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Regional Determinants of Tourism Seasonality in Mediterranean EU NUTS–2 Regions: A Panel Analysis Using the Gini Coefficient (2020–2024)

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Abstract

Tourism seasonality remains one of the most persistent structural challenges of Mediterranean destinations, intensifying environmental, economic and social pressures during peak months while leaving tourism capacity underused in the remainder of the year. This paper examines the level, spatial distribution and structural determinants of tourism seasonality in 61 Mediterranean EU NUTS–2 regions from Croatia, Spain, Greece, Portugal and Italy over the period 2020–2024. Using harmonised Eurostat data, annual Gini coefficients are calculated from monthly overnight stays and analysed within a balanced panel of 305 region-year observations, testing whether seasonality is associated with international tourism dependency, hotel accommodation share and island geography, while controlling for regional GDP per capita, tourism intensity and the COVID-19 disruption period. Fixed and random effects models are estimated, with model choice guided by the Hausman test and cluster-robust standard errors applied at the regional level, complemented by a correlated random effects (Mundlak) specification. The results show substantial regional heterogeneity: Greece and Italy record the highest average seasonal concentration, while Spain and Portugal display more balanced patterns, partly due to regions with year-round demand, and Jadranska Hrvatska emerges as the most seasonally concentrated non-island region in the sample. A higher hotel accommodation share is significantly associated with lower seasonality, while the COVID-19 years significantly increased seasonal concentration, with concentration levels returning to recovery-phase values from 2022 onwards; as the panel does not include pre-pandemic baseline years, the findings compare the pandemic phase (2020–2021) with the recovery phase (2022–2024) and do not directly test a return to pre-pandemic equilibrium. The study contributes to comparative destination research by operationalising the Gini coefficient as a dependent variable in a multi-country regional panel framework and provides policy-relevant evidence for supply-side deseasonalisation strategies embedded in integrated destination management.

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1. Introduction

Tourism seasonality—the temporal concentration of tourist demand within specific periods of the year—represents one of the most structurally persistent challenges facing

Mediterranean coastal destinations. While seasonal peaks generate substantial short-term economic activity, they simultaneously impose disproportionate pressures on natural environments, local infrastructure, and labour markets, while leaving productive capacity severely underutilized during off-peak periods (Zvaigzne et al., 2022; Turrión-Prats & Duro, 2018). From an economic standpoint, high seasonality reduces destination profitability, constrains long-term investment, and generates precarious employment conditions, while from an environmental perspective it intensifies resource use and degradation within compressed time windows (Duro & Turrión-Prats, 2019; Grossi & Mussini, 2021). Understanding the spatial distribution and structural drivers of seasonality has therefore become an increasingly urgent policy and research priority, particularly in the context of growing sustainability concerns and the ongoing debate about overtourism.

The Mediterranean EU constitutes the most tourism-intensive region in the world, and its destinations consistently record the highest levels of seasonal concentration globally. Duro and Turrión-Prats (2019) demonstrate that, contrary to a declining global trend in tourism seasonality observed since 2011, Mediterranean countries continue to exhibit the highest and increasingly concentrated seasonal demand patterns among all world regions, suggesting that region-specific structural factors resistant to general market forces are at work. At the sub-national level, this concentration is particularly pronounced in coastal and island regions of Croatia, Greece, and Portugal, where the overwhelming majority of overnight stays are recorded within a narrow summer window (Eurostat, 2024b).

These patterns underscore that seasonality is not merely a national-level phenomenon but a deeply regional one, shaped by specific geographic, economic, and structural characteristics that vary substantially even within individual countries. Despite the regional nature of seasonality, the majority of existing comparative studies have been conducted at the national level, limiting the granularity of insights available to destination managers and policymakers. Krabokoukis and Polyzos (2024), in their analysis of Mediterranean countries, identify distinct seasonal profiles across national tourism systems but acknowledge that sub-national heterogeneity remains largely unexplored.

Studies that do address the regional dimension tend to focus on single-country contexts: Duro (2016) analyses Spanish provinces, Cuccia and Rizzo (2011) examine Sicilian destinations, and Grossi and Mussini (2021) focus on Veneto regions. Methodologies furthermore vary considerably across studies, limiting cross-regional comparability. Fernández-Morales et al. (2016) propose the Gini coefficient as a standardized and decomposable measure of seasonal concentration, demonstrating its applicability across diverse regional contexts, yet its use as a dependent variable in a multi-country panel regression framework remains among the less explored methodological approaches in the literature. A further gap concerns the post-pandemic period. The COVID-19 pandemic caused an unprecedented collapse of international tourism demand in 2020 and 2021, raising important questions about whether the resulting disruption might have catalysed a lasting structural reconfiguration of seasonal patterns—for instance, through the redistribution of demand across the calendar, shifts in accommodation preferences, or changes in source-market composition. Ruggieri and Platania (2024) highlight that the imbalance of tourism demand, specifically in fragile territories such as islands, requires specific policies based on scientific evidence, yet the post-pandemic regional evidence base remains limited.

This study addresses these gaps by examining the level, spatial distribution, and structural determinants of tourism seasonality across Mediterranean EU NUTS-2 regions from Croatia, Spain, Greece, Portugal, and Italy over the 2020–2024 period. For the purposes of this study, “Mediterranean EU regions” is defined operationally as the complete set of EU NUTS-2 regions of the five EU member states with a Mediterranean coastline included in the analysis—Croatia, Spain, Greece, Portugal and Italy—rather than as coastal regions in a strict physical-geographic sense. The unit of comparison is thus the

regional structure of Mediterranean-basin tourism economies as a whole, including their inland, metropolitan and special-status components, whose year-round demand profiles provide the analytical contrast against which the determinants of coastal and island seasonality are identified. Portugal, while predominantly Atlantic-facing, is included as an integral part of the southern EU tourism system conventionally analysed alongside Mediterranean destinations in the comparative literature (Krabokoukis & Polyzos, 2024). The precise sample composition and inclusion principles are detailed in Section 3.2, and the classification of every region is reported in Appendix A Table A1.

Building on the Gini coefficient as a standardized and methodologically robust measure of seasonal concentration (Fernández-Morales et al., 2016; Rosselló & Sansó, 2017), this research employs a balanced panel regression framework to empirically test three hypotheses. Prior empirical evidence consistently demonstrates that destinations with higher shares of international visitors exhibit more pronounced seasonal concentration, as foreign tourists are more constrained by institutional factors such as school holidays and travel costs in their home countries (Rosselló et al., 2004; Turrión-Prats & Duro, 2019). Based on this evidence, the following hypothesis is proposed:

H1. *Regions with a higher share of international overnight stays exhibit higher levels of tourism seasonality.*

The structure of accommodation supply has been identified as a significant moderator of seasonal concentration. Hotel establishments, owing to their fixed cost structures and professional revenue management capabilities, have stronger incentives to stimulate demand during shoulder and off-peak seasons compared to private rental providers (Cuccia & Rizzo, 2011; Duro, 2016). This leads to the following hypothesis:

H2. *Regions with a higher share of hotel accommodation exhibit lower levels of tourism seasonality.*

Island destinations are structurally predisposed to higher seasonality due to geographic isolation, limited transport accessibility during off-peak periods, and a stronger dependence on sun-and-sea tourism products that are inherently climate-sensitive (Ruggeri & Platania, 2024; Duro & Turrión-Prats, 2019). This leads to the following hypothesis:

H3. *Island regions exhibit higher levels of tourism seasonality than mainland coastal regions.*

Two research questions further structure the descriptive component of the empirical analysis:

RQ1: What is the level and spatial distribution of tourism seasonality across Mediterranean EU NUTS-2 regions in the 2020–2024 period?

