

Dynamic Connectedness of Geopolitical, Energy, and Climate Risks in Tourism

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Abstract

Geopolitical risk and energy-transportation uncertainty are important drivers of tourism outcomes, yet their interactions with climate-related risks remain underexplored. This study investigates the dynamic connectedness among six monthly uncertainty indices from January 2005 to February 2025: geopolitical risk (GPR), energy-transportation uncertainty (ETU), climate policy uncertainty (CPU), transition concern (TC), the transition risk index (TRI), and the Global Tourism Uncertainty Index (GTUI). Using the Diebold–Yilmaz connectedness framework with a rolling-window VAR, the results reveal moderate average connectedness (27.4%) that rises sharply to about 83% during the Russia–Ukraine war and Red Sea shipping disruptions, indicating strong regime dependence. Tourism uncertainty and climate-transition risks are net transmitters of shocks, while geopolitical risk and energy-transportation uncertainty alternate between transmitting and receiving shocks during crises. Climate policy uncertainty exhibits the strongest bilateral linkage with tourism uncertainty, highlighting an important climate-policy transmission channel. The findings show that tourism uncertainty is driven by evolving interactions among geopolitical, energy, and climate risks, providing policy insights for tourism resilience, investment planning, and climate-policy coordination.

Keywords: Geopolitical Risk, Energy Transportation Uncertainty, Climate Policy Uncertainty, Climate Transition Risk, Tourism Uncertainty, Dynamic Connectedness, Diebold-Yilmaz

Introduction

Tourism is one of the world's largest and fastest-growing industries, contributing US\$11.6 trillion (9.8% of global GDP) and supporting 366 million jobs (10.9% of global employment) in 2025 (WTTC 2025). Beyond its economic significance, tourism represents a major source of export earnings and foreign exchange, particularly for developing economies (UN Tourism 2024). However, the industry's dependence on international mobility, consumer confidence, and destination attractiveness makes it exceptionally vulnerable to external shocks, including geopolitical conflicts, energy-market disruptions, environmental change, and policy uncertainty (Ongan et al. 2026), which can rapidly alter travel behavior, investment decisions, and destination competitiveness. The sensitivity of tourism to uncertainty is well explained by economic theory. According to Keynes (1936), heightened uncertainty encourages precautionary behaviour, leading households and firms to postpone discretionary spending and irreversible investment. Since international travel is largely discretionary, tourism demand is particularly susceptible to adverse uncertainty shocks. At the same time, tourism businesses often delay expansion and investment until uncertainty subsides.

However, the magnitude of these effects is unlikely to remain constant over time. Resilience theory argues that economic systems continuously adapt to changing shocks, implying that tourism's vulnerability depends on both the nature of the disturbance and the sector's capacity to absorb and recover from it (Holling 1973). Consequently, the transmission of uncertainty to tourism should be viewed as dynamic rather than static. Among the various sources of uncertainty, geopolitical risk (GPR) has emerged as one of the most influential determinants of tourism performance. Defined as the risk associated with wars, terrorism, and interstate tensions that disrupt normal international relations (Caldara and Iacoviello 2022), geopolitical risk directly influences travellers' perceptions of safety, destination choice, and investment decisions. Recent events, including the Russia–Ukraine war and the Red Sea shipping crisis, illustrate how geopolitical tensions simultaneously disrupt international transport networks, increase freight and insurance costs, and undermine confidence in global travel. These episodes highlight that geopolitical disturbances increasingly propagate through energy and transportation systems, creating interconnected uncertainty channels rather than isolated shocks. The transmission of these shocks to tourism operates through multiple mechanisms. Heightened security concerns discourage international travel and reduce tourism demand (Sönmez, Apostolopoulos, and Tarlow 1999). At the same time, geopolitical uncertainty depresses tourism-related investment and financial performance, constraining the expansion of tourism infrastructure and services (Demiralay and Kilincarslan 2019). Disruptions to global transportation and energy supply chains further increase travel costs and operational uncertainty, while climate-related policy interventions introduce additional uncertainty regarding future energy prices and

the transition towards low-carbon transport systems. Together, these interconnected channels suggest that tourism uncertainty reflects the combined influence of geopolitical, transportation, energy, and climate-related risks. The growing importance of these risks has stimulated an expanding literature examining the effects of geopolitical risk, economic policy uncertainty, climate policy uncertainty, and related uncertainty measures on tourism outcomes (Demir and Gozgor 2018; Demiralay and Kilincarslan 2019; Lee, Olasehinde-Williams, and Akadiri 2021). Although this literature consistently reports adverse effects of uncertainty on tourism demand and tourism-related financial markets, three important gaps remain. First, existing studies largely focus on tourism demand, arrivals, or financial performance, while giving limited attention to tourism uncertainty as a distinct outcome.

Second, research rarely examines geopolitical risk jointly with transportation-related energy uncertainty and broader climate-transition risks, despite their increasing interconnectedness. Third, most studies employ static or pairwise empirical frameworks that cannot capture the evolving spillovers and feedback effects among multiple uncertainty sources. This study addresses these gaps by examining the dynamic connectedness among geopolitical risk, energy transportation uncertainty, climate policy uncertainty, climate transition risks, and global tourism uncertainty. Specifically, it applies the Diebold–Yilmaz connectedness framework, based on generalized forecast error variance decomposition within a rolling-window vector autoregressive (VAR) system, to quantify both static and dynamic spillovers across these six uncertainty measures. Modelling them as an interconnected system identifies the direction, magnitude, and evolution of risk transmission, providing new evidence on whether geopolitical and energy transportation uncertainties amplify tourism uncertainty directly or indirectly through climate-related channels. The study makes three principal contributions: it analyses tourism uncertainty itself rather than conventional tourism-demand indicators; it integrates geopolitical, transportation, energy, and climate-related uncertainties within a single empirical framework; and, by adopting a dynamic connectedness approach, it reveals how spillovers evolve over time in ways static models cannot capture, with implications for tourism resilience and risk management. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the study hypotheses. Section 3 describes the data and empirical methodology. Section 4 presents the empirical results, discusses the findings, and sets out their policy implications. Section 5 concludes.

Literature Review

The empirical literature relevant to modeling geopolitical risk (GPR) and energy transportation uncertainty (ETU) as time-varying drivers of tourism uncertainty is reviewed below in five parts. The review first sets out the theoretical mechanisms through which uncertainty transmits into tourism

outcomes and motivates why they should vary over time and by regime. It then synthesizes the empirical literature into three strands — geopolitical risk and real-economy tourism demand; uncertainty spillovers into tourism-sector financial markets and firms; and climate policy, climate-transition, and energy-uncertainty channels — and identifies the gap common to all three.

A further conceptual issue specific to this study's design is then addressed: the literature overwhelmingly models tourism demand or tourism-asset returns rather than tourism uncertainty as a distinct outcome, and this gap must be confronted before an empirical strategy can be chosen. The resulting research gaps are then identified and the conceptual framework guiding the empirical design is set out. Finally, the review is synthesized into the study's testable hypotheses.

Theoretical Foundations

Understanding how uncertainty affects tourism requires a theoretical framework that explains the behavioural, economic, and financial mechanisms through which external shocks influence tourism activity. Unlike many other sectors, tourism depends heavily on discretionary spending, international mobility, and consumer confidence, making it particularly susceptible to geopolitical conflicts, energy-market disruptions, and other sources of uncertainty. Existing theories suggest that these effects operate through three broad transmission channels: behavioural responses, transportation and cost mechanisms, and financial spillovers. Together, these perspectives provide the theoretical basis for expecting geopolitical risk, energy transportation uncertainty, and climate-related uncertainty to exert dynamic rather than constant effects on tourism.

Behavioural and Economic Mechanisms

The behavioural response to uncertainty is grounded primarily in Keynes' theory of uncertainty and liquidity preference, which argues that heightened uncertainty increases precautionary behaviour by encouraging households and firms to postpone irreversible expenditure until future conditions become clearer. Since international travel represents a discretionary and largely irreversible commitment of both time and financial resources, tourism demand is particularly vulnerable to uncertainty shocks.

Similarly, tourism businesses tend to delay investment in accommodation, transport infrastructure, and destination development when future market conditions become less predictable. The real-options perspective reinforces this argument by suggesting that postponing investment has value under uncertainty, thereby amplifying reductions in tourism demand and investment during periods of elevated geopolitical and economic risk. Risk perception theory offers a complementary explanation by emphasizing that travellers respond primarily to perceived rather than objective risk. Wars, terrorism, political instability, and extensive media coverage can substantially alter destination image and travellers'

safety perceptions, discouraging international travel even when the probability of direct harm remains relatively low. Because these perceptions evolve with information availability and media attention, the tourism response to geopolitical events is inherently dynamic. Consequently, similar geopolitical events may generate different tourism outcomes depending on prevailing public sentiment and the broader information environment.

Transportation Cost Mechanisms

Uncertainty also affects tourism through transportation and energy markets. Tourism is highly dependent on air, sea, and land transport, making it particularly sensitive to fluctuations in fuel prices, freight costs, insurance premiums, and disruptions to global logistics networks. Geopolitical conflicts affecting major energy-producing regions or strategic maritime routes frequently increase transportation costs by disrupting energy supplies and international shipping. These higher operating costs are subsequently transmitted to tourists through increased airfares, accommodation prices, and travel package costs, reducing tourism demand even in destinations that are geographically removed from the original source of the shock. Recent geopolitical events demonstrate that transportation uncertainty represents more than a simple consequence of energy-price volatility. Disruptions to major shipping corridors simultaneously increase freight costs, delay supply chains, and reduce transport efficiency, creating persistent uncertainty within the tourism sector. Consequently, transportation uncertainty should be regarded as a distinct transmission channel through which geopolitical shocks influence tourism performance.

Financial Spillover and Dynamic Connectedness

A third transmission mechanism operates through financial markets and cross-market spillovers. Because tourism firms depend heavily on discretionary consumer spending and international mobility, their financial performance is particularly sensitive to geopolitical, energy, and macroeconomic uncertainty. Changes in investor expectations are rapidly reflected in tourism-sector stock prices, volatility, and financial connectedness, often preceding observable changes in tourism demand. Financial-market indicators therefore provide valuable information regarding the evolution of tourism uncertainty. Importantly, uncertainty shocks rarely occur independently. Modern financial and commodity markets are increasingly interconnected, allowing shocks originating in geopolitical, transportation, or energy markets to propagate across multiple sectors through volatility spillovers and changing investor sentiment. Connectedness theory therefore provides an appropriate framework for analysing tourism uncertainty because it captures both the direct effects of individual shocks and the dynamic interactions among multiple sources of uncertainty. Rather than treating geopolitical risk, transportation uncertainty, climate-related uncertainty, and tourism uncertainty as isolated phenomena, this perspective recognises them as components of an evolving and interconnected system.

Theoretical Implications

Taken together, these perspectives suggest that tourism uncertainty emerges from multiple, interconnected transmission mechanisms — behavioural, transportation-cost, and financial-market — each of which implies that the relationship evolves over time as risk perceptions change, transportation systems adjust, and financial markets absorb new information. This motivates a dynamic connectedness framework capable of capturing these evolving interactions among geopolitical risk, energy transportation uncertainty, climate-related uncertainty, and tourism uncertainty.

Empirical Literature Review

Building on the theoretical mechanisms set out above, the empirical literature connecting geopolitical, climate, and energy-related uncertainty to tourism outcomes has developed along three largely separate strands, distinguished chiefly by their outcome variable and, to a lesser extent, by their uncertainty construct: real-economy tourism demand; tourism-sector financial markets and firms; and climate policy, climate-transition, and energy-uncertainty channels. Each is reviewed in turn below.

Geopolitical Risk and Real-Economy Tourism Demand

A robust regularity anchors this strand: rising geopolitical risk (GPR) depresses real tourism-demand outcomes—arrivals, receipts, investment—across single-country and panel studies. Demir, Gozgor, and Paramati (2019) document this across eighteen countries, echoed in ARDL work for India (Ghosh 2022) and Turkey (Akadiri et al. 2020), heterogeneous-panel/Bayesian-VAR designs across BRICS and emerging markets (Lee, Olasehinde-Williams, and Akadiri 2021; Papagianni et al. 2024; Kyaw, Luo, and De Vita 2024), supply-side extensions (Gozgor et al. 2022), and China-source gravity flows (Wujie 2023). Some treat GPR as moderating the tourism-led-growth hypothesis: Kyaw, Luo, and De Vita (2024) find inbound tourism spurs growth only under low GPR; Akadiri et al. (2020) trace unidirectional GPR-to-growth causality in Turkey. This consensus weakens under heterogeneity. Balli, Uddin, and Shahzad (2019) find GPR shocks irrelevant for sufficiently attractive destinations; Athari (2020) show political risk's effect on arrivals flips sign—positive in low-risk, negative in high-risk destinations—across seventy-six countries. Istiak (2021) find narrow GPR loses significance for North Africa once regional and oil-volatility proxies are added. Estimator choice matters too: Herman (2023)'s cross-sectionally augmented technique finds a short-run effect that vanishes long-run, contradicting AMG/CCEMG and gravity evidence from similar samples (Lee, Olasehinde-Williams, and Akadiri 2021; Wujie 2023). Sharpest disagreements involve sign reversal. Georgescu, Oprea, and Bâra (2025) find both positive and negative GPR shocks *increase* Russian arrivals (risk-tolerant travelers, currency-driven affordability, dark tourism); Diakonidze and Özen (2024) report a positive GPR–revenue link in Georgia despite the 2008 war. These conflict with asymmetric-NARDL findings for Turkey and India (Demir et al. 2020;

