitutability, and service relationships. The same caution applies to performance measurement. Shipment activity, vessel-call frequency, congestion, connectivity, recovery duration, and network impact capture different aspects of port performance and may legitimately produce different structural-response relationships. Directional claims should also be based on formal import-versus-export contrasts rather than on separate significance tests. In this study, those contrasts do not support a general diversification asymmetry, and the isolated trade-imbalance contrast is not robust to multiplicity adjustment.

Several boundaries remain. The sample covers ten major conventional West African ports selected from the upper quartile of 2019 estimated maritime shipment activity, so the findings should not be extended automatically to smaller ports, offshore facilities, or other regional systems. The effective number of independent structural units is ten ports, which limits precision despite the much larger number of port-event-day observations. The design is observational, and all sampled ports experience the externally dated disruptions, so the estimates remain associational even with port-by-event and event-by-date fixed effects. Structural characteristics are fixed at a common 2019 baseline, which protects them from contamination by later disruptions but cannot capture subsequent structural change. Finally, PortWatch measures estimated maritime shipment activity rather than audited throughput or customs trade, and the three disruptions and 180-day horizon do not establish generality across all shock types or recovery periods. Future work should combine

broader port samples with network, hinterland, and operational-capability measures and evaluate resilience across multiple outcomes and longer horizons.

6. Conclusion

This study examined whether baseline port structure helps explain heterogeneous operational responses to common external disruptions across ten major conventional West African ports. Using fixed 2019 measures of cargo diversification and import–export maritime-activity imbalance, the analysis finds no evidence that either characteristic functions as a general resilience indicator. Cargo diversification is positively associated with estimated maritime shipment-activity response at day 30 in the primary specification, but this relationship does not survive event-specific structural-trend adjustment and does not extend to cargo-call or total-call frequency. Trade imbalance shows no systematic principal association with disruption response.

The main contribution is therefore a boundary on how baseline structural indicators should be interpreted. Cargo mix and directional orientation describe a port's functional position and may condition its response to disruption, but they should not be interpreted as stand-alone measures of resilience. For port authorities and terminal operators, structural indicators are most useful when combined with information on operational flexibility, network connectivity, hinterland alternatives, disruption type, and the performance dimension being protected. More broadly, resilience assessment should distinguish observable structural characteristics from the operational capabilities and outcomes through which resilience is actually realised.

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