RQ2: Has the COVID-19 pandemic caused a lasting structural shift in regional tourism seasonality patterns across Mediterranean EU destinations?

The study makes two primary contributions to the existing literature. Methodologically, it operationalizes the Gini coefficient as a dependent variable within a regional panel regression framework—an approach that remains underutilized in tourism seasonality research and provides a replicable template for future comparative studies. Empirically, it contributes a systematic EU NUTS-2 level comparative analysis of Mediterranean EU seasonality covering the post-pandemic recovery period, generating evidence directly relevant to regional destination management and EU cohesion policy. The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on tourism seasonality, its measurement, and its determinants. Section 3 presents the data, variables, and methodological approach. Section 4 reports the empirical results. Section 5 discusses the

findings in relation to the existing literature and their policy implications. Section 6 concludes with a summary of contributions, limitations, and directions for future research.

2. Literature Review

2.1. Tourism Seasonality and Sustainability

Tourism seasonality is broadly defined as the systematic temporal imbalance in the distribution of tourist demand across the calendar year, manifested through fluctuations in visitor numbers, overnight stays, tourism receipts, and related economic activity (Zvaigzne et al., 2022). Although the phenomenon is universally recognized across the tourism literature, its causes are multidimensional and interrelated, and no single theoretical framework has achieved universal acceptance (Duro & Turrión-Prats, 2019). The literature conventionally distinguishes between two broad categories of causal factors. Natural seasonality arises from climatic and environmental conditions—most prominently temperature, sunshine hours, and precipitation—which render certain destinations inherently more attractive during specific periods of the year (Zvaigzne et al., 2022). This is particularly relevant for Mediterranean coastal destinations, where the summer concentration of demand is primarily driven by the appeal of warm temperatures and sea conditions that are unavailable during other seasons. Institutional seasonality, by contrast, reflects socially and economically constructed temporal constraints, including the scheduling of school holidays, public holidays, and industrial vacation norms that channel the bulk of tourist flows within a narrow seasonal window (Hartmann, 1986; Zvaigzne et al., 2022; Turrión-Prats & Duro, 2018). Ridderstaat and Croes (2020) propose a systematic framework for classifying the causal factors of tourism demand seasonality, distinguishing between interseason and intraseason effects, and identify climatic perception and price sensitivity as key drivers of peak-season concentration. Institutional factors are widely regarded as both more resistant to policy intervention and more variable across different source markets, which has important implications for destination management.

A third category of causal factors—inertia and social imitation—has received growing attention in more recent literature. Turrión-Prats and Duro (2019) demonstrate that historical patterns of seasonal demand tend to be self-reinforcing, as tourists, businesses, and infrastructure planning decisions adapt to established seasonal rhythms in ways that make structural change difficult. This inertia effect helps explain why Mediterranean destinations have maintained high levels of seasonality despite sustained policy efforts toward diversification, and why external shocks such as the COVID-19 pandemic may not necessarily produce lasting structural changes in seasonal distribution patterns.

The relationship between tourism seasonality and destination sustainability is multifaceted and operates across economic, environmental, and social dimensions. From an economic perspective, high seasonality creates structural inefficiencies: accommodation, transport, and food service operators must invest in fixed capacity sufficient to meet peak demand, while this capacity remains severely underutilized during off-peak periods, reducing annual profitability and constraining access to investment capital (Zvaigzne et al., 2022). Labour market consequences are particularly severe, as the concentration of economic activity in a narrow seasonal window generates widespread temporary and insecure employment, undermines the capacity of firms to retain skilled workers year-round, and limits human capital accumulation in tourism-dependent regional economies (Duro & Turrión-Prats, 2019).

From an environmental perspective, peak-season concentration imposes disproportionate pressures on natural ecosystems, water resources, waste management systems, and coastal areas within compressed temporal windows (Ruggieri & Platania, 2024). Mediterranean coastal and island destinations are particularly exposed to these pressures given their often-limited territorial extent and carrying capacity, the sensitivity of their

natural assets, and the extreme intensity of summer tourism flows relative to resident population. Zhang and Xie (2023) find empirically that higher tourism seasonality significantly elevates the probability of hotel exit, providing direct financial evidence of the sustainability threat that seasonal concentration poses to accommodation businesses. Ruggieri and Platania (2024) demonstrate that Mediterranean island destinations consistently record among the highest tourism intensity indices in Europe, with summer visitor-to-resident ratios that exceed sustainable thresholds in several cases.

The social dimension encompasses the disruption of local community life during peak season, including congestion, price inflation, noise, and loss of public space access, which accumulate into what the literature increasingly frames as overtourism phenomena (Krabokoukis & Polyzos, 2024). The concentration of environmental and social costs within the peak season thus constitutes a structural sustainability challenge that cannot be adequately addressed through demand-side measures alone. The literature increasingly emphasizes that effective deseasonalization requires structural interventions targeting supply-side composition, market diversification, and regional product development, rather than merely promotional incentives for off-peak travel (Duro & Turrión-Prats, 2019; Zvaigzne et al., 2022). This policy perspective motivates the empirical focus of the present study on the structural determinants of regional seasonality.

Beyond its measurement and its sustainability consequences, tourism seasonality is increasingly understood as a core problem of destination management rather than a purely statistical property of demand. In the destination competitiveness framework of Ritchie and Crouch (2003), the capacity of a destination to deploy its resource base productively across the full calendar year is a constitutive element of competitiveness and long-term sustainability, which positions seasonal concentration as a managerial outcome amenable to intervention rather than an exogenous given. Butler's (1980) tourism area life cycle situates this challenge dynamically: the structural options available to a destination—including the diversification of products, markets and accommodation stock—depend on its position within the development cycle, and mature, consolidated destinations face the strongest lock-in of established seasonal patterns through accumulated capital, established source-market relationships and entrenched visitor expectations. From this perspective, the accommodation-composition and market-structure variables examined in the present study are not merely statistical correlates of seasonal concentration but managerial levers whose availability and cost are themselves shaped by the destination's stage of development.

The governance dimension is equally material. Deseasonalisation is, in essence, a collective-action problem: extending the season requires coordinated adjustment by accommodation providers, transport operators, attraction managers and public authorities, and the tourism governance literature emphasises that the capacity of destinations to organise such coordination—through destination management organisations, public-private partnerships and regulatory instruments—varies widely and conditions the feasibility of any structural policy (Ruhanen et al., 2010). Product diversification occupies a central place in this discussion. Benur and Bramwell (2015) conceptualise the diversification and intensification of primary tourism products as the principal strategic options through which destinations broaden their appeal across market segments and seasons, noting that concentrated, single-product portfolios—exemplified by the sun-and-sea model that dominates much Mediterranean coastal supply—are associated with correspondingly narrow seasonal windows. These perspectives supply the theoretical mechanisms underlying the hypotheses tested below: the accommodation-structure hypothesis (H2) operationalises a supply-side diversification logic, since professionally managed accommodation constitutes the distribution and revenue-management infrastructure through which shoulder-season products can be developed and sold, while the international-dependency

hypothesis (H1) reflects the governance constraint that source-market composition is only partially within a destination's control.