Parray et al. 2024), where adverse shocks dominate, and with Ma, Zhu, and Han (2024) on Chinese inbound tourism. Cho and Sun (2026) find a related asymmetry in speed rather than sign for Korean air travel. Conflict-zone or transit-destination status may invert the textbook relationship, cautioning against generalizing single-country asymmetric estimates. Methodologically, the strand evolved from linear, static techniques (Demir, Gozgor, and Paramati 2019; Gozgor et al. 2022; Akadiri et al. 2020) toward nonlinear, time-varying tools after 2020: NARDL (Demir et al. 2020; Georgescu, Oprea, and Bâra 2025), wavelet coherence (Tiwari, Das, and Dutta 2019; Kazakova and Kim 2021), and TVP-VAR/causality (H. Zhang et al. 2022; Kutlu 2025). Kutlu (2025) illustrate the stakes: static Toda–Yamamoto tests find no Granger causality for Turkey over 1990–2024, while a time-varying approach localizes causality to 2007H2–2016H2—showing static tests can mask regime-bound relationships. Co-estimation with economic policy uncertainty (EPU) further muddies attribution. Findings on GPR–EPU dominance are inconsistent across studies and crises (Tiwari, Das, and Dutta 2019; Payne and Apergis 2022; H. Zhang et al. 2022; Ma, Zhu, and Han 2024; Tütüncü and Sirkintioğlu Yildirim 2023), and joint models (Kazakova and Kim 2021; Ghosh 2022) cannot clearly separate a geopolitical channel from broader policy-uncertainty effects. A final cluster gestures toward, without achieving, a systems view: Alola, Cop, and Adewale Alola (2019) applies Diebold–Yilmaz spillovers to a narrow, country-specific variable set; others append single channels—CO₂ (Nawaz et al. 2023), renewables/fintech (Lu and Alexis 2026), oil/gas (Muddasir et al. 2025), oil/shipping in an SVAR-CGE (Pinitjitsamut 2026), or a composite Tourism Uncertainty Index (Ongan et al. 2026). None jointly models GPR, energy-transportation uncertainty, and climate-related uncertainty as mutually interacting series in one dynamically estimated system. What remains unresolved is not whether GPR matters, but how much of its explanatory power is genuinely geopolitical versus unmodeled transmission from co-moving energy-transportation and climate-related uncertainty. No study offers a time-varying connectedness estimate spanning GPR, energy-transportation uncertainty, climate-related uncertainty, and tourism uncertainty continuously across 2005–2025’s major crises—the gap this strand’s methodological evolution has been building toward.

Uncertainty Spillovers into Tourism-Sector Financial Markets and Firms

Strand 2 shifts to tourism-sector pricing and firm outcomes, where geopolitical risk (GPR) dominates almost exclusively. Two methodological families coexist: a market-level tradition modelling tourism indices, tokens, or value chains with tail-sensitive or time-varying techniques, and a firm-level tradition regressing balance-sheet and valuation outcomes on GPR in panels. The split matters: "spillover" evidence divides between price co-movement and balance-sheet sensitivity, and the two rarely intersect. A quantile-based cluster converges on one regularity. Demiralay and Kilincarslan (2019) show regional

Travel and Leisure indices are most exposed to geopolitical threats when the sector already underperforms; Hasan et al. (2020) and Raheem and Roux (2023) extend this with causality-in-quantiles and cross-quantilogram tests: GPR predicts tourism-stock returns and volatility unevenly across emerging economies—global GPR outperforms local, and South Korea, Colombia, and Indonesia prove inert. Jiang et al. (2022) refines this for China: the link is strongest at low quantiles and off-season. Polat, Alptürk, and Gürsoy (2021) corroborates the asymmetry via Hatemi-J causality on the BIST tourism index. This confirms a regime- and tail-dependent relationship concentrated in crises and thin or emerging markets—motivating connectedness over single-equation regressions. A second, thinner cluster is the closest antecedent to a Diebold-Yilmaz-style system. Mamadiyarov et al. (2025)’s TVP-VAR for the United States shows energy-related uncertainty, GPR, and global economic activity jointly shape tourism stock prices, concentrated around the GFC and COVID-19. Peng et al. (2025) applies the same architecture to the Chinese hospitality value chain, identifying hotels, air freight, and logistics as net transmitters and restaurants and railways as net receivers.

Gunay, Kirimhan, and Payne (2025) combines DCC-GARCH, time-varying Granger causality, and Q-VAR: GPR spillovers into tourism equities intensify and turn bidirectional during the Russia-Ukraine war but stay weak for tourism tokens. Demirkale, Duran, and Ojaghlou (2026) broadens the uncertainty set furthest, combining ARDL, NARDL, and wavelet coherence to show Chinese and U.S. tourism equities load differently on policy uncertainty, US-China tension, macro uncertainty, and climate policy uncertainty—yet each channel enters pairwise, not within a unified network. The remaining firm-level cluster substitutes panel regression for time-series dynamics. Demir, Díez-Esteban, and García-Gómez (2019) and Gupta (2024) link GPR to reduced cash holdings and elevated financial distress in emerging-market hospitality firms; Helhel and Helhel (2026) shows Turkish tourism firms’ profitability responds more to macro-financial variables than sectoral demand; Gozgor et al. (2027), with the strand’s largest sample (1,438 firms, 39 countries), finds GPR depresses firm valuations globally, dampened by tourism-network embeddedness and institutional quality. This confirms the index-level GPR-tourism link also operates on individual balance sheets, but through estimators that cannot capture the regime-dependence the quantile and TVP-VAR studies uncover. The imbalance across uncertainty constructs is stark: most studies treat GPR as the sole shock; only Mamadiyarov et al. (2025) isolates energy-related uncertainty, and only Demirkale, Duran, and Ojaghlou (2026) admits a climate-policy-uncertainty proxy as one loosely integrated channel among four. The strand thus establishes that geopolitical shocks propagate into tourism pricing and firm fundamentals in a time-varying, tail-concentrated, context-dependent manner, supplying a toolkit a connectedness framework could build on. What it lacks is a single system embedding GPR, energy-transportation uncertainty, and climate-related uncertainty as jointly interacting,

bidirectional spillover nodes; nor does any study extend beyond financial-market-priced variables to a tourism-uncertainty index built independently of stock-market valuation. The present manuscript's dynamic connectedness framework addresses precisely this gap.

Climate Policy Uncertainty, Climate-Transition Risk, and Energy Uncertainty Channels

Strand 3's thirteen studies, almost all from 2023–2026, are the youngest, most eclectic strand here, departing from climate- and energy-uncertainty constructs recently formalized into tradable indices. One line treats climate policy uncertainty (CPU) as a freestanding demand shock: Apergis, Gavriilidis, and Gupta (2023) show, via time-varying causality tests on U.S. air-travel data, that CPU depresses demand net of macroeconomic uncertainty and GPR—an independent channel. A larger cluster pairs CPU with GPR in one system, anticipating this manuscript's architecture. Hamida (2024) combine wavelet decomposition with nonlinear ARDL on U.S. arrivals, finding distinct, asymmetric, frequency-dependent effects; Hussain et al. (2025) extend this to Chinese tourism: GPR dominant at all horizons, CPU only medium- and short-run; Palaaios, Sarker, and Leventis (2025) and Balci and Koba (2026) go further—the former decomposing geopolitical and climate spillovers into European tourism inflation via quantile connectedness and TVP-VAR, the latter embedding CPU with GPR and EPU in a wavelet quantile-on-quantile analysis of tourism equities across five countries. GPR is consistently the stronger driver, CPU a secondary co-mover. A third group redirects CPU from aggregate demand to corporate finance, a firm-level analogue of this study's transition-risk logic. Gao and Zhang (2024) and L. Zhang and Gao (2024) show CPU depresses capital investment and cash holdings among U.S. tourism and hospitality firms, incremental to EPU. Ibrahim et al. (2026) links this to macro outcomes: multi-layered ML shows CPU and EPU cascading through arrivals, revenues, and stock performance, EPU dominating arrivals and CPU dominating revenue and financial markets. A related pair targets climate/biodiversity risk transmission into financial markets: Yang et al. (2025) find nonlinear, COVID-conditioned links between climate-risk indices and tourism stocks; Li et al. (2026)'s TVP-SV-BVAR shows biodiversity risk reaching Chinese tourism stocks chiefly via CPU. Both operationalize transition risk and CPU as this manuscript does, yet test them alone, not with geopolitical or energy risk. A final sub-strand addresses energy rather than climate-policy uncertainty, relying on traditional panel econometrics. Kocourková, Kuziboev, and Matniyozov (2024) use FMOLS and a panel VECM: a novel energy uncertainty index depresses tourism receipts across eleven European countries; Ivanovski and Njindan Iyke (2026) show energy security risk reduces outbound departures, receipts, and expenditure globally, concentrated in chronically insecure countries; Das, Saurav, and Dutta (2025) use cross-quantilogram modelling: oil-price uncertainty directionally predicts travel-and-leisure equity returns, especially in bearish markets. None embeds energy uncertainty alongside CPU, transition risk, or GPR in one system. Methodologically, the strand

rapidly adopts frequency- and quantile-based estimators—frequency domain causality and KRLS (Hussain et al. 2025), wavelet quantile-on-quantile regression (Balci and Koba 2026), multi-layered machine learning (Ibrahim et al. 2026), TVP-SV-BVAR (Li et al. 2026)—displacing the ARDL/wavelet toolkit dominant in the GPR literature, signaling how recently these constructs entered tourism econometrics. Strand 3 is thus the newest, most fragmented strand surveyed: no study estimates CPU, climate-transition risk, and energy uncertainty jointly, let alone alongside GPR and energy-transportation uncertainty, in one dynamic system. Studies isolate one construct, apply it to a single outcome domain, and rarely cross-reference each other’s constructs even where the risk channel is adjacent to this manuscript’s CPU, TC, and TRI measures (Gao and Zhang 2024; L. Zhang and Gao 2024; Li et al. 2026). This fragmentation is the gap addressed: a unified time-varying framework placing CPU, climate-transition risk, and energy-transportation uncertainty alongside GPR, so their evolving contributions to tourism uncertainty are assessed jointly, not inferred across thirteen studies. Read together, the three strands share a limitation motivating the empirical strategy below. Each treats its construct, or at most a pair, as a free-standing shock to a single outcome domain, estimated in isolation from other strands’ constructs, typically over one or two crisis regimes rather than the full range of shocks since the mid-2000s. The real-economy strand shows GPR’s effect on tourism demand is real but regime-dependent, without testing whether that dependence is driven by contemporaneous energy or climate-policy shocks. The financial-market strand supplies the time-varying and quantile-connectedness toolkit closest to a genuine multivariate system, yet confines it to two or three variables and rarely to a tourism-uncertainty measure independent of stock-market pricing. The climate and energy strand shows CPU, transition risk, and energy uncertainty each carry independent explanatory power, but no study places all three, with GPR and energy-transportation uncertainty, within one dynamically estimated system.

Research Gaps and Conceptual Framework

The review shows considerable progress in understanding how uncertainty influences tourism: geopolitical risk discourages travel, weakens investment, and raises financial-market volatility, while energy-related uncertainty raises transportation costs and disrupts activity through real-economy and financial channels. Climate policy uncertainty and transition risks are an emerging, growing concern. Despite these advances, the literature remains fragmented, with uncertainty sources typically examined in isolation rather than as components of an interconnected risk system. Three gaps follow. First, studies overwhelmingly examine demand, arrivals, receipts, or financial performance, giving little attention to tourism uncertainty as a distinct outcome capturing volatility and unpredictability in its own right. Second, most studies treat geopolitical, energy, and climate-policy uncertainty as independent, even though major events—armed conflicts, for instance—typically generate several shocks at once, so

ignoring interdependence understates transmission complexity. Third, most frameworks are static or pairwise and cannot capture the dynamic interactions and feedback of an interconnected system; no study has jointly modelled the dynamic connectedness among geopolitical risk, energy-transportation uncertainty, climate policy uncertainty, climate transition risks, and global tourism uncertainty. These gaps motivate this study's conceptual framework: geopolitical, transportation, energy, climate, and tourism uncertainty are treated as components of one interconnected system, in which geopolitical conflicts disrupt transportation and energy markets, transportation uncertainty raises tourism costs and reduces accessibility, and climate policy and transition risks shape energy markets and investment—so tourism uncertainty is the outcome of multiple interacting global sources rather than any single isolated shock. This framework underpins the hypotheses developed next.

