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Tourism Resilience from Networks: Diversity and Hierarchy

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We propose an interpretable, network-based measure of tourism resilience that maps destinations on a two-dimensional plane combining pre-shock market diversity and shock-period hierarchisation. Using monthly inbound international arrivals of non-resident foreigners to Colombian cities, we compute (i) pre-shock Shannon entropy of origins (2018–2019) and (ii) the maximum absolute residual from a monthly log–log Katz–size scaling during the COVID-19 shock (2020–2021). Applied to Colombia, the resilience plane identifies a core-centric system: most international arrivals concentrate in a few diversified gateways that nonetheless experienced large hierarchy spikes under stress. A smaller set of "resilient hubs" combine high diversity with low hierarchisation but account for a minor share of volume. Results are robust to thresholding with interquartile cutoffs and to an alternative city–city projection (cosine similarity). The findings suggest that, for major gateways, market diversification alone is insufficient if access remains structurally compressed into a small set of dominant channels; for more fragile destinations, priorities include broadening source portfolios and improving connectivity to regional hubs. The approach is replicable with open data and standard network tools, and is portable to other countries to benchmark destination systems on a common, interpretable resilience scale.

Keywords: Tourism resilience, bipartite networks, Shannon entropy, Katz residual, destination hierarchy.

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1. Introduction

Tourism scholarship increasingly adopts a network perspective to understand destinations as sets of interdependent actors and flows rather than isolated units, drawing on traditions in sociology and organizational theory [4, 11, 15, 17, 37]. This lens is particularly suitable for tourism because origins, destinations, intermediaries, infrastructures, and policies co-evolve over time, so that structure—who connects to whom, and how strongly—conditions both opportunity and vulnerability.

Within this perspective, studies have examined supply chains, destination systems, policy linkages, and tourist mobilities using social network analysis [15]. Recent work models spatial tourism networks across regions and time to evaluate connectivity and structural change, showing how network properties shift with development or shocks [11]. Such analyses move beyond attributes of single places and toward the relational architectures that enable or constrain tourism. In parallel, debates on community-based tourism in urban settings remind us that tourism systems are also governance arrangements, not only market aggregates. In cities, community-based approaches have often been viewed with skepticism or reduced to product labels rather than treated as organizing principles for participation and sustainability [3, 6, 19, 24, 35, 38]. This broader discussion reinforces the need for structural diagnostics that can characterize how urban destination systems are organized and how they respond under stress.

Centrality metrics are a cornerstone of this literature. Degree, betweenness, and closeness capture, respectively, local connectedness, brokerage, and accessibility, informing the "power status" of cities or attractions in tourism economic networks [11, 43]. Newer approaches extend to structural holes—quantifying gaps and constraints—and to multi-scale hierarchical patterns, where tourists assemble into multi-core structures and use strategic nodes as exploration bases [20, 25]. Together, these tools reveal that hierarchy and redundancy are not peripheral features of tourism systems, but part of the way performance and vulnerability are organized. From a social-science perspective, the city–origin matrix can be read as a form of relational economic geography [5] and as a real-world instance of the embedded market relations emphasised in economic sociology [14]. However, existing studies rarely connect ex-ante market diversity to the shock-time reordering of network hierarchy within a single empirical diagnostic. We therefore ask the following research question: to what extent does pre-shock source-market diversity condition the magnitude of shock-time hierarchisation, and how do destinations distribute across that two-window resilience diagnostic?

A parallel line of inquiry studies diversification. Empirical evidence shows that diversification's effects depend on what is being diversified: some market-mix strategies have uneven payoffs, while activity diversification (broadening product offerings) more consistently supports expansion [34]. Yet most measures emphasize macroeconomic outcomes rather than the structural properties—who a destination connects to and how—that might underpin resilience.

Resilience research since COVID-19 has quantified how shocks propagate through tourism networks. For instance, a 10% rise in seven-day smoothed cases was associated with a 0.0658% decline in year-over-year bilateral demand, moderated by cultural distance and trip length [39]. Broader frameworks in tourism and hospitality highlight that single-industry dependence heightens vulnerability, while strategic policy support and portfolio breadth improve recovery [1, 23]. Still, much of this work tracks levels (drops and rebounds) rather than the network structures that absorb or transmit shocks.

Information theory helps bridge diversification and resilience because entropy provides a compact description of how balanced or concentrated a destination's source-market portfolio is. In that sense, entropy operationalizes diversification as a structural property of the destination–origin system rather than merely as an outcome summary. When this ex-ante portfolio balance is contrasted with the reconfiguration of destination hierarchy during a shock, information-theoretic diversity becomes directly relevant to resilience analysis. Existing entropy-based measures have been applied to tourism demand to assess complexity and predictability across granularities; sample and multi-scale entropy quantify regularity and scale-dependent structure, and information-theoretic bounds link entropy to achievable forecast accuracy [27, 44]. However, these applications largely address temporal complexity, not how diversity interacts with network hierarchy to condition shock response.

The Latin America and Colombia literature adds crucial context. Post-conflict and post-crisis recovery pathways diverge: some destinations redeploy legacy assets, while others re-position around new products [26]. Medellín's "phoenix" narrative around controversial heritage coexists with untapped nature-based opportunities, suggesting that portfolio breadth—across markets and products—may be decisive for sustainable resilience in the region.

Across these strands, we find no parsimonious, interpretable indicator that jointly captures (i) diversity of source markets within destinations and (ii) hierarchy in the destination network, while distinguishing between pre-shock structure and shock-time response. This paper addresses that gap using monthly *inbound international arrivals of non-resident foreigners* as an administrative, mobility-based proxy for destination demand.

We propose an interpretable measure of tourism resilience built from network diversity and hierarchy. Each month we model a country $\longleftrightarrow$ city bipartite graph; on the city projection we compute Shannon entropy of source-market shares (diversity) and a Katz residual (hierarchization): the residual from regressing log(Katz) on log(strength), which indicates influence above/below what size alone predicts. Rather than collapsing both concepts into the same temporal slice, we use them to characterize two linked but distinct moments of system organization: ex-ante portfolio redundancy and shock-time structural compression. We then define a resilience plane by crossing average entropy in 2018–2019 (H_{pre}) with the maximum absolute residual during 2020–2021 (F_{shock}). The resulting quadrants are interpretable in substantive terms because each axis has a direct meaning: one summarizes how balanced a destination's portfolio of origins is before disruption, and the other captures how strongly its network influence deviates from what size alone would predict under shock.