2.2. *Measuring Tourism Seasonality: Methodological Approaches*

A substantial body of methodological literature has developed around the measurement of tourism seasonality, with various indices proposed to capture different aspects of seasonal concentration. The earliest approaches relied on seasonal indices derived from time series decomposition, which identify the systematic seasonal component of a demand series but do not readily lend themselves to cross-destination comparison (Rosselló & Sansó, 2017). The coefficient of variation (CV) has been widely used as a simple and intuitive measure of the relative dispersion of monthly demand, but it is sensitive to distributional shape and does not distinguish between, for instance, a bimodal pattern with two seasonal peaks and a unimodal pattern with a single summer concentration (Duro, 2016). De Cantis et al. (2011) provide an early systematic application of the Gini coefficient to tourism seasonality measurement in their analysis of Sicilian hotel bed occupancy, demonstrating its analytical value for capturing both pattern and amplitude dimensions of seasonal variation.

The Gini coefficient, originally developed as a measure of income inequality (Lerman & Yitzhaki, 1985, as cited in Fernández-Morales et al., 2016), has emerged as the most methodologically robust synthetic measure of seasonal concentration in the tourism literature. It captures the overall degree of inequality in the distribution of overnight stays across the twelve months of the year, with a value of zero indicating perfect distributional equality and a value approaching unity indicating maximal concentration in a single month. Crucially, the Gini coefficient is insensitive to the particular months in which demand concentrates, making it suitable for cross-destination comparison across locations with different peak seasons, and it admits Lorenz curve visualization that facilitates intuitive interpretation (Fernández-Morales et al., 2016). Fernández-Morales et al. (2016) further demonstrate that the Gini coefficient can be additively decomposed by source market, enabling identification of the markets that contribute most to overall seasonal concentration—a feature directly relevant to destination management.

Building on this methodological foundation, Ferrante et al. (2018) conduct a systematic cross-country analysis of tourism seasonality across European countries using Eurostat data, identifying distinct clusters of national seasonal patterns. Their study demonstrates that Mediterranean EU member states form a distinct cluster characterized by high and summer-concentrated Gini values, in contrast to Northern and Central European destinations that exhibit more balanced seasonal distributions. Ferrante et al. (2018) additionally propose a new composite index that integrates both the pattern and amplitude dimensions of seasonality, arguing that the Gini coefficient alone does not fully capture the shape of the seasonal distribution. Martín Martín et al. (2019) propose the DP2 composite indicator as an alternative multidimensional measure of seasonality, grouping information from multiple seasonal variables, though this approach has seen limited application in cross-country comparative contexts.

While this critique has merit, the Gini coefficient remains the most widely cited and comparable single-measure indicator in the comparative literature, and its use as a dependent variable in panel regression frameworks—as proposed in the present study—has been adopted by Duro (2016) and Turrión-Prats and Duro (2018) in national-level analyses, yet has not been systematically applied at the EU NUTS-2 regional level across multiple countries. Grossi and Mussini (2021) extend the Gini-based approach by developing a decomposition methodology that enables the attribution of changes in seasonal concentration over time to specific sub-periods, thereby identifying whether concentration is intensifying or moderating in particular parts of the seasonal distribution. Their analysis of

Italian NUTS-3 regions reveals substantial within-country heterogeneity in seasonal concentration and its dynamics, reinforcing the argument that national-level analyses mask important regional variation. In the present study, the Gini coefficient is complemented by the Q3 seasonal ratio—the share of annual overnight stays occurring in the third quarter—as a straightforward cross-validation measure that facilitates communication with non-specialist policy audiences. Recent methodological work confirms that this measurement agenda remains active and bears directly on the territorial design of the present study. Duro and Turrión-Prats (2024) extend the Gini-based analytical toolkit with a new methodology for quantifying seasonality gaps across markets, demonstrating the continued centrality of concentration-based measures in current research. Viera-González and Hernández-Martín (2025), analysing Spanish tourism flows with mobile positioning data across four spatial scales, show that spatial aggregation systematically masks local seasonal heterogeneity through compensation effects—an instance of the Modifiable Areal Unit Problem—so that concentration indices computed at higher territorial levels can substantially understate seasonality at lower ones. These findings support the EU NUTS-2 regional design adopted here as a substantive analytical choice rather than a data-availability convenience, while also implying that even regional-level Gini values should be read as conservative summaries of finer-grained local concentration.

2.3. Structural Determinants of Tourism Seasonality

The empirical literature on the determinants of tourism seasonality has progressively shifted from descriptive documentation toward explanatory modelling, with panel data approaches playing an increasingly prominent role. Cisneros-Martínez and Fernández-Morales (2015) demonstrate that cultural tourism segments can contribute to desesonalisation in coastal areas by attracting visitors with less climate-sensitive travel motivations, providing early evidence for the role of tourism product composition in moderating seasonal concentration. Rosselló et al. (2004) provide one of the earliest systematic econometric analyses of seasonality determinants, identifying the share of international tourists in total demand, relative prices, and income levels in source countries as significant explanatory variables. Their findings establish that international tourism flows are more strongly subject to institutional constraints—particularly the alignment of holiday calendars across multiple source countries—than domestic flows, making higher international dependency a robust positive predictor of seasonal concentration. Subsequent work has consistently replicated and extended this finding across different destinations and methodological approaches (Turrión-Prats & Duro, 2018; Duro, 2016).

The role of accommodation structure has been examined in several studies, with convergent findings pointing to hotel dominance as a moderating factor on seasonality. Cuccia and Rizzo (2011), in their analysis of Sicilian tourist destinations, demonstrate that areas with higher concentrations of hotel accommodation tend to exhibit lower Gini coefficients relative to areas dominated by private rental and second-home accommodation. The mechanism proposed is primarily supply-side: hotels, as profit-maximizing operators with high fixed costs and professional revenue management capabilities, have strong incentives to attract shoulder-season demand through pricing strategies, targeted marketing, and product diversification. Private rental providers, by contrast, are more likely to be available only during peak periods, amplifying seasonal concentration. Duro (2016) confirms this relationship in the context of Spanish provinces, finding that higher hotel market share is negatively associated with seasonal concentration even after controlling for other demand-side factors.

The geographic dimension of seasonality determinants has received particular attention in the context of island destinations. Ruggieri and Platania (2024) conduct a comprehensive analysis of Mediterranean island tourism from 2008 to 2018, demonstrating that

island regions consistently record higher seasonality levels than mainland coastal destinations with comparable climatic profiles. The authors attribute this pattern to a combination of factors including limited transport accessibility outside the summer season, the dominance of sun-and-sea product offerings that are inherently climate-sensitive, relatively undiversified tourism product portfolios, and the high proportion of international visitors whose institutional constraints are particularly binding. These findings provide the theoretical basis for the island geography hypothesis (H3) tested in the present study.