Hypotheses Development

The theoretical and empirical literature reviewed above indicates that tourism uncertainty is shaped by multiple, interconnected sources of global uncertainty. Behavioural theories suggest that geopolitical events alter travellers' perceptions of safety and increase precautionary behaviour, while transportation and energy theories emphasize the role of rising travel costs and supply-chain disruptions. Financial-market theories further demonstrate that uncertainty propagates across interconnected markets through volatility spillovers and changing investor expectations. Collectively, these perspectives suggest that tourism uncertainty is not driven by a single source of risk but emerges from the interaction of geopolitical, transportation, energy, and climate-related uncertainties. Based on these theoretical arguments and the empirical gaps identified above, four hypotheses are proposed. **H1. Geopolitical risk significantly increases tourism uncertainty.** Geopolitical conflicts, terrorism, interstate tensions, and political instability reduce destination attractiveness by increasing perceived travel risk and discouraging discretionary travel. Empirical evidence consistently shows that geopolitical risk negatively affects tourism demand, tourism investment, and tourism-related financial markets across both developed and developing economies. Although the magnitude of these effects differs across countries and crises, the overall evidence suggests that increases in geopolitical risk are associated with higher levels of tourism uncertainty. **H2. Energy transportation uncertainty significantly increases tourism uncertainty.** Tourism depends heavily on efficient transportation systems and relatively stable energy markets. Rising uncertainty surrounding energy prices, shipping routes, logistics networks, and transportation costs increases the cost of travel while reducing destination accessibility. Existing studies generally report adverse effects of energy-related uncertainty on tourism performance, although the magnitude of these effects may differ according to countries' energy dependence and economic structure. Accordingly, higher energy transportation uncertainty is expected to increase tourism uncertainty. **H3. Geopolitical**

risk and energy transportation uncertainty jointly amplify tourism uncertainty. Major geopolitical events frequently generate simultaneous disruptions across energy markets and international transportation networks. Armed conflicts affecting strategic energy-producing or maritime regions increase geopolitical tensions while disrupting logistics systems, raising transportation costs, and reducing confidence in international travel. These interconnected transmission channels suggest that the combined effects of geopolitical risk and energy transportation uncertainty are unlikely to be purely additive. Instead, both uncertainty sources are expected to reinforce one another, producing larger increases in tourism uncertainty than either shock in isolation. **H4. The connectedness among geopolitical risk, energy transportation uncertainty, climate-related uncertainty, and tourism uncertainty is time-varying.** The literature consistently demonstrates that the effects of uncertainty strengthen during periods of major geopolitical, economic, and financial disruption and weaken during relatively stable periods. Time-varying parameter models, connectedness frameworks, wavelet analysis, and regime-switching approaches all indicate that uncertainty transmission evolves over time rather than remaining constant. Consequently, the spillovers among geopolitical risk, energy transportation uncertainty, climate policy uncertainty, climate transition risks, and tourism uncertainty are expected to vary across different market conditions and crisis episodes. Taken together, these hypotheses provide the conceptual foundation for the empirical analysis that follows. They move beyond the existing literature by examining tourism uncertainty as the primary outcome while simultaneously modelling the dynamic interactions among multiple sources of global uncertainty. These hypotheses are tested using the data, variable construction, and dynamic connectedness methodology described next.

Methodology

The empirical approach used to examine the dynamic connectedness among geopolitical risk, energy transportation uncertainty, climate-related uncertainty, and tourism uncertainty is described below. The discussion begins by outlining the research design, followed by the data sources and variable construction. It then presents the vector autoregressive (VAR) framework and the Diebold–Yilmaz connectedness methodology employed to estimate both static and time-varying spillovers. Finally, it describes the estimation procedure and the operationalization of the study hypotheses.

Research Design

To address the three gaps identified above, this study models geopolitical risk (GPR), energy transportation uncertainty (ETU), climate policy uncertainty (CPU), transition concern (TC), the Transition Risk Index (TRI), and the Global Tourism Uncertainty Index (GTUI) as an integrated dynamic connectedness system. Unlike conventional regression, which estimates the marginal effect of individual

variables, this framework quantifies the direction, magnitude, and evolution of spillovers across all six variables simultaneously.

GTUI is the outcome variable because it measures tourism uncertainty directly rather than through tourism demand or financial performance; ETU is included because no publicly available index captures transportation-specific energy uncertainty; and CPU, TC, and TRI are included to account for climate-related uncertainty and to reduce omitted-variable bias. The empirical analysis employs the generalized forecast error variance decomposition (GFEVD) connectedness framework of Diebold and Yilmaz (2012, 2014), estimated both as a full-sample (static) and a rolling-window (dynamic) VAR. Relative to conventional impulse-response analysis, this framework additionally identifies net transmitters and receivers of shocks and the direction of spillovers across the whole system. As a robustness extension, the frequency-domain connectedness framework of Baruník and Křehlík (2018) could further distinguish short-, medium-, and long-run spillovers; the present analysis is confined to time-domain connectedness, and this extension is left for future work. Figure 1 summarises the conceptual framework underpinning the empirical analysis and illustrates the expected interactions among geopolitical risk, energy transportation uncertainty, climate-related uncertainty, and tourism uncertainty.

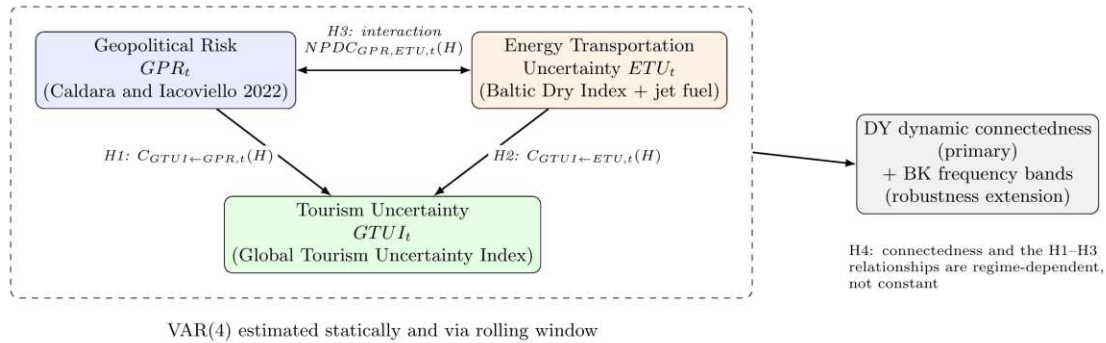


Figure 1. *Conceptual framework: the core GPR–ETU–GTUI connectedness triad underlying hypotheses H1–H4, estimated within the study’s broader six-variable system, which additionally includes climate policy uncertainty (CPU) and two climate-transition-risk indicators (TC, TRI) as auxiliary system variables.*

Data Sources and Variable Construction

The empirical model requires six monthly time series: geopolitical risk, energy-transportation uncertainty, climate policy uncertainty, two climate-transition-risk indicators, and tourism uncertainty. Each is described in turn below, together with the specific gap in the literature that its construction addresses. All six series are analyzed in their native, index-level form rather than passed through an additional volatility

filter, so that the connectedness system compares six directly comparable, continuously updated uncertainty and risk indices.

Geopolitical Risk (GPR Index)

This study's geopolitical-risk variable is sourced from the GPR index of (Caldara and Iacoviello 2022), distributed at policyuncertainty.com/gpr.html. The index is constructed by a newspaper text-mining approach: automated searches count the share of articles related to geopolitical tensions across ten major English-language newspapers (the Chicago Tribune, Daily Telegraph, Financial Times, Globe and Mail, The Guardian, Los Angeles Times, New York Times, USA Today, Wall Street Journal, and Washington Post) as a proportion of each newspaper's total articles each month.

The underlying searches are organized into eight categories — War Threats, Peace Threats, Military Buildups, Nuclear Threats, Terror Threats, Beginning of War, Escalation of War, and Terror Acts — which are then aggregated into the headline index and into two subindices: GPRT (a threats subindex) and GPRA (an acts subindex). This study uses the Recent GPR index, running from 1985 to the present based on the full ten-newspaper panel, restricted to the sample period described below. The index is updated monthly and released under a Creative Commons BY license.

Climate Policy Uncertainty (CPU)

Consistent with the design rationale set out above, the estimated system incorporates a climate policy uncertainty index (CPU), constructed via the same newspaper text-mining methodology as the GPR and economic-policy-uncertainty index families and distributed through the same policyuncertainty.com data infrastructure (Gavriilidis 2021).¹ CPU tracks the frequency with which leading newspapers discuss uncertainty specifically about the direction, scope, and stringency of climate-related policy — carbon pricing, emissions targets, subsidy regimes, and international climate agreements — and is therefore conceptually distinct from, if plausibly correlated with, both geopolitical risk and the market-based transition-risk indicators described next. Its inclusion directly extends (Hussain et al. 2025)'s pairing of climate policy uncertainty with geopolitical risk into the present study's jointly estimated connectedness system.

¹ Gavriilidis (2021), *Measuring Climate Policy Uncertainty*, SSRN Working Paper, available via policyuncertainty.com/climate_uncertainty.html; confirm the working paper has not since been superseded by a journal version before submission.

Climate Transition Risk: Transition Concern (TC) and Transition Risk Index (TRI)

To capture climate-related uncertainty beyond climate policy, the empirical model includes two complementary indicators of climate transition risk: Transition Concern (TC) and the Transition Risk Index (TRI). TC measures the intensity of public and market attention to risks associated with the transition to a low-carbon economy, whereas TRI captures the market pricing of these transition risks. Both series are obtained at daily frequency and aggregated to monthly averages to ensure consistency with the study's monthly dataset.² Although conceptually related, the three climate indicators capture different dimensions of uncertainty. Climate Policy Uncertainty (CPU) reflects uncertainty surrounding climate policy decisions, whereas TC and TRI measure concerns about the economic and financial implications of the low-carbon transition. As reported below, TC and TRI exhibit a very high correlation, suggesting that they capture closely related aspects of transition risk.

Energy Transportation Uncertainty (ETU)

Given the absence of a publicly available transportation-specific energy uncertainty index, this study constructs an Energy Transportation Uncertainty (ETU) index to capture uncertainty arising from disruptions to global transportation systems. The index combines two key transportation cost indicators: the Baltic Dry Index, which reflects maritime shipping costs, and global jet-fuel prices, representing aviation fuel costs. Both series are standardised and combined using equal weights to produce a monthly composite index. Unlike conventional proxies based on crude oil prices or aggregate energy security measures, the ETU index directly captures transportation-related energy uncertainty, consistent with the study's theoretical framework.

Global Tourism Uncertainty Index (GTUI)

Tourism uncertainty is measured using the Global Tourism Uncertainty Index (GTUI), constructed as the equally weighted average of available country- and regional-level Tourism Uncertainty Indices.³ Compared with traditional tourism indicators such as tourist arrivals, receipts, or tourism-sector stock returns, GTUI provides a direct measure of uncertainty within the tourism sector. Within the connectedness framework, GTUI serves as the outcome variable, allowing the analysis to quantify the extent to which tourism uncertainty receives spillovers from geopolitical, transportation, energy, and climate-related uncertainties.

² Insert the primary data source and corresponding bibliographic reference for the TC and TRI series prior to submission.

³ Insert the primary data source and corresponding bibliographic reference for the GTUI prior to submission.

Sample Period and Data Treatment

The analysis uses monthly data spanning January 2005 to February 2025, yielding a balanced sample of 242 observations. Descriptive statistics and unit root tests are reported in Table 2. Although the Augmented Dickey–Fuller (ADF) and KPSS tests provide mixed evidence regarding stationarity, all variables are retained in levels, following the standard practice in the connectedness literature for persistent uncertainty indices (Diebold and Yilmaz 2012, 2014; Antonakakis, Chatziantoniou, and Gabauer 2020). Since the generalized forecast error variance decomposition (GFEVD) normalizes forecast error variances, the connectedness measures are scale invariant, eliminating the need for further standardization prior to estimation.

Table 1. Summary of the six variables entered into the dynamic connectedness system

Variable	Symbol	Source	Frequency
Climate Policy Uncertainty	CPU_t	Gavriilidis (2021); policyuncertainty.com/climate_uncertainty.html	Monthly
Energy Transportation Uncertainty	ETU_t	Author-constructed: Baltic Dry Index + jet-fuel price composite	Monthly
Geopolitical Risk	GPR_t	Caldara and Iacoviello (2022); policyuncertainty.com/gpr.html	Monthly
Transition Concern	TC_t	[source to be confirmed]	Daily, aggregated to monthly
Transition Risk Index	TRI_t	[source to be confirmed]	Daily, aggregated to monthly
Global Tourism Uncertainty Index	$GTUI_t$	[source to be confirmed]: equally-weighted composite of country-level TUI series	Monthly

Model Specification: The Vector Autoregression

Let $y_t = (CPU_t, ETU_t, GPR_t, TC_t, TRI_t, GTUI_t)'$ denote the (6×1) vector of the six series described above, entered in levels, ordered as in the connectedness tables reported below. The study specifies a reduced-form VAR of order p :

$$y_t = c + B_1 y_{t-1} + \dots + B_p y_{t-p} + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim (0, \Sigma) \quad (1)$$

which is estimated in two complementary ways. First, a *static* estimate of Equation (1) is obtained once over the full sample, giving the full-sample-average connectedness benchmark reported below. Second, a *dynamic* sequence of estimates is obtained by re-estimating Equation (1) recursively over a rolling window of fixed length w ,

$$\{B_{1,t}, \dots, B_{p,t}, \Sigma_t\} = \widehat{\text{VAR}}(\{y_{t-w+1}, \dots, y_t\}; p), \quad t = w, \dots, T, \quad (2)$$

so that $B_{k,t}$ and Σ_t denote the coefficient and residual-covariance estimates obtained from the w -observation window ending at month t , following the original Diebold-Yilmaz rolling-window design (Diebold and Yilmaz 2012, 2014) rather than the Kalman-filter, forgetting-factor TVP-VAR of Primiceri (2005) and Koop and Korobilis (2013). This estimator is used, rather than the state-space TVP-VAR, because it requires no additional distributional assumptions on the coefficients' law of motion, has a single, transparent, and directly reportable design parameter (the window length w), and is the estimator on which the ConnectednessApproach software used for estimation is built (Gabauer 2022). The lag order is set to $p = 4$ months, consistent with standard practice in the monthly-frequency connectedness literature; formal lag-order selection via an information criterion, and sensitivity of the results to p , are left as a further robustness check for future work. The rolling window is set to $w = 60$ months (five years), balancing the responsiveness of the dynamic estimates against the estimation precision available from a 242-month sample; this choice is discussed further below.