Applied to Colombia, the framework is designed to reveal whether the destinations that appear diversified ex ante also remain less hierarchized under shock, or whether structural concentration persists despite broad source-market portfolios. This distinction is central to interpreting positions in the resilience plane and to understanding how diversification and hierarchy interact under systemic stress. The approach is method-agnostic, uses transparent statistics grounded in network theory and information theory [11, 15, 17, 25, 44], and complements resilience findings from COVID-19 by focusing on structure rather than levels [1, 23, 39].

The remainder of the paper reviews related work across networks, diversification, resilience, and entropy; details data and construction of the bipartite/projection panels; defines the entropy and Katz-residual indicators and the two-window design; presents results and the resilience plane with policy translation; and concludes with limitations and avenues for comparative and cross-regional extensions [26, 27, 34].

2. Data and Methods

2.1 *Data and panel construction*

We use the monthly administrative register of *Arrivals of Non-Resident Foreigners* to Colombia by country of residence and destination city (2015–2025), compiled by the national migration authority with the Ministry of Trade, Industry and Tourism. Aggregated counts only; no personally identifiable information is included. The series is interpreted here as an administrative proxy for inbound international arrivals, rather than as a direct measure of tourism expenditure, overnight stays, or final trip purpose. A definitional change applies from January 2020: residents in Venezuela reporting the motive *leisure* are included. We handle this explicitly with a two-window design. The raw file provides, for each month, non-negative integer counts of arrivals by city and origin country. After standardizing labels (accents, homonyms) and consolidating duplicates, we build a city–country–month panel:

$$\mathscr{W} = \left\{ w_{c,o,t} \in \mathbb{N}_0 : \; c \in C, \; o \in O, \; t \in \mathscr{T} \right\}, \tag{2.1}$$

where $w_{c,o,t}$ is the number of arrivals from origin country o to destination city c during month t. This object is the empirical backbone of the study: it preserves the *direction* of flows (from o to c) and their *timing* (at the monthly scale), enabling both cross-sectional and longitudinal network views. For each city–month we define the market size (node strength on the bipartite side)

$$s_{c,t} = \sum_{o \in O} w_{c,o,t}, \tag{2.2}$$

and the set of active origins $O_{c,t} = \{o \in O : w_{c,o,t} > 0\}$. We later take logarithms for scale-free comparisons; to avoid $\log 0$ we add a small constant $\varepsilon = 10^{-12}$ wherever logs appear. Two temporal windows are central to our resilience design: a pre-shock baseline (2018–2019), representative of "normal" conditions, and a shock period (2020–2021), when mobility restrictions sharply constrained the network. Windowing is conceptually important because it decouples structural conditions *before* the shock from the network's *response* during the shock. More specifically, the two-window design links pre-shock source-market diversity to shock-time hierarchisation, rather than forcing both dimensions into the same temporal slice. Finally, we note a standard caveat at this spatial scale: airport cities may act as gateways for broader regions; recorded arrivals may therefore conflate gateway and destination functions. Accordingly, our inferences are *structural* (how the network is organized), not causal (what generates demand).

From the cleaned universe of monthly records, we define the analytic sample as the 150 destination cities with the largest cumulative inbound arrivals during the 2018–2019 baseline period. The cleaned file contains these 150 destination cities, 250 origin countries and 451 613 city–origin–month observations, covering January 2015–April 2025 (124 monthly snapshots). In total, the series reports 27.9 million non-resident entries after aggregation of duplicates and harmonisation of city names. All variables are released by the Colombian migration authority through the *Extranjeros No Residentes* open-data portal[1].

To construct the network panel we pivot each month into a country-by-city matrix of arrivals, retaining the full set of 250 origin codes. The pre-shock baseline (2018–2019) registers 5.5 million arrivals, with a monthly average of 230 000 and a December-2019 peak of 260 000. Demand is highly concentrated, even before the COVID-19 shock: the five largest origin markets (United States, Venezuela, Ecuador, Mexico and Peru) already account for 50.6 % of baseline arrivals, foreshadowing the centrality patterns revealed by the network analysis.

2.2 *Network model and indicators (diversity and hierarchy)*

We represent each month as a weighted bipartite graph $B_t = (C \cup O, E_t)$ [9, 30, 36], where C is the set of Colombian destination cities and O the set of origin countries; an edge (o, c) exists with weight $w_{c,o,t}$ if at least one traveler from o arrived to c in month t. This representation keeps the *two-mode* nature of the system: destinations connect to origins, not to one another directly. To study similarities between destinations we project B_t onto the city mode, obtaining a weighted, undirected graph $G_t = (C, E'_t)$ with adjacency $A_t = \left(a^{(t)}_{c,c'}\right)_{c,c' \in C}$. We set the city–city weight to the *weighted intersection* of their origin

[1] Data are available from Colombia's Open Data platform (*Datos Abiertos*) at `https://www.datos.gov.co/Comercio-Industria-y-Turismo/Extranjeros-No-Residentes/7wm8-w5ad/about_data`. Source: Migration Colombia, with calculations by the Office of Economic Studies (OEE) of the Ministry of Commerce, Industry and Tourism (MINCIT).

portfolios,

$$a^{(t)}_{c,c'} \;=\; \sum_{o\in O} \min\{w_{c,o,t},\, w_{c',o,t}\}, \qquad a^{(t)}_{c,c} \equiv 0. \tag{2.3}$$

Intuitively, $a^{(t)}_{c,c'}$ grows when two cities receive sizable volumes from the *same* origins; it is bounded by $\min\{s_{c,t}, s_{c',t}\}$ and is robust to sparse overlaps. In this framework, diversity is read directly from the bipartite city–origin composition, whereas hierarchy is quantified on the projected city network. (We verify in robustness that cosine-based similarities lead to similar rankings.)

KATZ CENTRALITY ON THE PROJECTION. On G_t we compute Katz centrality $\mathbf{x}_t = (x_{c,t})_{c\in C}$ [7, 29, 41], defined for $0 < \alpha < 1/\lambda_{\max}(A_t)$ and $\beta > 0$ by

$$\mathbf{x}_t \;=\; \alpha A_t \mathbf{x}_t + \beta \mathbf{1} \quad\Longleftrightarrow\quad \mathbf{x}_t \;=\; \beta \sum_{k\geqslant 0} \alpha^k A_t^k \mathbf{1}. \tag{2.4}$$

This series shows the interpretation: $x_{c,t}$ counts walks of all lengths starting at c, discounting longer paths by α^k. A city can thus be "influential" either by connecting to many similar destinations (large $A_t\mathbf{1}$) or by being embedded in regions with dense second-order and higher-order overlaps (large $A_t^k\mathbf{1}$). We set α strictly below the spectral bound and confirm that $\pm 10\%$ perturbations leave conclusions unchanged.