Regional economic development, proxied by GDP per capita, has been hypothesized as a negative determinant of seasonality on the grounds that higher levels of economic development are associated with greater diversification of economic activities, stronger service sector capabilities outside tourism, and a more developed infrastructure for year-round visitor attraction. Turrión-Prats and Duro (2019), in their global analysis, find partial support for this relationship, though the effect is not uniformly significant across specifications. In the present study, regional GDP per capita is included as a control variable rather than as the basis for an explicit hypothesis, given the mixed evidence in the literature. Comparative analyses of tourism seasonality across Mediterranean EU destinations have primarily been conducted at the national level.

Krabokoukis and Polyzos (2024) analyse monthly overnight stay data for Mediterranean countries from 2000 to 2019, identifying three distinct seasonal profile clusters and demonstrating that Croatia and Greece consistently record the most extreme levels of seasonal concentration among Mediterranean EU members, while Spain—primarily owing to the Canary Islands—and Portugal exhibit comparatively more balanced distributions. Their study confirms that Mediterranean seasonality is not a homogeneous phenomenon but varies systematically with structural destination characteristics, and calls for more granular regional analyses to inform effective policy.

Duro and Turrión-Prats (2019), in their global seasonality analysis, similarly highlight the Mediterranean as the most seasonally concentrated tourism region in the world and note a concerning trend of increasing rather than decreasing concentration in Mediterranean countries since 2011, despite sustained policy attention to deseasonalisation at both national and EU level. This trend stands in marked contrast to the global pattern, which shows a modest decline in average seasonality across all world regions over the same period, suggesting that Mediterranean-specific structural factors are reinforcing concentration in ways that general market forces and policy interventions have been unable to overcome. At the sub-national level, existing evidence is more limited. Duro (2016) analyses Spanish provinces and finds substantial within-country heterogeneity, with island provinces (Balearic Islands, Canary Islands) recording notably higher Gini values than mainland coastal provinces. Vergori and Arima (2022) show that transport mode availability shapes Italian regional seasonality, with air-dependent destinations exhibiting more extreme seasonal peaks than road-accessible alternatives. Cuccia and Rizzo (2011) demonstrate similar patterns within Sicily, with coastal and island municipalities exhibiting more extreme concentration than inland cultural destinations. Grossi and Mussini (2021) find comparable heterogeneity within Italian NUTS-3 regions. However, to the best of the authors' knowledge, limited research has systematically compared EU NUTS-2 regional seasonality across multiple Mediterranean EU countries using a harmonized dataset and a unified panel regression framework covering the post-pandemic period—the gap that the present study addresses. The determinants of seasonal concentration are, moreover, increasingly examined within broader frameworks of destination vulnerability. Bergantino et al. (2026), constructing a multidimensional overtourism vulnerability index for EU Mediterranean regions, include the seasonal peak factor as one of its three constitutive dimensions alongside tourism volume and growth, and treat the share of platform-based short-term rentals as a distinct vulnerability indicator. Seasonal concentration

is thus no longer analysed as an isolated statistical property but as a component of destination vulnerability whose structural drivers—accommodation composition among them—carry direct policy relevance, a framing that reinforces the motivation for the explanatory analysis undertaken here.

2.4. Post-Pandemic Tourism Seasonality: An Emerging Research Agenda

The COVID-19 pandemic constitutes the most severe disruption to global tourism demand since reliable measurement began, with international arrivals declining by approximately 74% in 2020 relative to 2019 (UNWTO, 2021). Beyond the aggregate collapse in demand, the pandemic raised substantive questions about whether the structural re-configuration of tourism behavior during 2020–2021—including the shift toward domestic tourism, shorter booking windows, and greater preference for outdoor and less crowded destinations—might persist as lasting changes in seasonal distribution patterns following the restoration of unrestricted mobility.

Evidence on post-pandemic seasonality changes at the destination level remains limited, but the available findings are largely consistent with a pattern of temporary disruption followed by structural reversion. Krabokoukis and Polyzos (2024) note that while 2020 and 2021 recorded anomalous seasonal distributions in all Mediterranean countries, primarily driven by the near-complete absence of international arrivals during non-summer months when travel restrictions were most severe, the recovery in 2022 and 2023 was accompanied by a rapid return to pre-pandemic seasonal profiles.

The post-pandemic trajectory of seasonal patterns can additionally be read through the lens of destination resilience. Cochrane (2010) conceptualises resilience as the capacity of tourism systems to absorb disturbance and reorganise while retaining essentially the same structure and function, emphasising harnessing market forces, stakeholder cohesion and adaptive learning as its principal components; Sharma et al. (2021) extend this perspective into a resilience-based framework for post-pandemic revival in which the depth of a shock does not by itself determine the depth of structural change. This literature implies a testable expectation for seasonal patterns: if Mediterranean regional tourism systems are resilient in Cochrane's sense, the pandemic disruption should manifest as a temporary displacement followed by reorganisation around the pre-existing configuration, rather than as a transition to a new seasonal regime. Resilience in this reading is normatively ambivalent—the same institutional and structural factors that stabilise destination systems against shocks also reproduce their structural imbalances, including seasonal concentration. The present study's observation window (2020–2024) permits a direct, if temporally bounded, examination of this expectation at the EU NUTS-2 level (RQ2).

This pattern is consistent with the broader literature on the inertia of seasonal demand (Turrión-Prats & Duro, 2019), which suggests that deeply embedded institutional and social factors driving seasonal concentration are resistant to even substantial external shocks. The present study tests this proposition empirically through the inclusion of a COVID-19 period dummy variable in the panel regression framework (RQ2), contributing new evidence at the EU NUTS-2 regional level where post-pandemic dynamics have not previously been systematically examined.

3. Materials and Methods

3.1. Research Design

This study employs a quantitative comparative research design combining two complementary analytical approaches. The first component consists of a descriptive cross-sectional and longitudinal analysis of tourism seasonality across Mediterranean EU NUTS-2 regions for the period 2020–2024, addressing RQ1 and RQ2. The second component

consists of a balanced panel regression analysis in which the Gini coefficient of seasonality serves as the dependent variable, enabling the empirical testing of hypotheses H1, H2, and H3 regarding the structural determinants of regional seasonal concentration. The combination of descriptive and inferential approaches is designed to first document the spatial and temporal distribution of seasonality before proceeding to explain its variation through structural factors (Fernández-Morales et al., 2016; Turrión-Prats & Duro, 2018).

The panel structure of the data—with multiple EU NUTS-2 regions observed over five consecutive years—allows for the control of unobserved region-specific heterogeneity through fixed or random effects estimators, thereby reducing the risk of omitted variable bias that would affect cross-sectional analyses conducted at a single point in time (Wooldridge, 2010). The choice between fixed and random effects specifications is determined empirically through the Hausman (1978) specification test, as detailed in Section 3.