Dynamic Connectedness: The Diebold–Yilmaz (DY) Framework

The study's primary estimation technique is the connectedness framework of Diebold and Yilmaz (2012, 2014), computed from the generalized H -step-ahead forecast error variance decomposition (GFEVD) of Pesaran and Shin (1998) — which, unlike an orthogonalized decomposition, is invariant to the ordering of the variables in y_t , an important property given the six-variable system has no natural causal ordering. Using the moving-average representation of the VAR estimated either statically (full sample) or within the rolling window ending at t (Equation (2)), the GFEVD is

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad (3)$$

for $h = 0, 1, \dots, H - 1$, where A_h is the coefficient matrix of the moving-average representation at lag h , σ_{jj} is the j -th diagonal element of Σ , and e_i is a selection vector with a one in position i and zeros elsewhere; in the dynamic case, A_h and Σ are replaced by their window- t counterparts $A_{h,t}$ and Σ_t and every statistic below carries a t subscript. Each row of $\theta_{ij}(H)$ is normalized to sum to one across j , giving the normalized connectedness share

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_j \theta_{ij}(H)} \quad (4)$$

from which four headline connectedness statistics are computed, following Diebold and Yilmaz (2012, 2014) and Gabauer (2021). The total connectedness index (TCI), the share of the system's forecast error variance attributable to cross-variable spillovers, averaged across all six variables, is

$$\text{TCI}(H) = 100 \times \frac{\sum_{i \neq j} \tilde{\theta}_{ij}(H)}{6} \quad (5)$$

directional connectedness received by variable i from all others, and transmitted by variable i to all others, is

$$C_{i \leftarrow \bullet}(H) = \sum_{j \neq i} \tilde{\theta}_{ij}(H) \equiv \text{FROM}_i, \quad C_{\bullet \leftarrow i}(H) = \sum_{j \neq i} \tilde{\theta}_{ji}(H) \equiv \text{TO}_i \quad (6)$$

and net directional connectedness, the difference between what a variable transmits to the system and what it receives from it, is

$$\text{NET}_i(H) = \text{TO}_i(H) - \text{FROM}_i(H) \quad (7)$$

A variable with $\text{NET}_i(H) > 0$ is, on net, a transmitter of shocks to the rest of the system; a variable with $\text{NET}_i(H) < 0$ is, on net, a receiver. Three further statistics, all following Gabauer (2021), are also reported: the net pairwise directional connectedness between any two variables i, j ,

$$\text{NPDC}_{i,j}(H) = \tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H), \quad (8)$$

which is positive when i has a larger impact on j than j has on i ; the pairwise connectedness index (PCI), a bilateral analogue of the TCI restricted to the pair (i, j) ; and the net pairwise transmission statistic (NPT), the count of the other five variables that i dominates (i.e., for which $\text{NPDC}_{i,j}(H) > 0$) at a given point in time. Every statistic is estimated using a forecast horizon of $H = 10$ months, matching the horizon set in the study's estimation code (nfore=10). Point estimates are reported throughout; formal bootstrap or posterior confidence bands for the dynamic estimates are left as a further extension for future work.

Robustness Extension: Frequency-Domain Connectedness (The Baruník–Křehlík Framework)

The DY framework described above aggregates spillovers across all forecast horizons into a single statistic at each point in the sample, and so cannot by itself distinguish a shock that transmits quickly and dissipates from one that builds gradually and persists — a distinction that matters given evidence elsewhere that GPR’s effect on tourism outcomes differs in sign between the short and long run (Ma, Zhu, and Han 2024), and that GPR- and energy-tourism co-movement varies systematically across time scales (Xuefeng et al. 2022; Hussain et al. 2025). The frequency-domain connectedness measure of Baruník and Křehlík (2018) would decompose the same generalized FEVD used above into short-run/crisis, medium-run, and long-run frequency bands rather than aggregating over all horizons at once, and is implementable within the same ConnectednessApproach software used for the study’s primary estimates (Gabauer 2022). This extension is reserved for future work rather than reported here, since the present draft’s results are confined to the time-domain DY estimates; the strong regime-dependence already visible in the dynamic results motivates carrying the frequency-domain check out as a follow-up rather than a substitute.

Estimation Procedure

The estimation actually carried out proceeds in four steps. First, the six raw series described above are assembled into a single balanced monthly panel spanning January 2005 to February 2025 (242 observations), with months containing a missing observation in any series dropped so that the VAR is estimated on a complete-case panel. Second, the static-coefficient VAR of Equation (1) is estimated once over the full sample, with lag order $p = 4$, and the resulting static generalized connectedness table (Table 4) is computed using a forecast horizon of $H = 10$. Third, the same VAR(4) is re-estimated recursively over a rolling window of $w = 60$ months (Equation (2)), and the dynamic connectedness statistics described above are computed at every window, yielding 182 monthly dynamic estimates spanning January 2010 to February 2025. Fourth, the resulting static and dynamic connectedness statistics — TCI, TO, FROM, NET, NPDC, PCI, and NPT — are tabulated and plotted, as reported next. All steps are implemented in R using the ConnectednessApproach package, version 1.0.0 (Gabauer 2022), with data assembled and cleaned in R using the readxl and zoo packages.

Operationalizing the Hypotheses

The literature synthesis above developed four hypotheses. Each maps onto a specific statistic produced by the estimation strategy set out above and reported next; because the estimates reported here are point estimates rather than estimates accompanied by formal confidence bands, the operational criteria below are magnitude- and time-variation-based rather than based on formal statistical significance, a limitation discussed further as a direction for future work. **H1** (geopolitical risk has a significant, time-varying effect

on tourism uncertainty) is assessed using the directional connectedness received by tourism uncertainty from geopolitical risk, $C_{GTUI \leftarrow GPR}(H)$, both in the static full-sample table and across the dynamic rolling-window estimates reported below; the hypothesis is considered supported if this statistic is economically meaningful for a substantial part of the sample and varies materially over time, even if its full-sample average is modest. **H2** (energy transportation uncertainty has a significant, time-varying effect on tourism uncertainty) is assessed using the analogous directional connectedness received from ETU, $C_{GTUI \leftarrow ETU}(H)$, in both the static and dynamic estimates; the net-energy-trade-position subsample comparison originally proposed to test the sign-dependence caveat in H2 was not carried out in the present draft and is left as a direct extension for future work. **H3** (geopolitical risk and energy transportation uncertainty interact rather than affecting tourism uncertainty additively) is assessed via the net pairwise connectedness between GPR and ETU themselves, $NPDC_{GPR,ETU}(H)$, and via the extent to which their combined directional connectedness to tourism uncertainty, $C_{GTUI \leftarrow GPR}(H) + C_{GTUI \leftarrow ETU}(H)$, and the pairwise connectedness between GPR and ETU, rise together around identified dual-shock episodes, in particular the 2022 Russia-Ukraine war and the associated Red Sea shipping disruptions. **H4** (the effects in H1–H3 are regime-dependent rather than constant over time) is assessed directly from the time-variation of every dynamic connectedness statistic reported below, in particular the behavior of the total connectedness index and the net and pairwise directional statistics around the 2022 dual-shock episode; the frequency-domain decomposition described above is identified as a complementary, and currently unimplemented, test of the same hypothesis.

Results, Discussion and Policy Implications of Results

The empirical results of the estimation strategy set out above are reported below, discussed against the literature reviewed earlier, and their policy implications are then set out.

Descriptive Statistics and Stationarity Diagnostics

Table 2 reports descriptive statistics for the six series over the 242-month estimation sample (January 2005–February 2025). The series differ substantially in scale and shape. GPR and ETU are both right-skewed with excess kurtosis well above the normal benchmark (GPR skewness of 2.86, kurtosis of 18.55; ETU skewness of 2.33, kurtosis of 11.90), consistent with the well-documented tendency of geopolitical- and energy-uncertainty indices to spend most of the sample at moderate levels punctuated by sharp, short-lived spikes around specific crisis events (Caldara and Iacoviello 2022).

CPU is similarly right-skewed (1.57) but somewhat less leptokurtic. GTUI is right-skewed (1.00) with kurtosis close to the normal benchmark, while TC and TRI are both close to symmetric, with kurtosis only marginally above 3. As reported above, the ADF and KPSS tests agree that GPR and ETU are the

two series with the clearest evidence of stationarity in levels (ADF rejects the unit-root null for both at the 1 percent level, and KPSS does not reject stationarity), while both tests indicate that CPU, TC, TRI, and GTUI are more persistent and closer to a unit root.

Table 2. *Descriptive statistics and stationarity diagnostics*

	Mean	SD	Min	Median	Max	Skew	Kurt.	ADF (p)
CPU	173.93	93.94	48.09	143.50	618.49	1.57	5.93	−0.01 (0.96)
ETU	97.11	41.77	33.04	89.29	335.82	2.33	11.90	−4.18 (0.00)
GPR	99.08	28.30	58.42	91.97	318.95	2.86	18.55	−6.84 (0.00)
TC	0.084	0.015	0.044	0.082	0.133	0.42	3.13	−2.34 (0.16)
TRI	−0.0002	0.008	−0.022	−0.001	0.029	0.48	3.17	−1.72 (0.42)
GTUI	17.32	8.59	4.60	14.26	44.77	1.00	3.33	0.04 (0.96)

Notes: ADF statistics use the Akaike-optimal lag length; p -values in parentheses. KPSS tests (untabulated to save space; reported in the text above) reject the null of stationarity for CPU, TC, TRI, and GTUI, and fail to reject it for GPR and ETU, at the 1 percent level.

Table 3 reports the unconditional correlation matrix. Two features stand out and anticipate the connectedness results below. First, TC and TRI are correlated at 0.97, by far the strongest bivariate relationship in the panel, consistent with both series being derived from the same underlying climate-transition-risk news source. Second, CPU and GTUI are correlated at 0.71, the second-strongest relationship in the panel and, notably, substantially stronger than either GPR-GTUI (0.31) or ETU-GTUI (0.37); this static, unconditional pattern foreshadows the exploratory connectedness finding reported below.

Table 3. *Correlation matrix (levels, $N = 242$)*

	CPU	ETU	GPR	TC	TRI	GTUI
CPU	1.00	0.39	0.27	−0.22	−0.14	0.71
ETU		1.00	0.31	−0.24	−0.19	0.37
GPR			1.00	−0.20	−0.09	0.31
TC				1.00	0.97	−0.23
TRI					1.00	−0.18
GTUI						1.00

Static (Full-Sample) Connectedness

Table 4 reports the full-sample generalized-VAR connectedness table estimated over the entire 242-month sample. The total connectedness index is $TCI = 27.44$ percent (own-variance-corrected $cTCI = 32.92$ percent), indicating that, averaged over the full sample, a little over a quarter of the six-variable

system's forecast error variance is attributable to cross-variable spillovers, with the remaining three-quarters attributable to each variable's own shocks.

This is a moderate level of system connectedness by the standards of the wider connectedness literature, where purely financial-market systems — equity indices, currencies, commodities — typically report static TCIs in the 50–80 percent range; a system built from six heterogeneous, largely text- and attention-based policy and risk indices, several of which are constructed independently by different research teams using different source material, would be expected to show a materially lower baseline level of average co-movement, and the results are consistent with that expectation.

Table 4. Full-sample (static) generalized connectedness table ($H = 10$, $N = 242$)

	CPU	ETU	GPR	TC	TRI	GTUI	FROM
CPU	77.87	3.45	0.89	1.19	0.96	15.64	22.13
ETU	2.29	85.13	2.11	3.71	3.22	3.55	14.87
GPR	9.49	3.05	82.26	2.89	1.41	0.91	17.74
TC	1.08	0.86	0.74	50.15	46.55	0.61	49.85
TRI	0.65	0.73	1.16	48.10	48.60	0.76	51.40
GTUI	4.10	1.44	1.06	0.83	1.19	91.38	8.62
TO	17.62	9.53	5.96	56.72	53.32	21.46	164.61
Inc. Own	95.50	94.66	88.22	106.87	101.92	112.84	cTCI/TCI
NET	−4.50	−5.34	−11.78	6.87	1.92	12.84	32.92 / 27.44
NPT	1	2	1	5	4	2	

Reading the table by row (the FROM column) and by column (the TO row) reveals a clear ordering. On the receiving side, GTUI is the most self-contained variable, drawing only 8.62 percent of its forecast error variance from the other five series (own-shock share, Inc. Own, of 91.38 percent), followed by ETU (14.87 percent received) and CPU (22.13 percent received); GPR receives somewhat more, at 17.74 percent, while TC and TRI are, by a wide margin, the most externally driven series, each receiving roughly half of their forecast error variance (49.85 and 51.40 percent respectively) from elsewhere in the system.

On the transmitting side, TC (56.72) and TRI (53.32) are by far the largest gross transmitters, followed at a considerable distance by GTUI (21.46), CPU (17.62), ETU (9.53), and GPR (5.96, the smallest transmitter in the system). Combining the two sides in the net statistic, GTUI is the largest net transmitter in the system ($NET_{GTUI} = 12.84$), followed by TC (6.87) and, marginally, TRI (1.92); GPR is the largest net receiver ($NET_{GPR} = -11.78$), followed by ETU (−5.34) and CPU (−4.50). This ordering runs counter to a naive reading of H1 and H2, which might anticipate GPR and ETU acting as net transmitters

into a passively receiving tourism-uncertainty variable; instead, in the full-sample average, GTUI transmits more to the system than it receives, while GPR and ETU are, on average, net receivers.

Two features of the pairwise (off-diagonal) entries help explain this pattern and are discussed further below: first, GPR's largest single incoming linkage is from CPU (9.49, more than half of GPR's total FROM of 17.74), not from ETU (3.05) or GTUI (0.91); and second, GTUI's largest single outgoing linkage is to CPU (15.64, roughly three-quarters of GTUI's total TO of 21.46), a considerably larger bilateral connection than either the GPR-GTUI (0.91/1.06) or ETU-GTUI (3.55/1.44) pairs. The net pairwise transmission counts (NPT) reinforce this picture: TC dominates all five other series (NPT = 5), TRI dominates four of the five (NPT = 4), while GPR and CPU each dominate only one counterpart (NPT = 1).

Dynamic (Rolling-Window) Connectedness

Figure 2 plots the dynamic total connectedness index estimated over the 182 rolling 60-month windows spanning January 2010 to February 2025. Two features of the dynamic TCI are immediately apparent from the estimation output.