DIVERSITY (SHANNON ENTROPY). For each city–month we convert counts into a probability vector over origins,

$$p_{c,o,t} = \frac{w_{c,o,t}}{s_{c,t}} \quad (s_{c,t} > 0), \qquad \sum_{o\in O} p_{c,o,t} = 1, \tag{2.5}$$

and compute Shannon entropy [16, 28]

$$H_{c,t} = -\sum_{o\in O} p_{c,o,t} \log_2 p_{c,o,t} \quad \text{(bits)}. \tag{2.6}$$

Entropy rises when a city draws from *many* origins in *balanced* proportions, and falls when a few origins dominate. Interpreting $2^{H_{c,t}}$ as the *effective number of markets* helps translate bits into an intuitive "how many equally-sized origins would produce this diversity?" proxy. We compute $H_{c,t}$ for every city and every month in the panel; window-specific summaries are introduced in the next subsection.

HIERARCHY (KATZ RESIDUAL). Size alone ($s_{c,t}$) often predicts a large share of influence ($x_{c,t}$). To isolate *hierarchization*—influence *beyond* what size explains—we fit, within each month t, the log–log scaling

$$\log\bigl(x_{c,t} + \varepsilon\bigr) \;=\; a_t \;+\; b_t \log\bigl(s_{c,t} + \varepsilon\bigr) \;+\; \varepsilon_{c,t}, \tag{2.7}$$

by ordinary least squares over cities with $s_{c,t} > 0$. The residual $\varepsilon_{c,t}$ is positive if c exhibits *more* network influence than expected for its size, conditional on the monthly scaling relation—an indicator of relative hierarchical prominence in the projected network—and negative if it exhibits *less*. Because monthly samples differ, we also use standardized residuals $\tilde{\varepsilon}_{c,t} = (\varepsilon_{c,t} - \bar{\varepsilon}_{\cdot,t})/\mathrm{sd}(\varepsilon_{\cdot,t})$ in sensitivity checks. As with entropy, the Katz residual is computed for all city–month observations; the pre-shock and shock summaries used in the resilience plane are defined subsequently. Conceptually, entropy captures redundancy in market portfolios [22], while the Katz residual captures hierarchy in the inter-destination fabric [13].

Figure 1 summarizes the overall methodological workflow, from the construction of the monthly city–country panel to the derivation of the diversity and hierarchy indicators and their combination in the resilience plane.

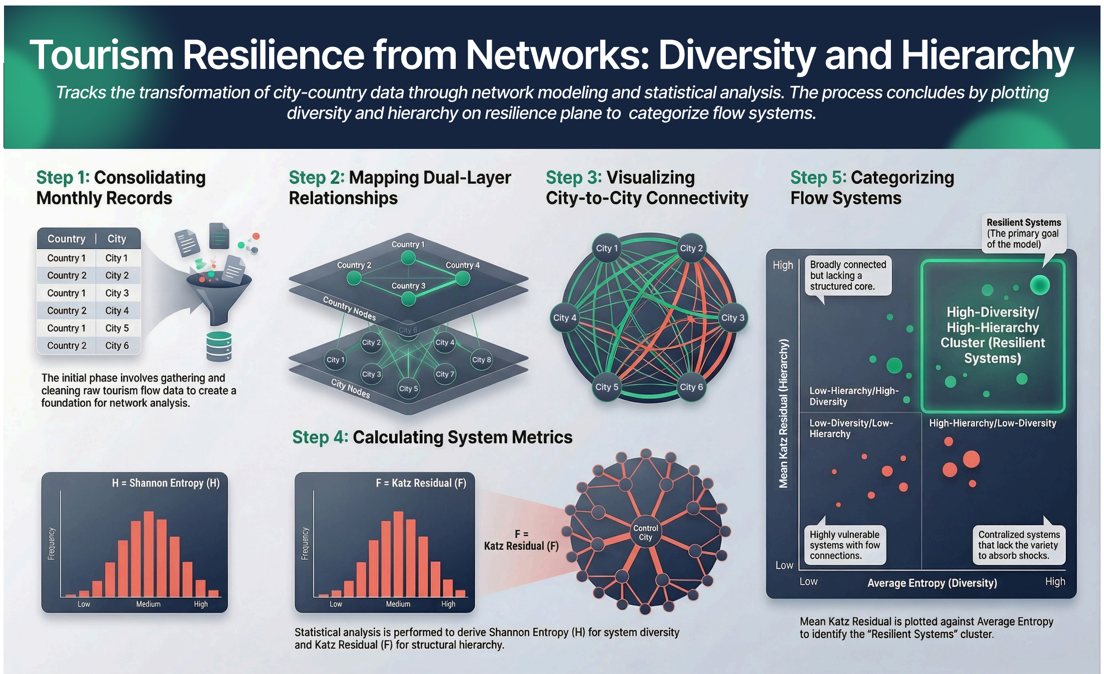


FIG. 1: Methodological pipeline of the network-based resilience framework. Monthly administrative records of inbound arrivals are first organized as a city–country matrix. Each month is represented as a weighted bipartite network linking origin countries and destination cities. The bipartite structure is then projected onto the city layer to obtain a destination similarity network. On this representation we compute two complementary indicators: source-market diversity, measured through Shannon entropy, and hierarchical prominence in the projected network, captured by the Katz residual. Finally, the resilience diagnostic combines pre-shock diversity (H_{pre}) and shock-period hierarchisation (F_{shock}) in a two-dimensional resilience plane that classifies destinations according to their structural position. Alt Text: Flow diagram showing how monthly inbound arrival data are converted into a bipartite country–city network, projected onto a city similarity network, and analyzed using entropy and Katz residual to position destinations within a two-dimensional resilience classification.