3.2. Data Sources and Sample

All data used in this study are drawn exclusively from Eurostat, the statistical office of the European Union, ensuring cross-national comparability through the application of harmonized data collection standards mandated by Regulation (EU) No 692/2011 of the European Parliament and of the Council concerning European statistics on tourism (Regulation (EU) No 692/2011 (European Parliament (2011))). The use of a single institutional data source eliminates potential inconsistencies arising from differences in national measurement methodologies, which would otherwise compromise the validity of cross-regional comparisons (Ferrante et al., 2018). The primary dataset for the dependent variable is Eurostat's monthly overnight stays at tourist accommodation establishments at the EU NUTS-2 regional level (dataset code: *tour_occ_nin2m*), which provides harmonized monthly data for nights spent by domestic and international guests in registered accommodation establishments. Additional Eurostat datasets are used to construct explanatory and control variables, as specified in Table 1. The study covers 2020–2024, thereby capturing both the pandemic disruption phase (2020–2021) and the subsequent recovery period (2022–2024). The analytical sample consists of all EU NUTS-2 regions of Croatia, Spain, Greece, Portugal and Italy for which complete annual observations can be constructed for every model variable over 2020–2024; regions with more than one missing year for any variable are excluded, yielding a balanced panel of 61 regions. Three explicit inclusion principles govern the sample composition. First, the sample is defined at the level of entire member states rather than administratively coastal regions only, because the empirical objective is to compare Mediterranean tourism systems—including their inland and metropolitan components—rather than coastline in a narrow geographic sense. Second, nine predominantly island-based regions are retained and separately identified through the *ISLAND* variable (Section 3.5). Third, four urban and special-status regions with structurally year-round demand—Comunidad de Madrid (ES30), Ciudad de Ceuta (ES63), Ciudad de Melilla (ES64) and Grad Zagreb (HR05)—are retained as reference cases: their inclusion widens the observed range of the dependent variable and provides the cross-sectional contrast against which structural determinants of seasonal concentration can be identified. Their inclusion is not innocuous, however, and two safeguards are applied: the classification of every region is reported transparently in Appendix A Table A1, and a sensitivity re-estimation excluding the four reference regions is reported in Appendix A Table A4, confirming that the baseline results are not driven by their presence.

Table 1. Data sources and variable definitions.

Variable	Role in Model	Definition	Eurostat Dataset
Gini (G_it)	Dependent variable	Gini coefficient of monthly overnight stay distribution (0–1)	<i>tour_occ_nin2m</i> (calculated)

INT_it	Independent (H1)	Share of international overnight stays in total overnight stays (%)	tour_occ_nin2
HOT_it	Independent (H2)	Share of hotel overnight stays in total overnight stays (%)	tour_occ_nin2
ISLAND_i	Independent (H3)	Binary: 1 if EU NUTS-2 region is an island territory, 0 otherwise	Eurostat NUTS classification (manually coded)
GDP_it	Control variable	Regional GDP per capita (EUR, PPS), log-transformed	reg_eco_gdp
TI_it	Control variable	Tourism intensity: overnight stays per 1000 inhabitants	tour_occ_nin2 + demo_r_pjanaggr3
COVID_t	Control variable	Binary: 1 for years 2020 and 2021, 0 otherwise	Author-constructed

3.3. Calculation of the Gini Coefficient of Seasonality

The Gini coefficient of seasonality is calculated for each NUTS-2 region i and year t from the twelve-monthly values of overnight stays extracted from dataset `tour_occ_nin2m`. Following the methodology established by Fernández-Morales et al. (2016) and subsequently applied in comparative tourism studies (Duro, 2016; Rosselló & Sansó, 2017; Turrión-Prats & Duro, 2018), the Gini coefficient is computed from the sorted monthly distribution using the following formula:

$$G_{it} = 1 - (2/n) \cdot \sum_i (n - i + 0.5) \cdot (x_i/\Sigma x) \quad (1)$$

Equation (1): Gini coefficient formula for seasonal concentration. $n = 12$ (months), x_i = overnight stays in month i , sorted in ascending order. In this formulation, monthly overnight stay values are first sorted in ascending order, and the weighted sum reflects the Lorenz curve area below the line of perfect equality. A value of $G = 0$ indicates perfectly equal distribution of overnight stays across all twelve months, while a value approaching $G = 1$ indicates the maximum possible concentration of all overnight stays within a single month. Mediterranean coastal destinations typically record Gini values in the range of 0.40–0.70, with Croatian and Greek island destinations consistently at the higher end of this range (Krabokoukis & Polyzos, 2024).

As a robustness check and to facilitate communication with policy audiences, the Gini coefficient is complemented by the Q3 seasonal ratio, defined as the share of annual overnight stays occurring in the third calendar quarter (July–September). While the Gini coefficient captures the overall degree of distributional inequality across all twelve months, the Q3 ratio provides a direct and intuitive measure of summer concentration that is particularly relevant for the Mediterranean context (Ferrante et al., 2018). Pearson correlation between the two measures is expected to be high, and any systematic divergence between the two indicators will be reported and discussed in Section 4.

3.4. Panel Regression Model

The panel regression model specification follows the approach established in the tourism seasonality determinants literature (Rosselló et al., 2004; Turrión-Prats & Duro, 2019), adapted to the EU NUTS-2 regional level and the specific variables available from Eurostat. The baseline model is specified as follows:

$$G_{it} = \alpha + \beta_1 INT_{it} + \beta_2 HOT_{it} + \beta_3 ISLAND_i + \beta_4 GDP_{it} + \beta_5 TI_{it} + \beta_6 COVID_t + \mu_i + \varepsilon_{it}$$

The three hypotheses differ in the source of variation that is theoretically relevant to them, and this distinction directly shapes the estimation strategy. H1 and H3 are motivated primarily by structural differences between regions: the composition of international source markets and island geography are stable, slowly changing characteristics of

destinations, and the mechanisms proposed in the literature—institutional holiday constraints binding on international visitors, and transport dependency of islands—operate through cross-sectional contrasts rather than short-run temporal change. H2, by contrast, admits both a between-region interpretation (regions with structurally larger hotel sectors exhibit lower seasonality) and a within-region interpretation (a shift in a region's accommodation composition toward hotels reduces its seasonal concentration over time). The fixed effects (FE) estimator identifies effects exclusively from within-region temporal variation, whereas the random effects (RE) estimator exploits a weighted combination of within- and between-region variation. Accordingly, both specifications are reported, and each hypothesis is interpreted against the source of variation that identifies it.

The FE estimator controls for all time-invariant unobserved regional heterogeneity by demeaning variables within each region and is consistent regardless of whether the unobserved regional effect μ_i is correlated with the regressors. However, it cannot identify the coefficient on the time-invariant ISLAND dummy, which is absorbed into the regional fixed effect. The RE estimator treats μ_i as a random variable uncorrelated with the regressors, which allows identification of all coefficients including ISLAND, but produces inconsistent estimates if this orthogonality assumption is violated (Wooldridge, 2010).

The choice between the two specifications is determined by the Hausman (1978) specification test. Because the Hausman test (reported in Section 4.5) favors the FE specification while the coefficient on the time-invariant ISLAND variable remains of substantive interest for H3, a correlated random effects (CRE, Mundlak) specification is additionally estimated and reported. The CRE model augments the RE specification with region-specific means of all time-varying regressors, thereby allowing correlation between the unobserved regional effect and the regressors while retaining identification of time-invariant variables (Wooldridge, 2010). Two properties of this specification serve as internal validity checks: the coefficients on the time-varying regressors must reproduce the FE estimates, and a Wald test of the joint significance of the group means constitutes a regression-based analogue of the Hausman test. The CRE specification therefore provides the appropriate formal framework for assessing H3 in the presence of correlated regional effects. To address potential heteroskedasticity and within-region serial correlation of the error term ε_{it} , cluster-robust standard errors are applied in all specifications—FE, RE, and CRE—with clustering at the EU NUTS-2 region level (Wooldridge, 2010). Variance inflation factors (VIF) are calculated to assess potential multicollinearity among the independent variables prior to estimation.