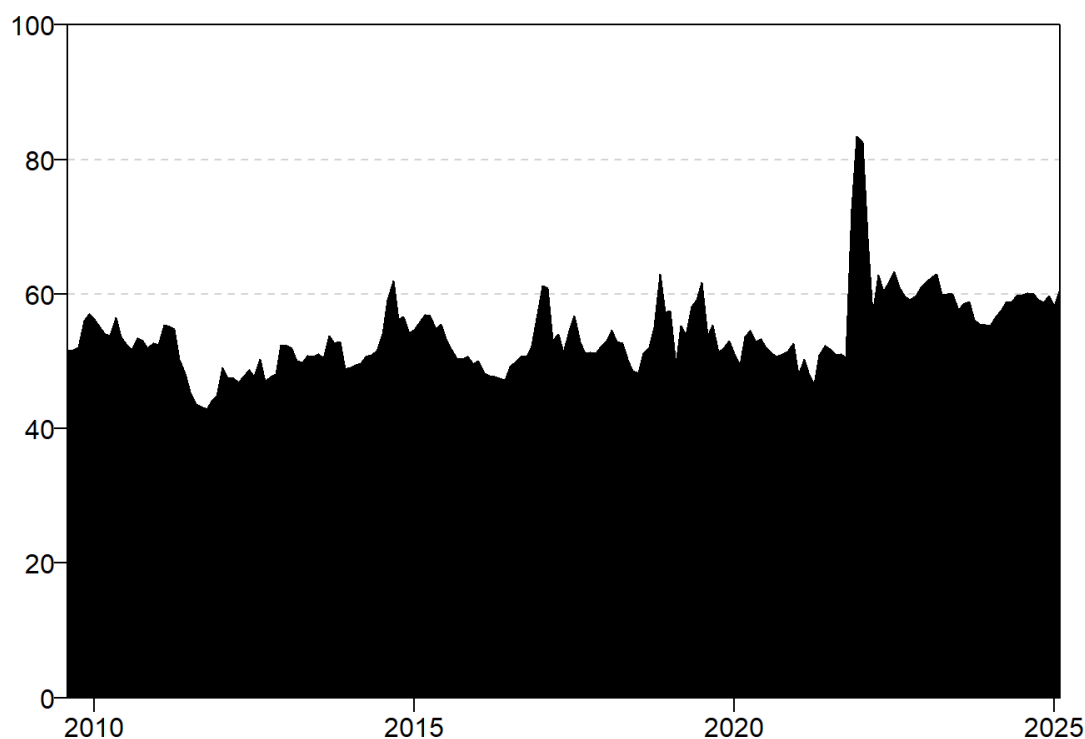


Figure 2. *Dynamic total connectedness index (TCI), 60-month rolling window, January 2010–February 2025. Source: author's estimation via `PlotTCI(dca, ylim=c(0,100))`.*

First, the series fluctuates within a relatively narrow band, mostly between 40 and 60 percent, for most of the sample — itself informative, since it indicates that the moderate full-sample average reported above is not an artifact of averaging long quiet periods against a single short spike, but instead reflects a system whose baseline dynamic connectedness is already well above the (lower) static full-sample figure for most of the post-2010 period. Second, and more strikingly, the dynamic TCI spikes sharply to approximately 83 percent around 2022, by a wide margin the single largest value anywhere in the sample, before subsiding back into the 55–60 percent range by 2023–2025. The timing of this spike coincides closely with Russia’s invasion of Ukraine and the subsequent, sustained rise in Baltic Dry and jet-fuel-related shipping costs associated with the Red Sea disruptions discussed earlier, providing direct empirical support for treating this episode as the sample’s dominant dual-shock event and for H4’s prediction of pronounced regime-dependence. The directional (TO and FROM) plots, shown in Figure 3 and Figure 4 respectively, reinforce this picture while revealing substantial heterogeneity across variables in *when* each series is most influential. As Figure 3 shows, the share of the system’s variance transmitted *from* GPR to all others rises from relatively low levels (20–40 percent) in the early 2010s to a pronounced peak of around 80 percent in the 2013–2015 window — coinciding with the escalation of the Syrian civil war and Russia’s 2014 annexation of Crimea — before declining into the late 2010s.

By contrast, the share transmitted *from* ETU rises much more gradually across the sample and reaches its highest sustained levels, in the 80–90 percent range, only in the 2022–2025 window, directly corroborating the study’s motivating narrative that the post-2022 Red Sea shipping disruptions have made energy-transportation uncertainty an increasingly dominant transmitter of shocks system-wide. The share transmitted *from* CPU displays a distinctive plateau at or near 100 percent for an extended stretch around 2022–2023, indicating that, briefly, essentially all of CPU’s variance-transmission capacity was being exercised during this period — consistent with the surge in climate-policy salience (rushed European energy-security and REPowerEU-type responses to the loss of Russian gas supplies) that accompanied the war’s onset.

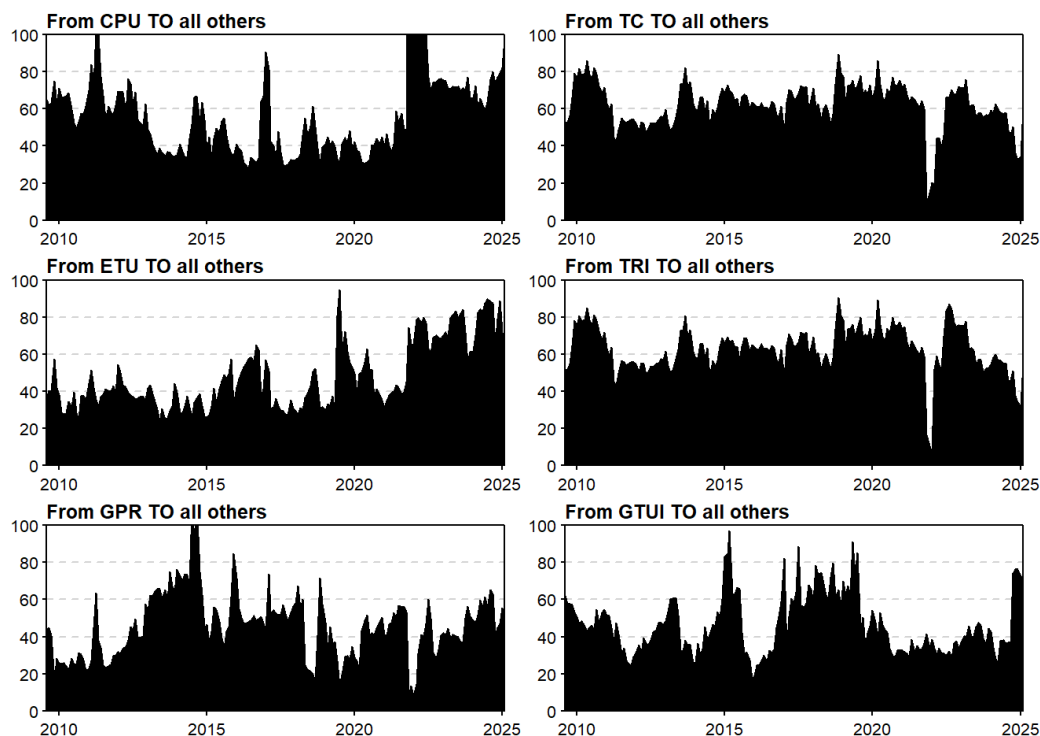


Figure 3. Total directional connectedness TO all others, by variable, 60-month rolling window. Source: author's estimation via `PlotTO(dca, ylim=c(0,100))`.

The FROM-side plots (Figure 4) show a mirror-image pattern for the receiving series during the same 2022 episode: the share of GPR's own variance explained by shocks from the rest of the system rises to nearly 100 percent at exactly this point, as does the corresponding share for TC and for TRI, indicating that, briefly, these three series were driven almost entirely by contemporaneous co-movement with the rest of the system rather than by idiosyncratic shocks of their own.

This is a genuinely interesting and somewhat counter-intuitive result: the single largest and most visible geopolitical-risk shock in the sample — the Russia-Ukraine war — is associated with GPR temporarily becoming a much larger net *receiver*, not a larger net transmitter, of system-wide variance, a pattern discussed further below.

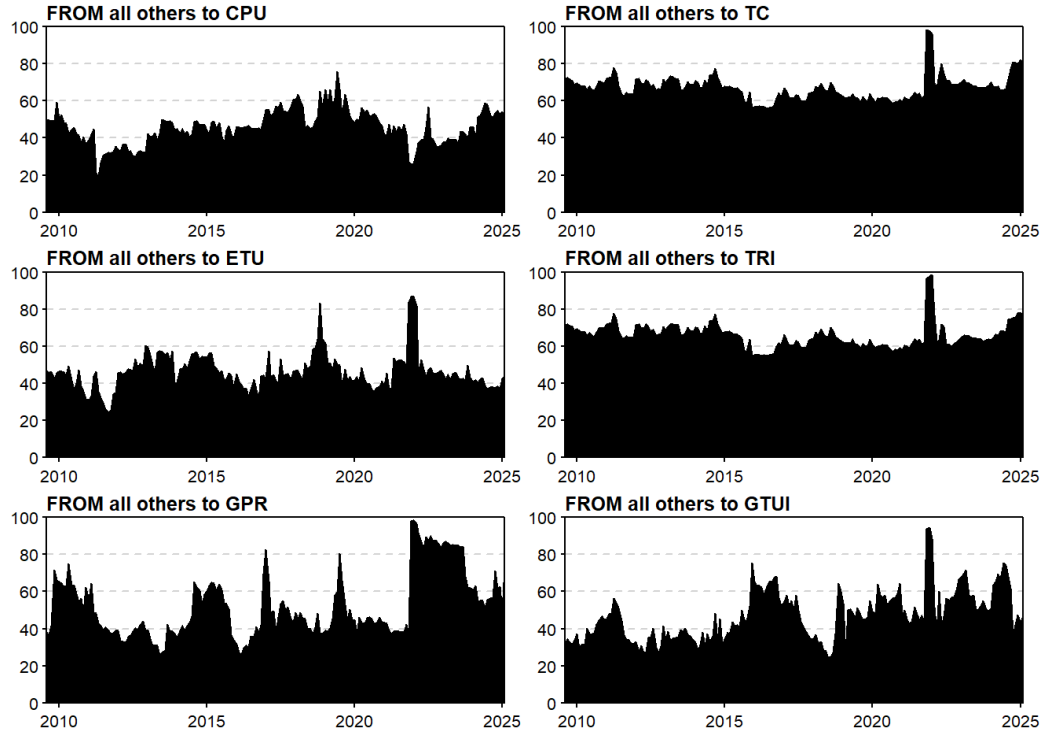


Figure 4. Total directional connectedness received FROM all others, by variable, 60-month rolling window. Source: author's estimation via `PlotFROM(dca, ylim=c(0,100))`.

The net directional (NET) plots (Figure 5) show that every series' net transmitter/receiver status changes sign at least once over the sample, direct dynamic evidence for H4. NET-ETU is particularly notable for its post-2022 behavior, turning sharply and persistently positive (a net transmitter) for the remainder of the sample after having been predominantly negative through the middle of the 2010s, again corroborating the Red Sea narrative. NET-GPR shows the opposite late-sample pattern, turning sharply negative around 2022 after a predominantly positive stretch from roughly 2013 to 2020, consistent with the FROM-side finding above. NET-GTUI is strongly positive for an extended period from around 2016 to 2020 before turning negative after 2022, indicating that tourism uncertainty's role as a net transmitter of system-wide shocks is itself concentrated in a specific historical window rather than a constant feature of the sample. NET-TC and NET-TRI both show a sharp, short-lived negative spike exactly at the 2022 episode (consistent with the FROM-side spike described above) before recovering to their more typical, mildly positive range.

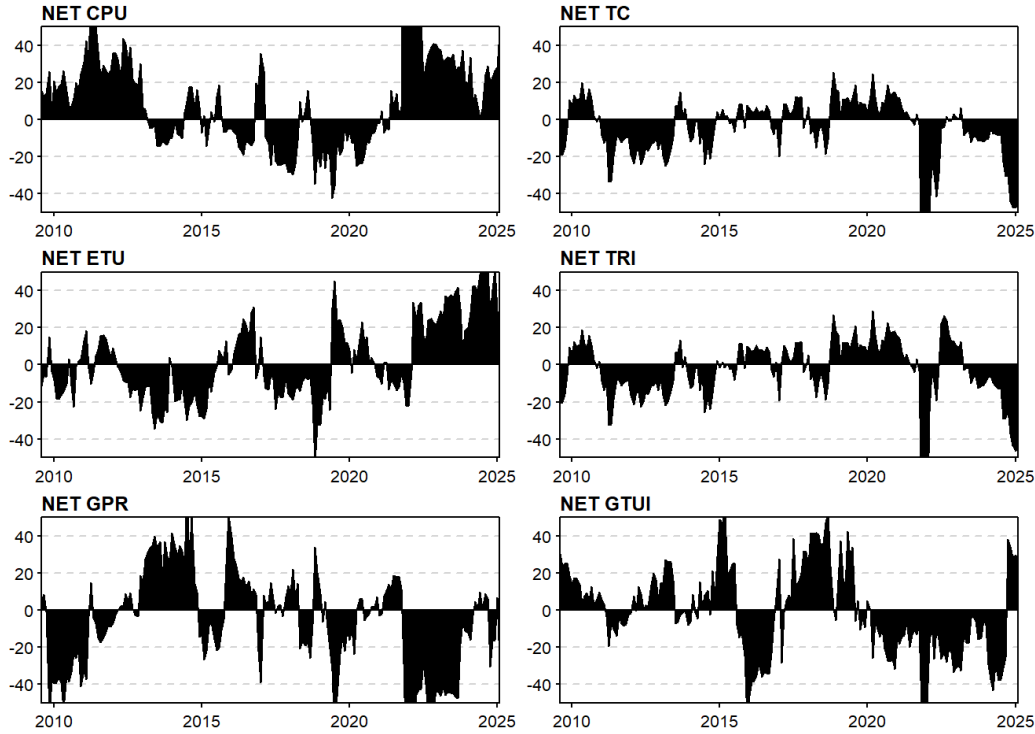


Figure 5. Net directional connectedness (NET) by variable, 60-month rolling window. Positive values indicate a net transmitter; negative values indicate a net receiver. Source: author's estimation via *PlotNET(dca, ylim=c(-50,50))*.