2.3 *Two-window resilience plane, estimation, and robustness*

Resilience is summarized at the city level by contrasting a baseline of *diversity in normal times* with a measure of *hierarchization under stress*. Although both monthly indicators, $H_{c,t}$ and $\varepsilon_{c,t}$, are computed for the full panel, the resilience plane is intentionally defined as a two-window diagnostic that links pre-shock portfolio structure to shock-time hierarchy response. We therefore define:

$$H_c^{\text{pre}} = \frac{1}{|\mathscr{T}_{18\text{–}19}|} \sum_{t \in \mathscr{T}_{18\text{–}19}} H_{c,t} \quad \text{(average entropy pre-shock; redundancy ex-ante)}, \tag{2.8}$$

$$F_c^{\text{shock}} = \max_{t \in \mathscr{T}_{20\text{–}21}} |\varepsilon_{c,t}| \quad \text{(maximum absolute Katz residual during the shock; hierarchy spike)}. \tag{2.9}$$

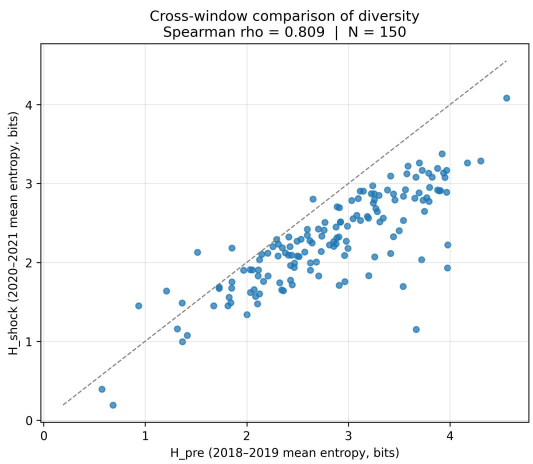
Plotting $\left(H_c^{\text{pre}}, F_c^{\text{shock}}\right)$ yields a resilience plane with four actionable quadrants: *high H/low F* (diversified, robust hubs that maintained alternative pathways), *low H/high F* (fragile mono-markets prone to bottlenecks), and two intermediate regimes that suggest either reducing gateway dependence (high H/high F) or expanding the market base (low H/low F). Unless stated otherwise, quadrant thresholds are the sample medians of $\{H_c^{\text{pre}}\}$ and $\{F_c^{\text{shock}}\}$, which we prefer over means because both dimensions are right-skewed and influenced by a small number of very large gateway cities; we confirm robustness with $(\text{P25}, \text{P75})$ cuts and with standardized residuals $\max|\tilde{\varepsilon}_{c,t}|$. In addition, we report the complementary summaries H_c^{shock} and F_c^{pre} to show how both indicators behave outside their primary window, even though the main resilience plane is defined by H_c^{pre} and F_c^{shock}.

Figure 2 shows that both diversity and hierarchisation are defined in both temporal windows, but with different degrees of persistence: diversity remains comparatively stable, whereas hierarchy spikes are more strongly reconfigured during the shock period.

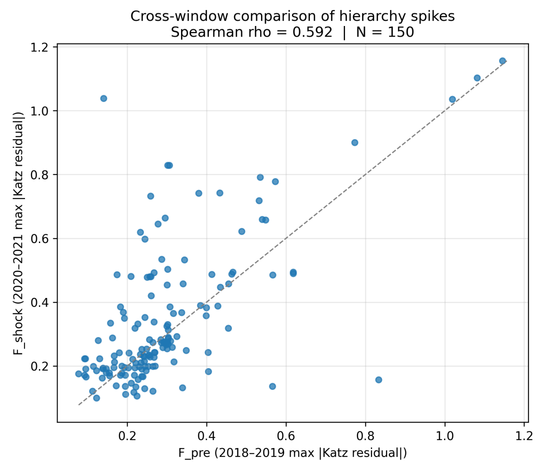
ESTIMATION DETAILS AND DIAGNOSTICS. Equation (2.7) is estimated per month using ordinary least squares (OLS); we report R_t^2 and residual distributions by month in the Supplement. Non-finite observations after log are dropped by construction. Katz centrality is computed on G_t with weights (2.3); we show that replacing (2.3) with cosine similarity of origin vectors $(w_{c,o,t})_o$ leaves rankings of H_c^{pre} and F_c^{shock} largely unchanged, thus our conclusions do not hinge on a specific projection kernel. Because $\varepsilon_{c,t}$ is used as a *structural indicator*, our focus is its sign and magnitude relative to peers in month t, not hypothesis tests on (a_t, b_t). This interpretation is descriptive rather than causal: a large positive residual indicates unusually high network prominence relative to city size in that month, but does not by itself identify the mechanism generating that prominence.

Table 1 reports the two-window summaries for a selection of representative Colombian destinations. The table illustrates how pre-shock diversity levels H_c^{pre} and shock-period hierarchy spikes F_c^{shock} jointly determine each city's position in the resilience plane. Major hubs such as Bogotá, Cartagena, Medellín, and Cali exhibit high baseline diversity but also pronounced hierarchy spikes during the shock window, placing them in the high-H/high-F quadrant associated with diversified yet stressed systems. By contrast, cities such as Cúcuta show relatively high pre-shock diversity but limited hierarchy amplification during the shock, thus falling into the high-H/low-F regime characteristic of more structurally stable diversification. These examples illustrate how the two-window diagnostic distinguishes between destinations that are diversified in composition and destinations whose structural prominence becomes disproportionately compressed under systemic stress [8, 32].

IMPLEMENTATION, REPRODUCIBILITY, AND LIMITATIONS. The pipeline is implemented in Python (`pandas`, `numpy`, `networkx`). We fix $\alpha = 0.9/\lambda_{\max}(A_t)$ and $\beta = 1$ in (2.4); rescaling β does not affect residuals beyond an additive constant. We release intermediate artifacts (city–month panels with $H_{c,t}, x_{c,t}, s_{c,t}, \varepsilon_{c,t}$ and city-level summaries $H_c^{\text{pre}}, F_c^{\text{shock}}$) and scripts to reproduce figures and tables. Limitations include the January-2020 definitional change (handled via windowing), potential



(a) Diversity persistence across windows.



(b) Hierarchy spikes across windows.

FIG. 2: Cross-window comparison of city-level diversity and hierarchisation. Panel (a) compares pre-shock and shock-period Shannon entropy summaries, showing that diversity is relatively persistent across windows, although generally lower during the shock period. Panel (b) compares pre-shock and shock-period hierarchy spikes, measured as the maximum absolute Katz residual, and reveals a weaker alignment across windows. This contrast indicates that while source-market diversity is partly preserved, shock-time hierarchisation reflects a stronger reordering of structural prominence. Both indicators are therefore well defined in both windows, even though the main resilience plane is constructed from H_c^{pre} and F_c^{shock}. Alt Text: Two-panel comparison of city-level metrics across time windows: diversity (Shannon entropy) shows similar values before and during the shock, while hierarchy (Katz residual) displays greater variability, indicating stronger structural reordering during the shock period.

gateway–destination conflation at the city level—that is, arrivals recorded in major airport cities may partly reflect access to a broader surrounding tourism region rather than final destination consumption within the city itself—, and the absence of concurrent supply-side covariates (e.g., air capacity), route frequency, fares, or airport-level operational restrictions. We mitigate these by interpreting results as *structural* (not causal), by reporting sensitivity to thresholds and kernels, and by documenting data provenance and code for replication.