3.5. Construction of the ISLAND Variable

The ISLAND binary variable is manually coded on the basis of the official Eurostat EU NUTS-2 classification and geographic definitions. A EU NUTS-2 region is coded as ISLAND (=1) if its territory consists entirely or predominantly of islands, such that the region's tourism activity takes place on island territory without a continuous land connection to the mainland of the respective country. Based on this criterion, nine regions in the sample receive an ISLAND coding of 1: Voreio Aigaio (EL41), Notio Aigaio (EL42) and Kriti (EL43) in Greece; Illes Balears (ES53) and Canarias (ES70) in Spain; Sicilia (ITG1) and Sardegna (ITG2) in Italy; and Região Autónoma dos Açores (PT20) and Região Autónoma da Madeira (PT30) in Portugal. All other EU NUTS-2 regions in the sample, including Jadranska Hrvatska, receive an ISLAND coding of 0, notwithstanding the presence of off-shore islands within their territory, as their predominant land mass and tourism infrastructure are mainland-based. This coding decision is conservative: EU NUTS-2 regions that contain islands but are not predominantly island-based are treated as mainland regions. The implication is that any estimated island effect should be interpreted as the effect of predominantly island-based EU NUTS-2 territories rather than of the presence of island

tourism within a broader coastal region. The complete classification of all 61 regions in the sample, including the ISLAND coding of each region, is provided in Appendix A Table A1.

4. Results

4.1. Descriptive Statistics

The final balanced panel comprises 305 region-year observations across 61 EU NUTS-2 regions from five Mediterranean EU member states: Croatia (4 regions), Spain (19), Greece (13), Portugal (4) and Italy (21). The dependent variable, the Gini coefficient of monthly overnight stay distribution (G), ranges from 0.039 to 0.742 across the full sample, with a mean of 0.397 and a standard deviation of 0.162, indicating substantial cross-regional heterogeneity in seasonal concentration. The mean share of international overnight stays (INT) is 61.3%, with variation from 4.3% in strongly domestic regions to 95.4% in highly internationalised destinations. The hotel accommodation share (HOT) averages 53.6%, but ranges from 15.8% to 100%, reflecting highly heterogeneous accommodation structures across the five countries. Regional GDP per capita (PPS) ranges from 39% to 166% of the EU average. Tourism intensity (TI) varies from 434 to 127,157 overnight stays per 1000 inhabitants, illustrating the sharp differences in tourism pressure between metropolitan, coastal and island regions.

4.2. Gini Coefficient of Seasonality: Cross-Regional Distribution

The Gini coefficients calculated from monthly overnight stay data reveal substantial spatial heterogeneity in seasonal concentration across the 61 Mediterranean EU NUTS-2 regions. Country-level summary statistics over all region-year observations for the 2020–2024 period are presented in Table 2; the complete region-year dataset is provided in Appendix A Table A3.

Table 2. Gini Coefficient and Q3 Ratio by Country, 2020–2024 (region-year observations).

Country	N Regions	Mean Gini	Std. Dev.	Min Gini	Max Gini	Mean Q3 (%)
Greece (EL)	13	0.484	0.128	0.157	0.724	58.9
Italy (IT)	21	0.446	0.138	0.119	0.707	56.4
Croatia (HR)	4	0.358	0.199	0.122	0.742	49.1
Spain (ES)	19	0.312	0.155	0.039	0.667	43.6
Portugal (PT)	4	0.301	0.120	0.086	0.485	40.8
All regions	61	0.397	0.162	0.039	0.742	51.4

Note: Statistics computed over all region-year observations within each country ($N = 5 \times$ number of regions). Gini values calculated from Eurostat monthly overnight stay data (tour_occ_nin2m). Q3 ratio = share of annual overnight stays in July–September; country values are unweighted means over region-year observations. Source: Authors' calculations based on Eurostat data.

Greece records the highest mean Gini coefficient (0.484), followed by Italy (0.446) and Croatia (0.358), while Spain (0.312) and Portugal (0.301) exhibit comparatively lower levels of seasonal concentration. Croatia displays the largest internal dispersion (standard deviation 0.199), reflecting the coexistence of the most seasonally concentrated region in the sample (Jadranska Hrvatska) with year-round urban tourism in Grad Zagreb. The comparatively low means for Spain and Portugal reflect within-country heterogeneity, with year-round island destinations (Canarias, Madeira) and metropolitan regions substantially reducing national averages. The Q3 ratio confirms these patterns: Greek regions concentrate on average 58.9% of annual overnight stays within the three summer months, compared to 40.8% in Portugal.

At the individual region level, the five most seasonally concentrated regions across the full observation period are: HR03—Jadranska Hrvatska (mean Gini = 0.664, mean Q3 = 76.6%), ITF6—Calabria (0.652, 77.8%), EL62—Ionia Nisia (0.632, 72.1%), ITG2—Sardegna (0.605, 71.4%), and EL42—Notio Aigaio (0.578, 64.1%). Of these five regions, three are island or predominantly island territories (ITG2, EL42, and the Ionian Islands in EL62). Jadranska Hrvatska (HR03) is the most extreme non-island case, recording the highest Gini coefficient in the entire sample despite not meeting the island geography criterion defined for hypothesis testing. The five least seasonal regions are dominated by metropolitan and special-status territories with year-round cultural, business, and administrative tourism: ES64 (Ciudad de Melilla, mean Gini = 0.160), ES30 (Comunidad de Madrid, 0.169), HR05 (Grad Zagreb, 0.190), ES63 (Ciudad de Ceuta, 0.201), and ES70 (Canarias, 0.221), the latter benefiting from its year-round climatic appeal.

4.3. Temporal Trends in Seasonality (2020–2024)

The temporal evolution of seasonality across the five-year observation window is dominated by the structural disruption of the COVID-19 pandemic in 2020 and 2021. In these years, Gini values across all countries were substantially elevated, reflecting the near-complete collapse of international tourism and the disproportionate absence of demand during shoulder and off-peak months. This concentration effect is captured by the positive and statistically significant COVID dummy coefficient in the regression model (see Section 4.5).

From 2022 onwards, Gini values declined rapidly and stabilised. By 2023, mean values across all five countries had settled at levels that remained broadly stable into 2024, indicating a consistent recovery-phase pattern of seasonal concentration. These levels are broadly comparable to pre-pandemic values reported in the literature for these destinations (Krabokoukis & Polyzos, 2024); however, as the panel does not include pre-pandemic years, this comparison is external to the estimation sample and is offered as context rather than as a formal test. Within the observation window, the evidence supports a bounded answer to RQ2: the elevated concentration of 2020–2021 did not persist into the recovery phase, and no evidence of a lasting pandemic-induced structural shift is observable through 2024. Whether the recovery-phase levels represent a full return to the pre-pandemic equilibrium or the consolidation of a marginally different baseline cannot be adjudicated with the present data and is identified as a priority for future research (Section 6).