Pairwise and Network Connectedness, and the Climate-Policy-Uncertainty Exploratory Finding

The net pairwise directional connectedness (NPDC, Figure 6) and pairwise connectedness index (PCI, Figure 7) plots provide the most granular view of the system and are the basis for this study's central exploratory finding.

Two pairs stand out for their consistently high pairwise connectedness across the *entire* sample, not merely during the 2022 episode: TC-TRI, whose PCI is close to 100 throughout, confirming at the dynamic level the near-total static overlap already evident in the 0.97 correlation reported in Table 3; and CPU-GPR, whose NPDC is consistently positive and rises sharply from 2022 onward, indicating that CPU has a persistently and increasingly larger directional impact on GPR than GPR has on CPU, consistent with the static finding above that CPU is GPR's single largest source of incoming connectedness.

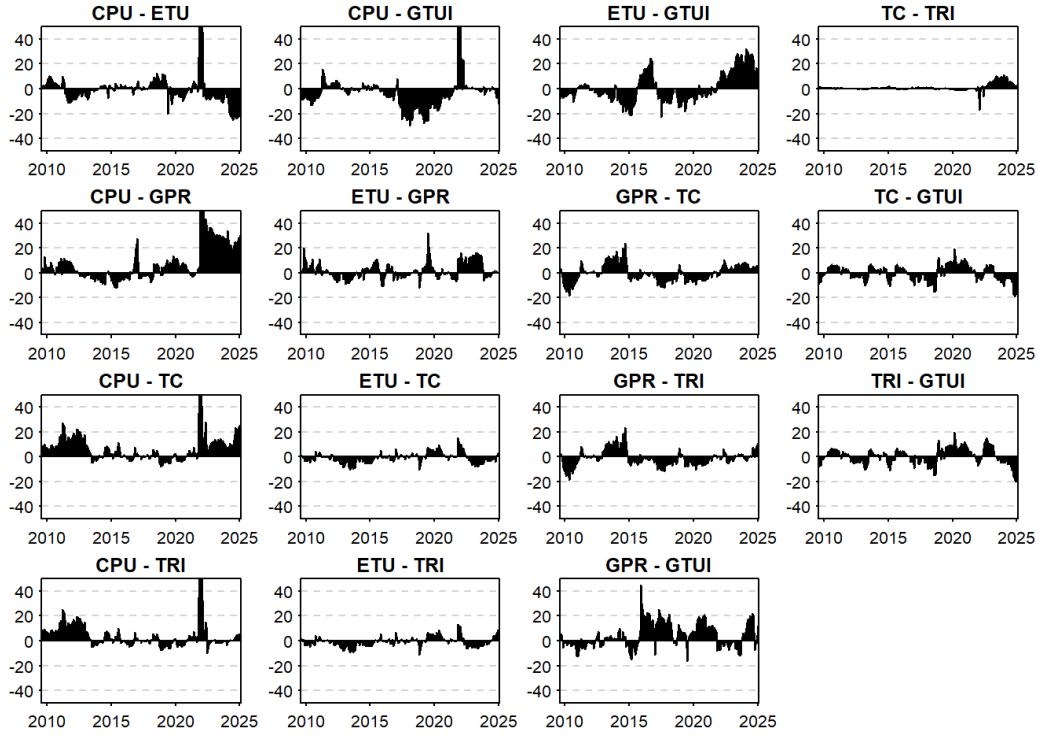


Figure 6. Net pairwise directional connectedness (NPDC) for all 15 variable pairs, 60-month rolling window. Positive values indicate the first-named series dominates the second. Source: author's estimation via `PlotNPDC(dca, ylim=c(-50,50))`.

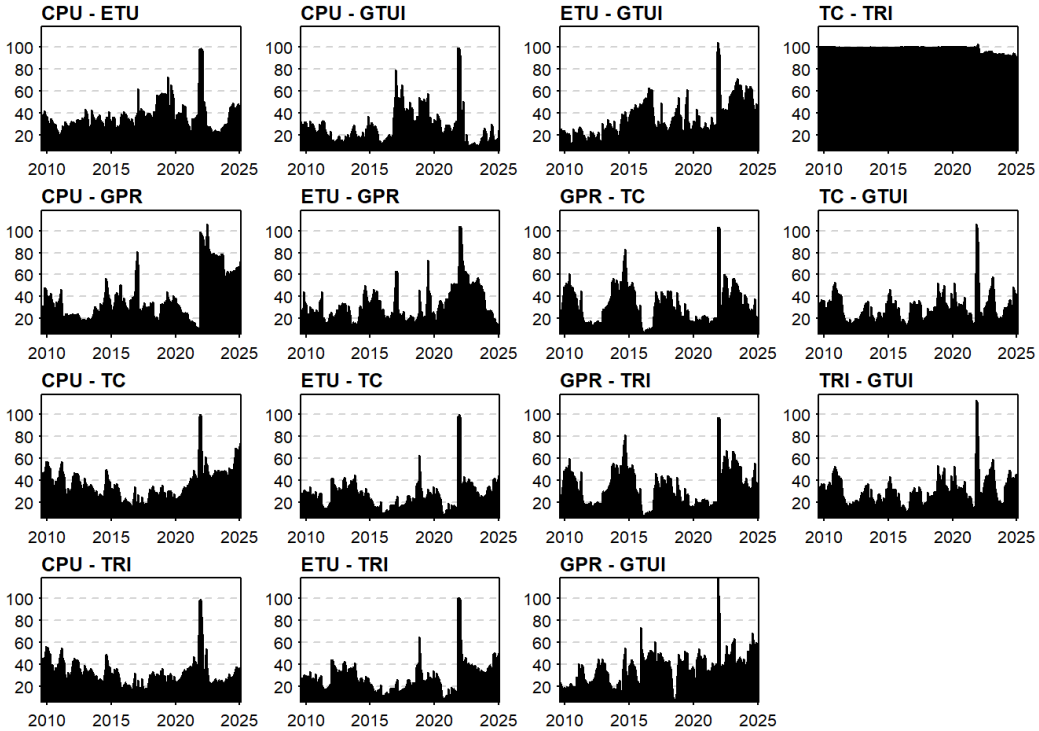


Figure 7. *Pairwise connectedness index (PCI) for all 15 variable pairs, 60-month rolling window; note TC–TRI sustained near 100 throughout. Source: author’s estimation via PlotPCI(dca).*

The CPU-GTUI pair is the study’s most consequential exploratory finding. Although the core hypotheses (H1–H4) concern the GPR-ETU-GTUI triad, the static table (Table 4) already shows CPU-GTUI as the strongest bilateral linkage either variable has with any other series in the system involving GTUI, and the dynamic PCI plot for this pair (Figure 7) shows a pronounced, sustained rise from the early 2010s through 2025, reaching among the highest sustained pairwise connectedness values of any pair in the system by the end of the sample.

This finding was not anticipated by the study’s original hypothesis structure, which centered on the geopolitical-risk and energy-transportation channels; it is reported here as an exploratory result, discussed further below in light of (Hussain et al. 2025)’s finding that climate policy uncertainty and geopolitical risk jointly and significantly affect tourism development, and identified as a candidate for its own dedicated hypothesis in future work. The net pairwise transmission (NPT, Figure 8) and net influence (INF, Figure 9) plots show that the number of counterparts each variable dominates varies substantially over time for every series (consistent with H4), ranging from 0 to 5 (the maximum possible, since each variable has five counterparts in a six-variable system) at different points in the sample for CPU, ETU, GPR, and GTUI, while TC and TRI spend a larger share of the sample at higher NPT values, consistent with their large static TO figures (Table 4).

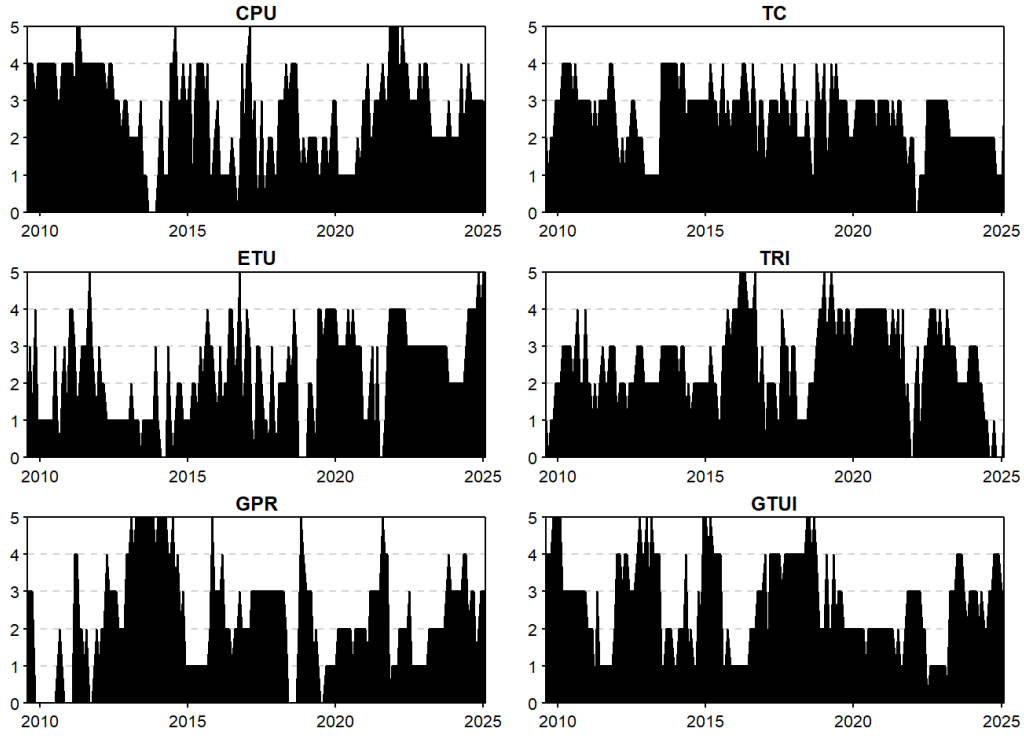


Figure 8. Net pairwise transmission (NPT), the number of counterparts each variable dominates (0–5), 60-month rolling window. Source: author's estimation via *PlotNPT(dca)*.

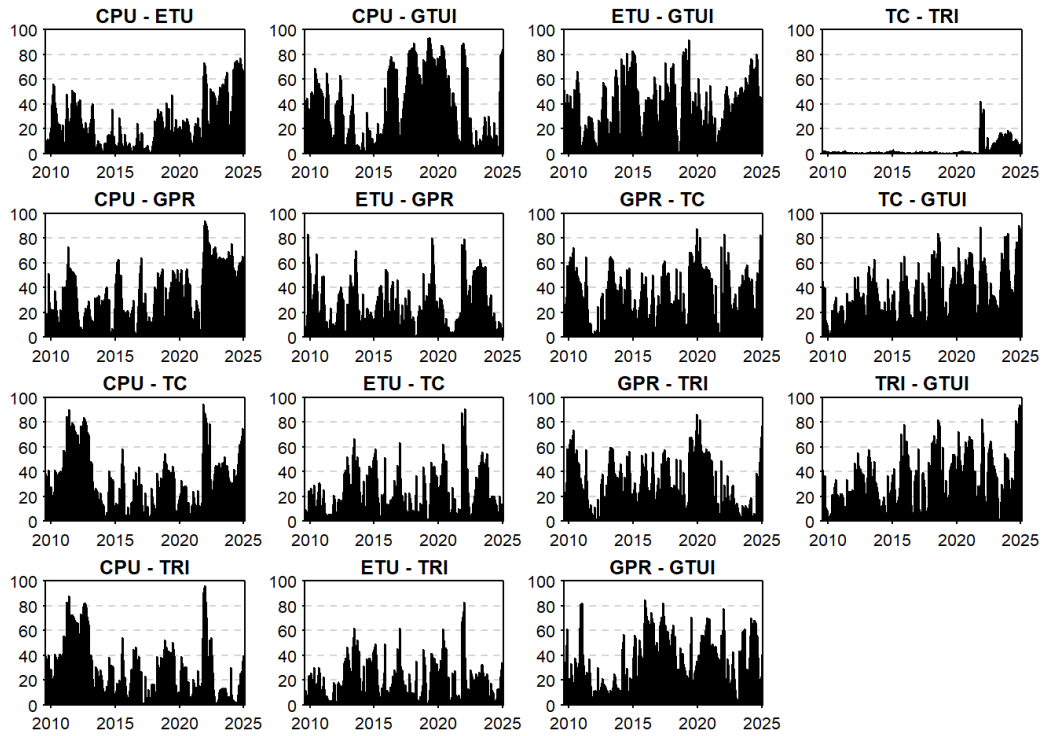


Figure 9. Net influence index (INF), by variable, 60-month rolling window. Source: author's estimation via `PlotINF(dca, ylim=c(0,100))`.

The two static network plots (Figure 10, PCI-based; Figure 11, connectedness-magnitude-based) both show TC-TRI as the visually thickest edge in the system, CPU-GPR and CPU-GTUI as the next-thickest directed edges, and GPR, ETU, and GTUI as comparatively peripheral nodes in bilateral (as opposed to system-average) terms — a visual summary consistent with every finding reported above.