3. Results and discussion

From January 2015 to April 2025, Colombia recorded 27.9 million arrivals of non-resident foreigners distributed across 150 destination cities. International demand expanded steadily up to the COVID-19 disruption: during the 2018–2019 baseline, the country received on average 230 000 arrivals per month, with a pre-pandemic peak of 260 000 in December 2019. The system was already highly concentrated before the shock. The five largest origin countries supplied 50.6% of baseline traffic, and a small number of gateway airports channelled most international demand. This pre-existing concentration provides the structural backdrop for interpreting the resilience plane.

Table 1: Selected destination cities under the two-window resilience diagnostic. For each city we report pre-shock and shock-period summaries of diversity and hierarchisation, together with their changes across windows and the resulting quadrant in the main resilience plane.

City	H^{pre}	H^{shock}	F^{pre}	F^{shock}	ΔH	ΔF	Quadrant
Bogotá, D.C.	4.56	4.09	1.02	1.04	-0.47	0.02	High-H / High-F
Cartagena	3.88	2.92	1.15	1.16	-0.96	0.01	High-H / High-F
Medellín	3.90	2.91	1.08	1.10	-0.99	0.02	High-H / High-F
Cali	3.89	2.91	0.77	0.90	-0.98	0.13	High-H / High-F
Barranquilla	3.80	2.95	0.57	0.78	-0.85	0.21	High-H / High-F
Jamundí	3.27	2.68	0.21	0.22	-0.59	0.01	High-H / Low-F
Santa Marta	4.30	3.29	0.18	0.39	-1.02	0.20	High-H / High-F
Bucaramanga	4.17	3.26	0.19	0.35	-0.91	0.16	High-H / High-F
Cúcuta	3.72	2.03	0.23	0.24	-1.69	0.00	High-H / Low-F
Quibdó	2.81	2.22	0.34	0.37	-0.59	0.03	Low-H / High-F
Pereira	3.70	2.88	0.13	0.28	-0.81	0.15	High-H / High-F
Villavicencio	3.88	3.19	0.30	0.27	-0.68	-0.03	High-H / High-F
Valledupar	3.79	2.77	0.29	0.27	-1.02	-0.01	High-H / High-F
Ibagué	3.94	3.13	0.30	0.32	-0.80	0.02	High-H / High-F
Florencia	3.24	2.97	0.24	0.13	-0.27	-0.11	High-H / Low-F
Tunja	3.73	3.17	0.31	0.26	-0.56	-0.05	High-H / Low-F

3.1 *Cross-window behavior of diversity and hierarchisation*

Before turning to the resilience plane itself, it is useful to examine how the two underlying indicators behave across the pre-shock and shock windows. Figure 2 shows that diversity and hierarchisation are both well defined in both periods, but with markedly different persistence. Source-market diversity remains comparatively stable across windows, although it is generally lower during the shock period. By contrast, shock-time hierarchy spikes display a weaker alignment with their pre-shock counterparts, indicating that the pandemic did not simply reduce volumes uniformly, but also reordered the relative structural prominence of destinations within the projected city network.

An alternative construction—crossing H and F within the same temporal window (e.g. $H_c^{\text{pre}} \times F_c^{\text{pre}}$ or $H_c^{\text{shock}} \times F_c^{\text{shock}}$) would reduce to a static profile of each period and would lose the comparative link between ex-ante portfolio structure and ex-post hierarchy response that is the conceptual core of our design. Figure 2 already provides this within-window view indirectly: the strong cross-window Spearman correlation for diversity ($\rho = 0.809$) versus the weaker one for hierarchy spikes ($\rho = 0.592$) suggests that a same-window plane would largely recapitulate the pre-shock ranking for diversity while mixing persistent and transient hierarchy signals. The two-window design is therefore preferred precisely because it separates the structural condition from the structural response, making the plane actionable for ex-ante planning rather than merely descriptive of a single moment.

This contrast is substantively important. If diversity and hierarchy moved in lockstep across both windows, the resilience plane would add little beyond a static characterization of destination profiles. Instead, the comparison suggests a more differentiated picture: portfolio composition retains some persistence, whereas hierarchy is more sensitive to the compression and rerouting induced by systemic stress. In other words, a destination may remain relatively diversified in terms of source markets while still becoming disproportionately prominent—or disproportionately bypassed—within the network under shock conditions.

Appendix A reports the full monthly trajectories of Shannon entropy and Katz residual for selected destinations, confirming that both indicators are defined throughout the panel and that the pandemic shock is associated with a heterogeneous but clearly visible structural reconfiguration.

This distinction is also visible in the city-level summaries reported earlier in Table 1. Major hubs such as Bogotá, Cartagena, Medellín, and Cali combine high pre-shock diversity with substantial hierarchy spikes during the shock window, placing them in the high-H/high-F quadrant associated with diversified yet stressed systems. By contrast, cities such as Cúcuta retain relatively high pre-shock diversity while showing limited hierarchy amplification during the shock, placing them in the high-H/low-F regime. These examples show that diversification alone does not guarantee low structural stress: what matters is whether broad source-market portfolios are accompanied by a shock-time network configuration that avoids excessive concentration of prominence.

3.2 *The resilience plane*

Figure 3 plots each city in the two-window resilience plane defined by pre-shock diversity H_c^{pre} and shock-period hierarchisation F_c^{shock}. Median thresholds ($\tau_H = 2.879$ bits and $\tau_F = 0.267$) divide the sample into four quadrants. Although the quadrant counts are balanced by construction, the volume represented by each quadrant is strongly asymmetric. Using pre-shock arrivals in 2018–2019, approximately 97.4% of national volume is concentrated in high-H/high-F cities, whereas only about 1.8% falls in the high-H/low-F quadrant. This asymmetry indicates that the Colombian inbound system is not only diversified in a few large gateways ex ante, but also highly exposed to stress-time concentration in those same nodes.

The high-H/high-F quadrant contains the country's main gateways, including Bogotá, Cartagena, Medellín, Cali, Barranquilla, and San Andrés. These cities combine broad source-market portfolios with pronounced hierarchy spikes during 2020–2021. In substantive terms, the result suggests that diversification of demand composition did not prevent stress from being channelled through a reduced set of structurally dominant nodes. This is consistent with a shock regime in which international traffic contracts, route options narrow, and prominence becomes more concentrated around the main gateways.

The high-H/low-F quadrant, by contrast, contains destinations that combine diversified source portfolios with relatively limited hierarchy amplification during the shock. Cúcuta is the clearest example in the main sample. Its position suggests that diversified composition can coexist with comparatively stable network prominence, rather than with a sharp concentration spike. From a resilience perspective, this is the quadrant that most closely aligns with the idea of maintaining redundancy without becoming a bottleneck.