4.4. Island vs. Mainland Regional Seasonality

A descriptive comparison between island and mainland EU NUTS-2 regions in the sample provides preliminary, unconditional support for H3. The nine island regions identified in the sample—Notio Aigaio (EL42), Voreio Aigaio (EL41), Kriti (EL43), Illes Balears (ES53), Canarias (ES70), Sicilia (ITG1), Sardegna (ITG2), Açores (PT20), and Madeira (PT30)—record a mean Gini coefficient of 0.453 compared to 0.387 for the 52 mainland regions, a difference of 0.066 Gini units. However, island regions exhibit considerable internal heterogeneity: Canarias (ES70) records among the lowest Gini values in the entire sample (mean 0.221) owing to its year-round climate appeal, while Notio Aigaio and Voreio Aigaio record among the highest. This within-group variation underscores the importance of controlling for additional structural factors in the regression framework, which is undertaken formally in Sections 4.5 and 4.6.

4.5. Panel Regression Results

Prior to model estimation, variance inflation factors (VIF) were calculated for all independent variables. All VIF values fall below the conventional threshold of 10 (INT: 1.81;

HOT: 1.11; GDP_log: 1.11; TI: 1.66; COVID: 1.11; ISLAND: 1.46), indicating the absence of problematic multicollinearity. The Hausman specification test, computed from the cluster-robust covariance matrices of the two estimators, yields a test statistic of $\chi^2(5) = 14.020$ ($p = 0.016$), rejecting the null hypothesis of no systematic correlation between regional effects and the regressors at the 5% level. Accordingly, the fixed effects (FE) estimator is preferred on consistency grounds (Hausman, 1978; Wooldridge, 2010), and FE estimates are treated as the primary specification. Random effects (RE) estimates are reported alongside for comparison. As the time-invariant ISLAND variable is absorbed into regional fixed effects under the FE specification, its coefficient is estimated in the RE and CRE models only.

Table 3 reports the regression results for the FE and RE specifications. Under the FE estimator, the hotel accommodation share (HOT) is negative and statistically significant ($\beta = -0.0038$, $p = 0.030$), supporting H2: regions in which hotels account for a larger share of overnight stays exhibit systematically lower Gini coefficients, net of within-region changes in other covariates. Regional GDP per capita (log-transformed) is also negative and highly significant ($\beta = -0.5245$, $p = 0.004$). The COVID-19 dummy is positive and highly significant ($\beta = 0.1395$, $p < 0.001$), confirming that the pandemic years 2020–2021 were associated with elevated Gini values. The share of international overnight stays (INT) is positive but statistically insignificant under the FE specification ($\beta = 0.0006$, $p = 0.556$), meaning that H1 is not supported in the within-region model; the interpretation of this result in light of the within/between distinction introduced in Section 3.4 is developed in the Discussion. Tourism intensity (TI) is also insignificant under FE ($p = 0.225$); because TI is measured on a large numerical scale, its coefficient rounds to approximately zero in the table and should be interpreted through its statistical significance rather than its rounded magnitude. Under the RE specification with cluster-robust standard errors, the ISLAND coefficient is positive but statistically insignificant ($\beta = 0.0439$, $p = 0.385$).

Table 3. Panel Regression Results—Determinants of Tourism Seasonality (Gini Coefficient).

Variable	FE β	FE SE	FE p	RE β	RE SE	RE p
INT (share int. nights)	0.0006	0.0010	0.556	−0.0001	0.0006	0.839
HOT (hotel share)	−0.0038 **	0.0017	0.030	−0.0031 ***	0.0009	0.001
GDP_log (PPS, log)	−0.5245 ***	0.1753	0.004	−0.1610 ***	0.0451	0.001
TI (tourism intensity)	≈0.000	0.000	0.225	≈0.000 ***	0.000	<0.001
COVID (2020–2021 dummy)	0.1395 ***	0.0120	<0.001	0.1630 ***	0.0129	<0.001
ISLAND (dummy)	(absorbed)	—	—	0.0439	0.0501	0.385
R ² (within/overall)	0.797	—	—	0.615	—	—
N observations	305	—	—	305	—	—
Hausman $\chi^2(5)$	14.020 ** ($p = 0.016$)	—	—	FE preferred	—	—

Note: Dependent variable: Gini coefficient of monthly overnight stay distribution. FE = Fixed Effects (within estimator), RE = Random Effects (FGLS). Cluster-robust standard errors at EU NUTS-2 level in both specifications. *** $p < 0.01$, ** $p < 0.05$. ISLAND is time-invariant and absorbed into regional fixed effects under FE; estimated under RE and CRE only. Source: Authors' calculations based on Eurostat data.

4.6. Correlated Random Effects (Mundlak) Estimation

To enable a formal assessment of H3 despite the rejection of the random effects specification, the correlated random effects (CRE, Mundlak) model described in Section 3.4 is estimated by augmenting the RE specification with region-specific means of all time-varying regressors. Table 4 reports the results. Two internal validity checks are satisfied. First, the coefficients on the time-varying regressors are numerically identical to the FE estimates reported in Table 3 (HOT: −0.0038; GDP_log: −0.5245; COVID: 0.1395), as theory

requires (Wooldridge, 2010). Second, the Wald test of the joint significance of the regional means is strongly rejected ($\chi^2(4) = 20.783$, $p < 0.001$), confirming that unobserved regional effects are correlated with the regressors and corroborating the conclusion of the Hausman test.

Table 4. Correlated Random Effects (Mundlak) Estimation—Gini Coefficient.

Variable	β	SE	p
INT (share int. nights)	0.0006	0.0010	0.559
HOT (hotel share)	−0.0038 **	0.0017	0.032
GDP_log (PPS, log)	−0.5245 ***	0.1768	0.004
TI (tourism intensity)	≈0.000	0.000	0.228
COVID (2020–2021 dummy)	0.1395 ***	0.0121	<0.001
Mean INT (region mean)	−0.0019	0.0012	0.120
Mean HOT (region mean)	0.0006	0.0022	0.774
Mean GDP_log (region mean)	0.3657 **	0.1712	0.037
Mean TI (region mean)	≈0.000 ***	0.000	0.004
ISLAND (dummy)	0.0346	0.0509	0.499
Wald test, group means: $\chi^2(4)$	20.783 *** ($p < 0.001$)	—	—
R ² (overall)	0.657	—	—
N observations	305	—	—

Note: Dependent variable: Gini coefficient of monthly overnight stay distribution. CRE estimated as RE (FGLS) augmented with region-specific means of time-varying regressors; the mean of COVID is omitted as it is constant across regions in the balanced panel. Cluster-robust standard errors at EU NUTS-2 level. *** $p < 0.01$, ** $p < 0.05$. Source: Authors' calculations based on Eurostat data.

The central result of the CRE estimation concerns the ISLAND coefficient: it is positive but small and statistically insignificant ($\beta = 0.0346$, $p = 0.499$). Once the structural covariates—international dependency, accommodation composition, economic development, and tourism intensity, together with their regional means—are controlled for, island geography per se does not exert a statistically distinguishable effect on seasonal concentration. The descriptive island–mainland gap of 0.066 Gini units documented in Section 4.4 therefore appears to be attributable to the structural composition of island regions rather than to island status as such. H3 is accordingly assessed as not supported in the formal framework, while the descriptive pattern remains directionally consistent with the hypothesis and substantively informative for destination management.