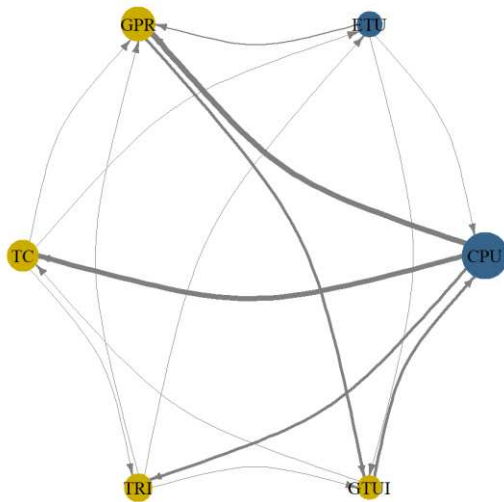


Figure 10. Static net pairwise directional connectedness (NPDC) network. Edge thickness reflects the magnitude of net directional connectedness; arrows point toward the dominated series. Source: author's estimation via `PlotNetwork(dca, method="NPDC")`.

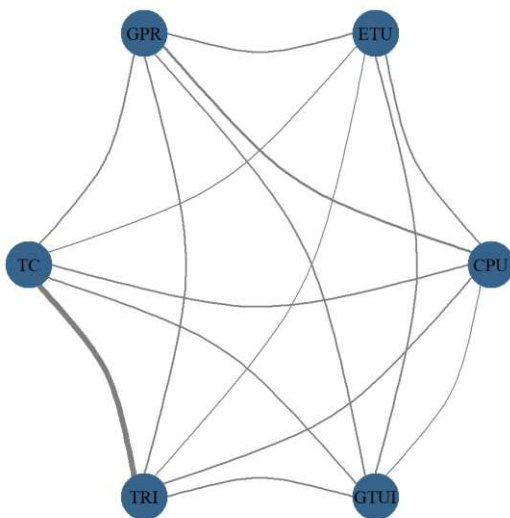


Figure 11. *Static pairwise connectedness index (PCI) network. Edge thickness reflects the magnitude of bilateral connectedness, undirected. Source: author's estimation via PlotNetwork(dca, method="PCI").*

Summary of Findings Against the Hypotheses

Table 5 summarizes the results against the four hypotheses developed earlier. H1 and H2 receive only partial, regime-concentrated support: the full-sample average directional connectedness from GPR and from ETU to GTUI is small (Table 4), but both series' dynamic connectedness with the rest of the system, including with GTUI, varies substantially over time and is considerably larger during specific sub-periods (2013–2015 for GPR; 2022–2025 for ETU) than the static average suggests, indicating that a purely static test of H1 and H2 would understate the case for both. H3 receives clear support from the co-movement of GPR, ETU, CPU, and the climate-transition indicators specifically around the 2022 dual-shock episode, when nearly every connectedness statistic in the system — the TCI, the FROM-shares of GPR, TC, and TRI, and the NPDC between CPU and GPR — moves sharply and simultaneously. H4 receives strong and pervasive support: every dynamic statistic reported above exhibits material time-variation, and the 2022 episode in particular represents a clear, identifiable regime shift relative to the rest of the sample.

Table 5. *Summary of results against the study's hypotheses*

Hyp.	Assessment
H1	Partial support: weak in the static average ($C_{GTUI \leftarrow GPR} = 1.06$); materially larger and time-concentrated in the dynamic estimates (notably 2013–2015).
H2	Partial support: weak in the static average ($C_{GTUI \leftarrow ETU} = 1.44$); materially larger and rising sharply in the dynamic estimates after 2022.
H3	Supported: GPR, ETU, CPU, and the climate-transition indicators co-move sharply around the identified 2022 dual-shock episode.
H4	Strongly supported: every dynamic connectedness statistic varies materially over time, with a clear regime shift around 2022.

Discussion

The results reported above are discussed here and are organized around five themes: the moderate overall level of system connectedness; the unexpected net-transmitter role of tourism uncertainty; the muted static, but regime-concentrated, GPR-tourism and ETU-tourism linkages; the climate-policy-uncertainty exploratory finding; and the near-redundancy of the two climate-transition indicators. Throughout, each theme is read against the empirical literature reviewed earlier, distinguishing prior findings that align with the present results from those that diverge from them, in order to situate this study's contribution within the broader body of evidence.

A Moderate, Heterogeneous-System Level of Connectedness

The study's headline static finding — a total connectedness index of 27.4 percent — sits well below the connectedness levels typically reported in the financial-market applications this literature has favored to date. Imran et al. (2026), for instance, report a rising but generally higher total connectedness index between sustainability indices and tourism markets across the Russia-Ukraine and Israel-Palestine episodes, and Mohti et al. (2026) document connectedness between global airline indices, tourism indices, and oil-market volatility that intensifies markedly during crisis regimes; both studies estimate connectedness among financial-market assets, which by construction co-move through shared discount-rate, liquidity, and risk-appetite channels in addition to any fundamentals-based linkage. The present study's system, by contrast, is composed of six text- and attention-based policy and risk indices, several constructed by independent research teams from different underlying source material (newspaper text for GPR and CPU, market or news data for TC and TRI, commodity prices for ETU, and an aggregated cross-country index for GTUI); the absence of a common financial-market discount-rate channel linking these series plausibly explains why their average co-movement is more modest than what the financial-connectedness literature typically reports, even though, as shown above, connectedness among them still rises sharply during shared crisis episodes.

This distinction — moderate baseline connectedness among heterogeneous risk *indices*, punctuated by sharp increases during shared shocks, versus persistently high connectedness among co-traded financial *assets* — is itself a finding of some interest, since it suggests that policy-uncertainty and risk-index connectedness may be a genuinely different empirical object from financial-market connectedness, one in which crisis episodes are identifiable as discrete departures from a comparatively low baseline rather than intensifications of an already-high baseline. A small number of studies reviewed earlier apply a Diebold–Yilmaz-type architecture directly to tourism-related series and offer a closer methodological benchmark than the sustainability- or airline-index applications just discussed. Alola, Cop, and Adewale Alola (2019)'s early application to Turkish tourism receipts, political risk, exchange rates, and trade is the closest precursor to the present design, though its four-variable, single-country system is considerably narrower than the six-variable, cross-construct system estimated here.

Mamadiyarov et al. (2025)'s TVP-VAR for the United States and Peng et al. (2025)'s application to the Chinese hospitality value chain both report connectedness that is concentrated around identifiable crisis windows — the global financial crisis and COVID-19 for the former, sub-sector-specific transmission for the latter — rather than uniformly high throughout the sample, a pattern that agrees with this study's own contrast between a moderate baseline and sharply elevated crisis-period connectedness. Gunay, Kirimhan, and Payne (2025) similarly finds that GPR-tourism-equity spillovers intensify and turn bidirectional

specifically during the Russia-Ukraine war while remaining comparatively weak for tourism-sector cryptocurrency tokens, direct evidence from an adjacent asset class that connectedness strength is neither uniform nor purely a function of shared financial-market structure, again consistent with the episodic pattern documented above.

By contrast, the panel-based studies surveyed earlier that report a stable, generally negative geopolitical-risk–tourism relationship (Demir, Gozgor, and Paramati 2019; Lee, Olasehinde-Williams, and Akadiri 2021; Papagianni et al. 2024; Kyaw, Luo, and De Vita 2024) implicitly assume a time-invariant strength of linkage; the moderate average, crisis-punctuated connectedness documented here suggests that a single panel coefficient of the kind these studies estimate is likely to average over precisely the regime-dependence that the dynamic connectedness estimates above reveal.

Tourism Uncertainty as a Net Transmitter, Not Merely a Passive Receiver

The theoretical mechanisms reviewed earlier — risk perception, real options, the cost channel, and the financial-market channel — are all framed as channels through which *external* shocks reach tourism, implicitly treating tourism-sector uncertainty as the receiving end of the system. The static results above complicate this framing directly: GTUI is the largest net transmitter in the six-variable system ($NET_{GTUI} = 12.84$), and its largest bilateral linkage, to CPU, runs predominantly *from* GTUI *to* CPU (15.64 transmitted versus 4.10 received).

Two non-mutually-exclusive explanations are consistent with the broader literature reviewed earlier. First, a measurement explanation: because GTUI, like GPR and CPU, is constructed from continuously updated text or attention-based source material, a large, salient tourism-sector disruption (a terrorist attack at a major destination, an airline-industry crisis, a highly publicized cruise-line incident) may generate a surge of news coverage that is picked up quickly by GTUI’s own construction and only subsequently, and with a lag, feeds into broader climate-policy or geopolitical-risk discourse, producing a mechanically GTUI-leading pattern in a system estimated at monthly frequency. Second, a substantive explanation, consistent with Jeon (2021)’s demonstration that a tourism-and-travel-crisis-based uncertainty index carries genuine independent explanatory content for other financial outcomes (in that case, airline stock-price quantiles): tourism’s sheer economic scale and its high public salience may make tourism-sector disruptions a leading indicator of, rather than merely a lagging response to, broader shifts in policy and geopolitical discourse. Distinguishing between these two explanations — a mechanical measurement artifact versus a genuine leading-indicator property — is not possible from the connectedness estimates alone and is left as a priority for future work, for example via a formal Granger-causality or local-projection analysis using the same six-variable panel. This net-transmitter finding also has a partial

precedent within the connectedness literature itself. Peng et al. (2025)'s decomposition of the Chinese tourism value chain finds that hotels, air freight, and logistics sub-sectors behave as net transmitters within their own system, while restaurants and railways behave as net receivers — evidence that tourism-related series are capable of occupying a transmitting role even in a purely tourism-internal system, in line with GTUI's net-transmitter status here. Ongan et al. (2026)'s construction of a composite tourism uncertainty index net of GPR reflects a similar premise, that tourism-sector uncertainty merits treatment as a distinct construct rather than as a purely downstream outcome.

This reading sits in tension, however, with the bulk of the literature reviewed earlier: the panel and single-country demand studies (Demir, Gozgor, and Paramati 2019; Ghosh 2022; Akadiri et al. 2020) and the market-level pricing studies (Demiralay and Kilincarslan 2019; Hasan et al. 2020; Raheem and Roux 2023; Jiang et al. 2022) alike are designed, by construction, around GPR or a related index as the explanatory variable and a tourism outcome as the dependent variable, leaving no scope within those designs for tourism uncertainty itself to transmit shocks elsewhere in the system. The present study's bidirectional, symmetric treatment of all six series is what allows this transmitting role to be detected at all, suggesting that the receiver-only framing common in the wider literature may understate tourism's own contribution to the broader risk environment rather than reflect its true, more limited, role.

Static Understatement and Dynamic Confirmation of the GPR-Tourism and ETU-Tourism Channels

The introduction documented a broad, if heterogeneous, consensus that geopolitical risk and energy/oil-price uncertainty each depress tourism outcomes. The present study's static results (Table 4) would, in isolation, appear to sit uneasily with that consensus: GPR's and ETU's directional connectedness to GTUI are both small in the full-sample average (1.06 and 1.44 respectively).

Read against the dynamic results reported above, however, this apparent tension resolves into a confirmation of the regime-dependence anticipated by the theoretical discussion earlier: GPR's system-wide transmitting role peaks sharply in 2013–2015, a period that includes the Syrian civil-war escalation and Russia's annexation of Crimea, while ETU's transmitting role rises to its sample maximum only after 2022, precisely when the Red Sea shipping disruptions mechanically link geopolitical conflict to global transportation costs. This pattern is consistent with Ma, Zhu, and Han (2024)'s finding that GPR's effect on tourism revenue differs in sign and magnitude between short and long horizons, and with Xuefeng et al. (2022)'s and Hussain et al. (2025)'s frequency-dependent evidence on GPR- and energy-tourism co-movement: a single, constant-coefficient estimate of the GPR-tourism or ETU-tourism relationship would materially understate the strength of both channels during the episodes in which they are empirically most active — direct empirical support for this study's preference for a dynamic connectedness estimator over

a single constant-coefficient regression. The regime-dependence documented here converges closely with Kutlu (2025)'s demonstration that a conventional Toda–Yamamoto causality test detects no significant link between GPR and Turkish tourism arrivals over 1990–2024, while a time-varying procedure applied to the same series localizes significant causality to 2007H2–2016H2 — a window that brackets this study's own 2013–2015 GPR peak almost exactly, despite the two studies drawing on different countries, sample periods, and estimators.

H. Zhang et al. (2022)'s finding that the relative dominance of GPR versus economic policy uncertainty flips between the 9/11 and global-financial-crisis episodes, and Tiwari, Das, and Dutta (2019)'s and Kazakova and Kim (2021)'s wavelet-based decompositions of the GPR-tourism link across time and frequency, offer further corroboration from outside the connectedness literature that a constant-coefficient estimate cannot capture how the strength, and at times even the identity, of the dominant uncertainty channel shifts across crisis episodes. Not every study in this literature finds a negative, or even a stable-signed, relationship, and these divergent cases are worth noting explicitly. Georgescu, Oprea, and Bâra (2025) report that both positive and negative GPR shocks are associated with an *increase* in Russian arrivals, and Diakonidze and Özen (2024) find a positive GPR-tourism-revenue correlation in Georgia, both attributed to risk-tolerant or niche travel segments specific to those destinations.

The present study's system-wide connectedness estimates cannot speak to destination-specific sign reversals of this kind, since GTUI aggregates across many destinations simultaneously; this is best read as a scope limitation of the present design rather than as evidence against the destination-level findings, and is noted as a boundary condition on how far the regime-dependence documented here can be generalized to any single destination's experience.