The low-H/high-F quadrant corresponds to destinations with narrow source-market portfolios and relatively high shock-time hierarchisation. These cities face a double structural vulnerability: limited ex-ante redundancy and elevated prominence distortion under stress. In practical terms, they are more exposed to disruptions affecting a small number of origins or channels, and they have fewer alternative pathways through which traffic can be redistributed [1, 33, 34].

Finally, the low-H/low-F quadrant includes more specialized destinations whose source portfolios remain narrow but whose network prominence does not become strongly amplified during the shock. These cases should not be interpreted as broadly resilient in a general sense, since their diversification remains limited. Rather, they appear structurally stable within their niche scale, combining modest exposure with modest reordering under systemic stress.

Taken together, the resilience plane suggests that diversity and hierarchy are related but not interchangeable dimensions of resilience. High diversity does not necessarily imply low stress-time concentration, and low hierarchy amplification does not by itself imply a broad or redundant market base. The value of the plane is precisely that it separates these two properties and allows destinations to be compared according to both.

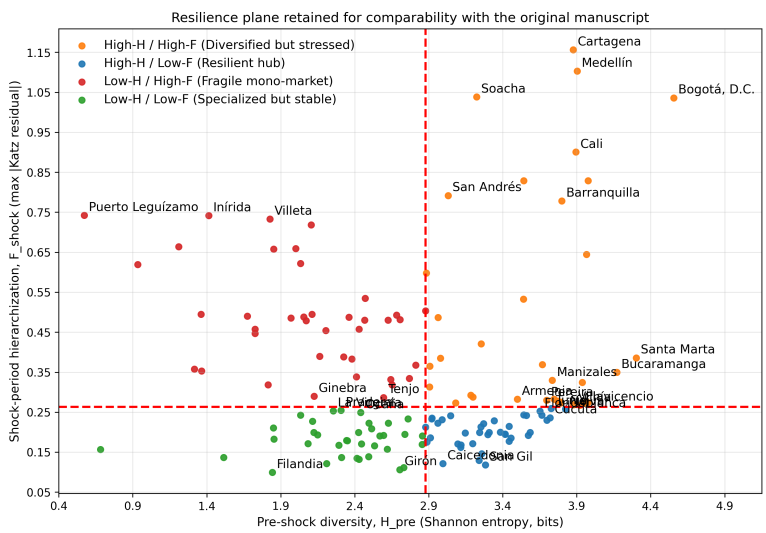


FIG. 3: Two-window resilience plane for the 150-city analytical sample. Each point represents a destination city positioned by pre-shock diversity H_c^{pre} and shock-period hierarchisation F_c^{shock}. Dashed lines mark the sample medians ($\tau_H = 2.879$ bits and $\tau_F = 0.267$), defining the four quadrants discussed in the text. Alt Text: Scatter plot of cities positioned by pre-shock diversity and shock-period hierarchy, divided into four quadrants by median reference lines to classify destinations according to their resilience profiles.

3.3 *Structural interpretation from network snapshots*

The structural interpretation of these findings is reinforced by direct visual comparisons of the origin–destination system before and during the shock. Figure 4 shows that the pandemic period did not merely reduce the number of active connections; rather, it contracted the bipartite system around a more visibly compressed core of origins and destinations. The reduction in breadth is therefore not random, but organized through a persistent subset of dominant source markets and gateway cities.

This visual contraction is consistent with the entropy and hierarchy summaries discussed above. A narrower and less balanced bipartite structure naturally lowers source-market diversity, while a more compressed projected city network increases the likelihood that some destinations become structurally more prominent than their size alone would predict. In that sense, the network snapshots provide an intuitive bridge between the two ingredients of the resilience plane: diversity is reduced because portfolios become less balanced, and hierarchisation increases because prominence is redistributed more unevenly across cities [21, 40].

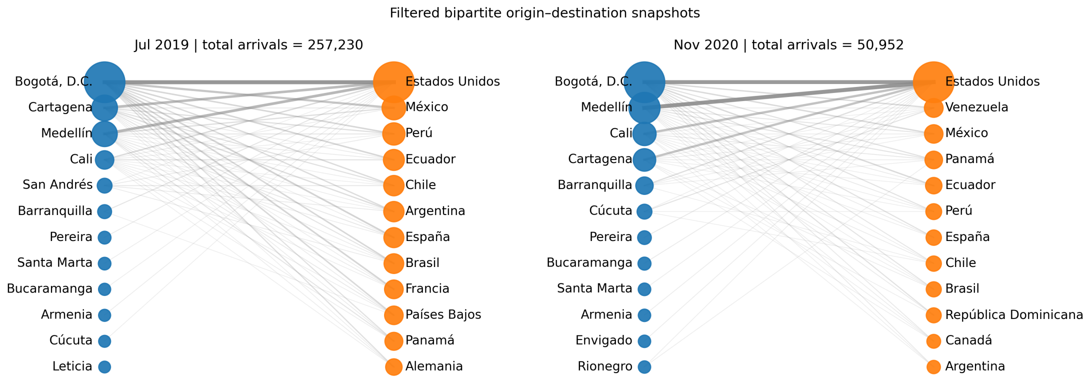


FIG. 4: Illustrative bipartite snapshots of the Colombian origin–destination system in a pre-shock month and a shock-period month. The figure highlights the contraction of active links and the increased concentration of flows around a smaller core of origin countries and destination cities during the pandemic period. Alt Text: Two network diagrams comparing a pre-shock and a shock-period month, showing fewer connections and a stronger concentration of flows among a smaller set of countries and cities during the shock.

A complementary view is provided by the city-level portfolio comparison in Figure 5, which shows how the composition of origin markets changes for a selected destination across the two windows. Even when a city remains internationally connected, the shock tends to reduce balance across origins, thereby lowering effective diversity. This pattern helps explain why high pre-shock diversity does not automatically translate into low shock-time hierarchisation: a destination can retain international relevance while becoming more structurally dependent on a narrower subset of origins and routes.

3.4 *Robustness and policy implications*

The main conclusions are robust to alternative identification choices. Replacing median thresholds with interquartile cutoffs preserves the qualitative segmentation of destinations across the resilience plane, with only marginal swaps near the thresholds. Likewise, replacing the weighted-intersection projection kernel with cosine similarity preserves a meaningful share of the ranking information in F_c^{shock}, indicating that the central pattern does not depend on a single projection rule. These checks support the interpretation that the Colombian inbound system is structurally core-centric and that the main gateways became the principal loci of shock-time hierarchisation during the pandemic.

From a policy standpoint, the results suggest different priorities across quadrants. For high-H/high-F gateways, the challenge is not simply to diversify source markets further, but to reduce the extent to which international access is compressed into a small set of structurally dominant nodes during crises. For high-H/low-F destinations, the priority is to preserve and incrementally strengthen the diversified configurations that already limit shock-time concentration. For low-H/high-F cities, the main concern is double exposure: narrow portfolios and strong hierarchy spikes. Here the emphasis should be on broadening market reach and improving alternative access channels. For low-H/low-F destinations, the

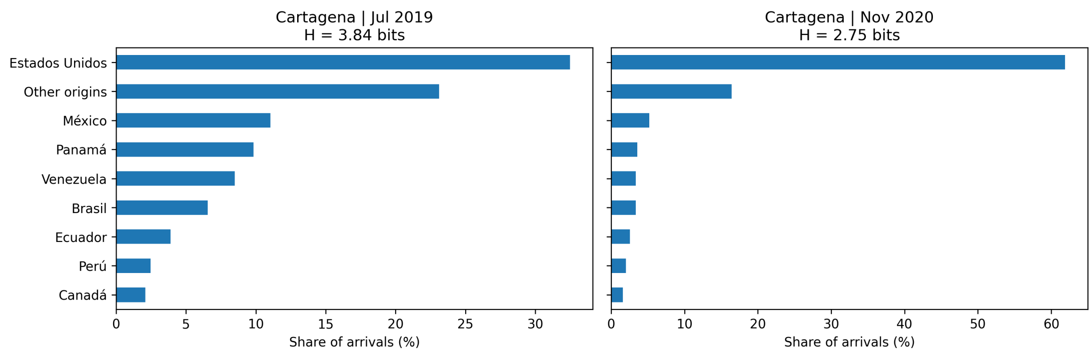


FIG. 5: Illustrative comparison of source-market composition for a selected destination city before and during the shock period. The shock window typically exhibits a less balanced portfolio, consistent with the decline in Shannon entropy and the contraction of alternative market channels. Alt Text: Comparison of a city's source-market composition before and during the shock, showing a more uneven distribution of arrivals during the shock period, consistent with reduced diversity.

policy issue is not urgent deconcentration but cautious broadening without eroding niche identity.

These implications should be interpreted structurally rather than causally. The analysis does not identify the operational mechanisms—such as airline scheduling, border regulation, or fare changes—through which hierarchy spikes emerge. Instead, it provides a transparent map of where diversification is present, where shock-time prominence becomes concentrated, and how those two dimensions combine across destinations [2, 10].

4. Conclusions

This paper introduced an interpretable, network-based measure of tourism resilience that combines *pre-shock diversity* of source markets, H^{pre} (Shannon entropy, bits), with a *shock-period hierarchisation* index, F^{shock} (maximum absolute residual from monthly log–log Katz–size scaling). Mapping Colombian destinations on the resilience plane $(H^{\text{pre}}, F^{\text{shock}})$ reveals a core-centric system: most international arrivals concentrate in a small set of diversified gateways that nevertheless experienced strong hierarchy spikes during the COVID-19 shock. Using median thresholds (τ_H=2.879 bits; $\tau_F = 0.267$), the *High-H/High-F* quadrant aggregates about 97% of pre-shock arrivals (2018–2019), whereas *High-H/Low-F* "resilient hubs" carry less than 2%. Thus, diversity of origin markets alone did not insulate the largest gateways from becoming bottlenecks under stress; resilience depends on both market redundancy and the ability of the network to redistribute flows through alternative channels.

At the other end of the plane, two smaller groups coexist. *Low-H/Low-F* destinations appear specialised yet stable (niche products, modest hierarchy spikes), suggesting room for gradual expansion of origin portfolios without eroding identity. *Low-H/High-F* "fragile mono-markets" combine concentrated demand with high stress hierarchisation, the classic double risk of low redundancy and single-channel dependence. Robustness checks confirm that these messages do not hinge on identification details: the quadrant structure persists under interquartile thresholds and the ranking of F^{shock} is meaningfully preserved when switching the city–city projection from weighted intersection to cosine similarity (Spearman $\rho \approx 0.45$, N=150). Overall, the proposed framework provides a compact structural diagnostic that is comparable across destinations while remaining transparent in its construction and interpretation.

POLICY IMPLICATIONS. Although the resilience plane is not a causal policy model, it does provide a structured way to differentiate destination types according to how diversity and hierarchisation combine under stress. In that sense, the quadrants can be read as broad planning profiles rather than as rigid prescriptions. The main implication is that resilience challenges are not the same across the system: some destinations mainly face excessive concentration of prominence during shocks, whereas others remain constrained by narrow origin portfolios or limited connectivity options.

1. **Diversified but stressed hubs (High-H/High-F).** For the largest gateways, the results suggest that market diversification alone may be insufficient if access remains concentrated through a small set of dominant channels. For this group, the most relevant strategies are those that preserve optionality under stress, such as strengthening secondary gateways, dispersing schedules, and improving alternative routings or intermodal connections [12, 31].

2. **Resilient hubs (High-H/Low-F).** These destinations show that diversified source portfolios can coexist with relatively stable structural prominence. Here, the main implication is to preserve that redundancy while expanding cautiously, avoiding forms of concentration that could move these cities toward the stressed quadrant.

3. **Fragile mono-markets (Low-H/High-F).** For this group, the structural challenge is dual: origin portfolios remain narrow while shock-time prominence becomes comparatively amplified. Accordingly, the most natural priorities are gradual source-market diversification together with improved connectivity to nearby hubs and alternative access channels.

4. **Specialised but stable (Low-H/Low-F).** These destinations appear comparatively stable within a narrower niche scale. For them, the relevant implication is not rapid expansion, but selective broadening of origin markets and access options without eroding the product identity that supports their current stability [18, 26, 42].

The analysis is structural rather than causal: the resilience plane summarizes how diversity and hierarchy combine across destinations and how that configuration changes under stress, but it does not identify the mechanisms driving recovery or concentration. The empirical application focuses on the 150 Colombian destination cities with the largest cumulative inbound arrivals during the 2018–2019 baseline period. Window choices (2018–2019 baseline; 2020–2021 shock) follow the administrative series and can be adapted in future work. Measurement relies on (i) Shannon entropy of arrivals by country of residence and (ii) monthly Katz residuals on the city projection; both are standard, yet alternative diversity or centrality definitions may refine classification in specific contexts. From January 2020, the source includes foreign residents in Venezuela reporting “rest and leisure”, which may slightly alter the measured composition of some origin portfolios at the margin. In addition, recorded arrivals at major airport cities may partly conflate gateway and final-destination functions, and F^{shock} depends on the projection kernel; robustness to cosine similarity (rank correlation $\rho \approx 0.45$) supports the findings, but richer mobility and airlift data (capacity, fares, restrictions) would help disentangle behavioural and supply-side mechanisms.