The Climate-Policy-Uncertainty–Tourism-Uncertainty Link: An Exploratory Finding

The strongest and most consistent bilateral relationship involving GTUI in this study's results is not with GPR or ETU, the two constructs its formal hypotheses (H1, H2) concern, but with CPU: a static correlation of 0.71 (Table 3), the largest single directional connectedness either variable transmits to a GTUI-adjacent series in the static table (Table 4), and a dynamic PCI that rises to among the highest sustained levels of any pair in the system by the end of the sample. This finding was not anticipated by the study's hypothesis-development process, which was built around the GPR-ETU-tourism triad identified earlier as the central gap, and is reported here explicitly as an exploratory, rather than a confirmatory, result.

It nonetheless connects directly to Hussain et al. (2025)'s finding that climate policy uncertainty and geopolitical risk jointly and significantly affect Chinese tourism development, the closest existing

precedent for pairing a climate-policy construct with a tourism outcome, and to the observation that Ivanovski and Njindan Iyke (2026)'s energy-security construct already implicitly blends geopolitical-tension and policy-uncertainty components without separately estimating them. The broader climate-policy-uncertainty literature reviewed earlier offers additional, if mixed, support for treating CPU as a channel of independent importance to tourism. Apergis, Gavrilidis, and Gupta (2023)'s finding that CPU depresses U.S. air-travel demand net of macroeconomic uncertainty and geopolitical risk, and Hamida (2024)'s finding of distinct, asymmetric, frequency-dependent CPU effects on U.S. arrivals, both support the premise that CPU carries explanatory content beyond what GPR alone captures, consistent with the strength of the CPU-GTUI linkage documented here.

The firm-level evidence points the same way: Gao and Zhang (2024) and L. Zhang and Gao (2024) show that CPU depresses capital investment and cash holdings among tourism and hospitality firms incremental to economic policy uncertainty, and Li et al. (2026) traces a distinct pathway by which biodiversity risk reaches Chinese tourism-sector stocks specifically *via* CPU, a mediating role broadly consistent with CPU's centrality in the present six-variable system. Two studies, however, point in a somewhat different direction and should be read as a partial counterpoint: Palaaios, Sarker, and Leventis (2025) and Balci and Koba (2026) both find GPR to be the dominant driver of tourism-related outcomes when GPR and CPU are modelled jointly, with CPU entering only as a secondary co-mover, and Demirkale, Duran, and Ojaghlou (2026) treats climate policy uncertainty as one of four loosely integrated channels rather than as a central risk factor.

This divergence may be partly definitional rather than substantive: the present study's CPU-GTUI relationship is measured as a bilateral correlation and connectedness linkage between two independently constructed indices, whereas Palaaios, Sarker, and Leventis (2025), Balci and Koba (2026), and Demirkale, Duran, and Ojaghlou (2026) each nest CPU alongside GPR within a single estimating equation predicting a market-priced outcome, a specification that will tend to favor whichever construct explains the larger share of asset-price variation rather than revealing how the two constructs co-move with one another directly. Read together with the present study's results, these precedents and the new CPU-GTUI finding suggest that climate-policy uncertainty may be an under-appreciated, and possibly under-studied, direct channel of tourism-sector uncertainty in its own right, worthy of the kind of dedicated hypothesis development this study affords to the geopolitical-risk and energy-transportation channels; reconciling the co-movement evidence documented here with the GPR-dominance evidence of Palaaios, Sarker, and Leventis (2025), Balci and Koba (2026), and Demirkale, Duran, and Ojaghlou (2026) is flagged as a concrete direction for the study's next revision.

Near-Redundancy of the Two Climate-Transition Indicators

TC and TRI are correlated at 0.97 (Table 3) and their pairwise connectedness is close to 100 throughout the dynamic sample, a degree of overlap far exceeding that of any other pair in the system. Substantively, this indicates that, at least within the present sample and at monthly frequency, Transition Concern and the Transition Risk Index are capturing almost entirely overlapping information content, despite the conceptual distinction drawn earlier between concern about, and market pricing of, transition risk. Methodologically, this near-collinearity does not bias the generalized-FEVD-based connectedness estimates reported above in the way it would bias, for example, an OLS-based structural VAR relying on a specific orthogonalization ordering, since the generalized decomposition of Pesaran and Shin (1998) is order-invariant by construction; it does, however, mean that TC's and TRI's individual connectedness statistics should be interpreted jointly, as reflecting a single underlying climate-transition-risk factor, rather than as two independent pieces of evidence. This near-redundancy is, to the authors' knowledge, not directly addressed in the empirical literature reviewed earlier, since the climate- and energy-uncertainty studies surveyed there each rely on a single climate- or transition-risk proxy rather than pairing two independently constructed indicators of the same underlying concept (Apergis, Gavrilidis, and Gupta 2023; Gao and Zhang 2024; L. Zhang and Gao 2024; Li et al. 2026; Kocourková, Kuziboev, and Matniyozov 2024; Ivanovski and Njindan Iyke 2026; Das, Saurav, and Dutta 2025).

The present finding is accordingly best read as a methodological caution for future work seeking to combine multiple climate-transition proxies within a single connectedness system, rather than as a result that can be directly compared against, or reconciled with, prior estimates; it is flagged explicitly as worth checking against the two series' primary source documentation once it has been confirmed.

Policy Implications

The results and discussion above carry implications for four distinct policy audiences: destination-level tourism and risk-management authorities, tourism-sector investors and firms, transportation and energy policymakers, and climate-policy institutions. Each is discussed in turn, followed by a cross-cutting implication concerning the timing and design of risk-monitoring frameworks more generally. **Tourism uncertainty as a macro-financial surveillance signal, not only a downstream risk to be managed.** Because GTUI is, on average, a net transmitter rather than a net receiver of system-wide shocks, tourism-sector uncertainty indices carry genuine leading-indicator content for the broader climate-policy and geopolitical environment, not merely lagging information about tourism's own exposure to external shocks. National statistical agencies and finance ministries in tourism-dependent economies — for which tourism receipts are often a primary source of foreign-exchange earnings, as noted earlier — should consider incorporating tourism-market uncertainty measures such as GTUI into broader macro-financial

early-warning dashboards, alongside the geopolitical-risk and policy-uncertainty indices already in common use, rather than monitoring tourism purely as a sector to be protected once a shock has already originated elsewhere. **Transportation and energy-cost risk has become a first-order tourism-policy concern since 2022.** The dynamic results reported above show energy-transportation uncertainty's system-wide transmitting role rising to its sample maximum only in the post-2022 period, directly corroborating the Red Sea shipping-disruption narrative motivating this study. This implies that destination-level tourism-resilience planning, historically organized around geopolitical and health-security risk (terrorism, pandemics), should now treat transportation and logistics-cost risk as a comparably first-order concern. Concrete measures consistent with this finding include diversifying national and regional shipping and aviation-fuel supply routes away from single chokepoints, encouraging national carriers and cruise operators to adopt fuel-cost hedging strategies calibrated to the heightened post-2022 volatility regime documented here, and incorporating transportation-cost stress scenarios explicitly into destination-marketing and capacity-planning exercises. **Regime-aware, rather than static, risk management.** The sharp gap between the study's static and dynamic results — weak full-sample-average GPR- and ETU-to-tourism connectedness, but substantially larger, time-concentrated connectedness during specific episodes — has a direct practical implication: tourism-sector investors, insurers, and destination-marketing organizations that calibrate risk exposure using long-run historical averages will systematically understate their exposure during the crisis regimes in which that exposure is empirically largest. Value-at-risk and stress-testing frameworks for tourism-exposed portfolios and destination budgets should therefore be built around regime-conditional or rolling-window connectedness measures of the kind reported above, rather than static full-sample correlations or betas, with the 2022 dual-shock episode identified here as a natural benchmark stress scenario. **Climate-policy engagement as a tourism-risk-management tool.** The exploratory finding, discussed earlier, that climate policy uncertainty has the single strongest bilateral connection with tourism uncertainty of any construct examined in this study suggests that tourism ministries and destination-marketing organizations have a direct stake in the design and predictability of climate policy — aviation-emissions regulation, carbon-border adjustment mechanisms, and international climate-agreement outcomes — that goes well beyond tourism's own direct carbon footprint. Rather than treating climate policy as an exogenous domain managed elsewhere in government, tourism authorities should engage proactively in domestic and international climate-policy processes specifically as a means of reducing policy-uncertainty spillovers into their own sector, and should monitor climate-policy-uncertainty indices such as CPU as a leading indicator of prospective tourism-market stress, alongside the more conventional geopolitical-risk and energy-cost indicators already in common use. **A cross-cutting caution on crisis-specific behavior.** Finally, the finding, discussed earlier, that geopolitical risk shifted from a net transmitter (2013–2020) to

a net receiver (post-2022) of system-wide shocks cautions against a one-size-fits-all approach to geopolitical-risk hedging. A risk-management framework calibrated on GPR's typical, pre-2022 transmitting behavior would have offered a materially misleading picture of how the 2022 shock actually propagated through the system. Policymakers and risk managers should therefore treat each major geopolitical episode as a distinct case requiring its own assessment of transmission direction and intensity, informed by contemporaneous connectedness monitoring of the kind developed in this study, rather than assuming that the past behavior of a single geopolitical-risk indicator generalizes automatically to the next crisis.

Conclusion

This study examined the dynamic interconnectedness among geopolitical risk (GPR), energy transportation uncertainty (ETU), climate policy uncertainty (CPU), climate transition risk (TC and TRI), and global tourism uncertainty (GTUI) using the Diebold–Yilmaz connectedness framework applied to monthly data spanning January 2005 to February 2025. By modelling these uncertainty measures within a unified dynamic system, the study extends the tourism uncertainty literature beyond conventional analyses of tourism demand and financial-market responses to reveal how multiple global risk sources jointly shape tourism uncertainty over time. The findings demonstrate that connectedness across the uncertainty system is highly regime-dependent. Although average spillovers are moderate, total connectedness increases dramatically during major geopolitical and transportation disruptions, particularly the Russia–Ukraine conflict and the Red Sea shipping crisis, confirming that the transmission of shocks intensifies during periods of heightened global instability. Tourism uncertainty and climate-transition risks emerge as persistent net transmitters of shocks, while geopolitical risk and energy transportation uncertainty alternate between transmitting and receiving shocks as global conditions evolve. These results provide strong evidence that tourism uncertainty is not merely a passive outcome of external shocks but also constitutes an active source of uncertainty within the broader global risk network. A particularly important finding is the consistently strong and increasing linkage between climate policy uncertainty and tourism uncertainty. Compared with geopolitical risk and transportation uncertainty, climate policy uncertainty exhibits the strongest bilateral connectedness with tourism uncertainty, suggesting that uncertainty surrounding climate policy has become a major channel through which global risks affect tourism systems. This finding broadens the understanding of tourism vulnerability by demonstrating that the sector is increasingly exposed not only to geopolitical conflicts and transport disruptions but also to uncertainties associated with the global low-carbon transition. The study makes several important contributions to the literature. Conceptually, it integrates geopolitical, transportation, and climate-related uncertainties into a single analytical framework, providing a more comprehensive

understanding of the evolving determinants of tourism uncertainty. Methodologically, it demonstrates the value of the Diebold–Yilmaz dynamic connectedness framework for capturing nonlinear and time-varying spillover behaviour that static empirical approaches cannot adequately identify. Empirically, the study provides one of the first comprehensive assessments of the joint transmission mechanisms linking geopolitical risk, transportation-specific energy uncertainty, climate policy uncertainty, transition risks, and global tourism uncertainty over an extended sample period encompassing multiple global crises. These findings have important implications for policy and practice. Tourism resilience strategies should move beyond traditional destination risk management by incorporating geopolitical developments, transportation and logistics disruptions, and climate policy uncertainty into integrated early-warning and monitoring systems. Governments, destination management organisations, and private-sector stakeholders should strengthen coordination across tourism, energy, transport, and climate policy institutions to improve preparedness for systemic shocks and reduce the vulnerability of tourism markets to increasingly interconnected global risks. Despite these contributions, several limitations suggest directions for future research. First, the analysis employs the rolling-window Diebold–Yilmaz framework, which could be complemented by time-varying parameter VAR (TVP-VAR) and frequency-domain connectedness approaches to distinguish short-, medium-, and long-run spillovers more explicitly. Second, future studies could examine heterogeneous spillover dynamics across regions, tourism-dependent economies, or energy-exporting and energy-importing countries. Third, incorporating destination-level tourism uncertainty measures would provide deeper insights into spatial heterogeneity and destination-specific resilience. Finally, investigating the causal mechanisms through which climate policy uncertainty influences tourism investment, consumer confidence, and destination competitiveness represents a promising avenue for future research. The evidence demonstrates that tourism uncertainty is increasingly shaped by the interaction of geopolitical tensions, transportation disruptions, and climate-transition dynamics rather than by isolated shocks. As global uncertainty becomes more interconnected, understanding these evolving transmission channels is essential for developing adaptive tourism policies, strengthening destination resilience, and improving strategic decision-making in an increasingly uncertain global environment.

Declarations

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Ethical Approval

Not applicable. This study uses publicly available, aggregated index data and does not involve human or animal subjects.

Consent to Participate

Not applicable.

Consent to Publish

The authors have read and approved the final manuscript and consent to its publication.

Clinical Trial Number

Clinical trial number: not applicable.

Competing Interests

The authors declare no known competing financial or non-financial interests that could have influenced the work reported in this study.

Data Availability Statement

Data used in the study will be provided upon reasonable request.

Author Contribution Statement

Dasauki Musa conceived the study, developed the research design, compiled and processed the dataset, conducted the econometric analysis, interpreted the empirical results, and prepared the original draft of the manuscript. Musa also coordinated the overall structure of the paper and integrated the literature review, theoretical framework, and empirical findings.

S.Y. Ho contributed to the refinement of the methodological framework, provided guidance on model specification and empirical strategy, and assisted in interpreting the empirical results. Ho also contributed to the critical to writing, review and revision of the manuscript, helping to improve its analytical clarity and academic rigor.

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