Although the empirical application developed here is grounded in the Colombian and broader Latin American context, the contribution of the paper is not limited to that setting. More generally, the study develops a network-based methodological framework for analyzing how pre-shock diversity and shock-time hierarchisation combine in destination systems. Because the framework relies on aggregated administrative counts of inbound international arrivals, it is portable to other national settings where comparable origin–destination panels are available. Comparable administrative datasets (e.g., Eurostat air-guest nights, the U.S. I-94 arrivals series, or Australia's TRA data) make the framework portable beyond Colombia. Future work could test whether similarly core-centric configurations emerge across Andean, Caribbean, and Pacific destination systems, and whether alternative projection rules or supply-side variables refine the resilience classification without changing its main structural message.

Data and reproducibility

All code and outputs (clean panels, city summaries, figures) are provided in a fully reproducible notebook with versioned dependencies. The administrative dataset *Extranjeros No Residentes* is publicly available from Colombia's open-data portal; we deposit a static snapshot, processed tables, and the notebook at Zenodo: Sierra Porta, D. (2025). Replication package and dataset for "An Interpretable Measure of Tourism Resilience from Network Diversity and Hierarchy" [Data set]. Zenodo. `https://doi.org/10.5281/zenodo.16762408`.

The repository includes a README with instructions to re-run the pipeline end-to-end and regenerate all figures (main plane and quadrant zooms), as well as robustness artefacts (kernel comparison and interquartile thresholds).

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Complementary information

A. Monthly trajectories of diversity and hierarchy for selected destinations

To complement the two-window summaries used in the main text, this appendix presents the full monthly trajectories of Shannon entropy and Katz residuals for a small set of illustrative destinations. The selected cities combine major gateways (*Bogotá, D.C.*, *Cartagena*, *Medellín*), a border hub (*Cúcuta*), and more specialized destinations (*Melgar* and *San Andrés de Tumaco*). This selection is not intended to be statistically exhaustive; rather, it is designed to show how the two indicators evolve over time for contrasting structural profiles.

Figure A.6 shows that Shannon entropy is well defined throughout the full panel and that the 2020–2021 shock window is associated with a visible contraction in source-market diversity for most cities. The decline is especially clear for the major gateways, whose pre-shock portfolios were broad and relatively stable but became less balanced during the pandemic period. At the same time, the magnitude and persistence of the drop differ across destinations. Cúcuta, for example, exhibits a distinct profile relative to the largest gateways, while smaller and more specialized cities show noisier dynamics consistent with thinner and more volatile origin portfolios.

Figure A.7 reports the corresponding Katz residual trajectories. In contrast to entropy, which remains comparatively smooth outside the shock window, the Katz residual shows a sharper structural reordering during 2020–2021. Major gateways experience abrupt deviations in relative prominence, confirming that the shock did not simply reduce flows uniformly, but also altered the hierarchical organization of the projected city network. Smaller destinations display more heterogeneous responses, including short-lived spikes and reversals, which is consistent with their weaker and more unstable embedding in the system.

Taken together, these trajectories support the interpretation adopted in the main text. The pre-shock and shock windows are not arbitrary slices imposed on unrelated quantities; rather, they summarize two indicators that are observed continuously over time and that exhibit qualitatively different responses to the pandemic disruption. Diversity shows partial persistence with a downward shock, whereas hierarchy is more strongly reconfigured under stress. This temporal evidence reinforces the rationale for constructing the main resilience plane from pre-shock diversity and shock-period hierarchisation.

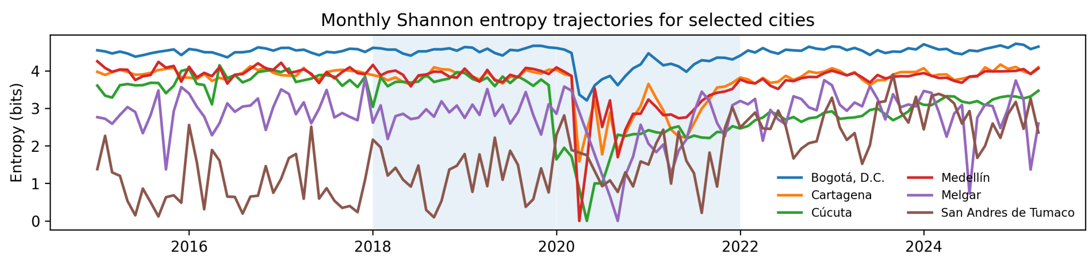

FIG. A.6: Monthly Shannon entropy trajectories for selected Colombian destinations. The shaded band marks the 2020–2021 shock window. Major gateways display high and relatively stable pre-shock diversity, followed by a visible contraction during the pandemic period. Smaller and more specialized cities exhibit lower and more volatile entropy levels throughout the panel. Alt Text: Line plots of monthly diversity for several cities, with a shaded period marking the shock, showing a decline during that interval and greater stability for major gateways compared to more variable patterns in smaller cities.

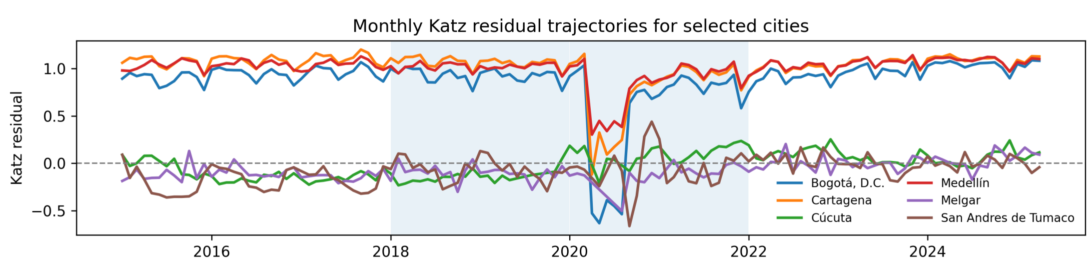

FIG. A.7: Monthly Katz residual trajectories for selected Colombian destinations. The shaded band marks the 2020–2021 shock window. The figure highlights the abrupt and heterogeneous reordering of relative structural prominence during the pandemic, particularly among the largest gateways. Alt Text: Time series of Shannon entropy for multiple cities, highlighting a drop in diversity during the 2020–2021 shock window, with large cities remaining more stable and smaller cities showing lower and more fluctuating values.

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