4.7. Hypothesis Testing Summary

H2 is supported: the hotel accommodation share emerges as a robust negative determinant of seasonal concentration under the FE, RE, and CRE specifications, consistent with findings of Cuccia and Rizzo (2011) and Duro (2016). H1 is not supported under the FE estimator: within-region variation in the international tourist share does not predict changes in Gini. As argued in Section 3.4, however, H1 is theoretically a between-region proposition; the within-region non-result is therefore interpreted as reflecting limited temporal variation in INT over a five-year window rather than as evidence against the cross-sectional mechanism documented in the literature (Rosselló et al., 2004). H3 is not supported in the formal framework: the CRE estimation, which permits correlated regional effects while identifying time-invariant variables, yields an insignificant ISLAND coefficient ($\beta = 0.0346$, $p = 0.499$), and the RE estimate is likewise insignificant ($\beta = 0.0439$, $p = 0.385$). The descriptive island–mainland difference of 0.066 Gini units is directionally consistent with H3 but is accounted for by structural covariates. The overall results of hypothesis testing are summarized in Table 5.

Table 5. Summary of Hypothesis Testing Results.

Hypothesis	Statement (Abbreviated)	Test Basis	Outcome
H1	Higher international share → higher seasonality	FE (within-region)	Not supported ($\beta = 0.0006$, $p = 0.556$)
H2	Higher hotel share → lower seasonality	FE/RE/CRE	Supported (FE: $\beta = -0.0038$, $p = 0.030$)
H3	Island regions → higher seasonality	CRE (Mundlak); RE	Not supported (CRE: $\beta = 0.0346$, $p = 0.499$)

Note: Statements are abbreviated versions of the study hypotheses. FE preferred based on the Hausman test ($\chi^2(5) = 14.020$, $p = 0.016$). H3 is testable only in specifications identifying time-invariant regressors; the CRE (Mundlak) estimate constitutes the primary formal assessment. Source: Authors' calculations based on Eurostat data.

4.8. Robustness Check

As a robustness check, the FE model was re-estimated using the Q3 seasonal ratio (share of annual overnight stays in July–September) as an alternative dependent variable in place of the Gini coefficient. The direction and significance of all coefficients remain consistent with the primary specification: HOT is negative and significant ($\beta = -0.074$, $p < 0.05$), GDP_log is negative and significant, and COVID is positive and highly significant. The consistency of findings across both seasonality measures reinforces the validity of the primary results and confirms that the identified relationships are not an artefact of the specific measurement approach adopted. A complementary sensitivity re-estimation excluding the four urban and special-status reference regions is reported in Appendix A Table A4 and yields materially identical conclusions.

5. Discussion

5.1. Regional Differences in Tourism Seasonality

Addressing RQ1, the analysis reveals that tourism seasonality across Mediterranean EU NUTS-2 regions in the 2020–2024 period is both high in absolute terms and markedly heterogeneous in spatial distribution. Mean Gini coefficients across all region-year observations range from 0.039 (ES70—Canarias, 2023) to 0.742 (HR03—Jadranska Hrvatska, 2020), with regional mean values ranging from 0.160 (ES64—Ciudad de Melilla) to 0.664 (HR03), and an overall sample mean of 0.397, placing the Mediterranean EU firmly within the high-seasonality cluster identified at national level by Duro and Turrión-Prats (2019) and Krabokoukis and Polyzos (2024). The spatial distribution is not random: coastal and island destinations in Greece and southern Italy systematically record higher Gini values than their mainland counterparts in Spain, Portugal, and northern Italy, while metropolitan regions with diversified tourism bases consistently record the lowest seasonal concentration in the sample.

Within-country heterogeneity is at least as large as between-country heterogeneity, confirming that national-level analyses are insufficient for understanding the spatial dynamics of Mediterranean seasonality and validating the EU NUTS-2 regional approach adopted in this study. The descriptive findings confirm and extend existing evidence on the spatial distribution of tourism seasonality across Mediterranean EU destinations. The country-level ranking—Greece, Italy, Croatia, Spain, Portugal in descending order of mean Gini—is broadly consistent with national-level analyses reported by Krabokoukis and Polyzos (2024) and Duro and Turrión-Prats (2019), providing cross-validation for the Gini-based measurement approach applied here at the EU NUTS-2 regional level. However, the sub-national analysis reveals important patterns that national averages obscure. This within-country heterogeneity is consistent with recent multiscale evidence: Viera-

González and Hernández-Martín (2025) show for Spain that national and regional aggregates conceal pronounced local differences in seasonal concentration through spatial compensation, which implies that the regional contrasts documented here would likely appear even sharper at finer territorial scales.

The high mean Gini for Italy (0.446) is driven predominantly by southern coastal regions such as Calabria (ITF6, Gini = 0.652) and Sardegna (ITG2, 0.605), while northern Italian metropolitan regions such as ITC1 (Piemonte) and major urban centres record lower seasonality relative to southern coastal regions, though they do not reach the low values observed in year-round destinations such as the Canary Islands or Ceuta. Similarly, Spain's comparatively low mean Gini (0.312) reflects the moderating influence of the Canary Islands (ES70, mean Gini = 0.221), whose year-round climate effectively distributes demand across all twelve months and substantially reduces the national average. The case of Jadranska Hrvatska (HR03) merits particular attention. With a mean Gini of 0.664 and a Q3 ratio of 76.6%, this region records the highest seasonal concentration among all non-island EU NUTS-2 regions in the sample and ranks first overall in four of the five observation years. This finding is consistent with Eurostat's own assessments of Mediterranean regional seasonality (Eurostat, 2024c) and underscores the structural nature of Croatia's seasonality challenge. The region's extreme concentration—nearly four-fifths of annual overnight stays occurring in a single quarter—is particularly notable given Croatia's high international tourism dependency ($INT \approx 90\%$), its dominance of private and holiday accommodation over hotels, and its geographic configuration as a long, narrow coastal region with limited inland tourism infrastructure.

5.2. The Role of Accommodation Structure

These structural characteristics, identifiable through the panel regression framework, collectively explain why deseasonalisation efforts to date have produced limited results. The confirmation of H2—that regions with higher hotel accommodation shares exhibit lower seasonal concentration—constitutes the central policy-relevant finding of this study. The FE estimate ($\beta = -0.0038$, $p = 0.029$) implies that a ten-percentage point increase in hotel market share is associated, on average, with a reduction in the Gini coefficient of approximately 0.038 units, holding all other within-region factors constant. This effect, while modest in absolute terms, is economically meaningful given the typical Gini range of 0.30–0.70 observed across Mediterranean coastal regions. The result replicates and extends findings from single-country analyses by Cuccia and Rizzo (2011) for Sicily and Duro (2016) for Spanish provinces to a broader multi-country regional context, enhancing the generalizability of the accommodation-structure hypothesis.

This result is further supported by Zhang and Xie (2023), who demonstrate that seasonality-exposed hotels face significantly elevated exit probabilities, confirming the two-way relationship between accommodation structure and seasonal concentration. The mechanism underlying this relationship is twofold. On the supply side, hotel operators—as profit-maximizing enterprises with high fixed costs—have strong incentives to deploy revenue management strategies, targeted promotional campaigns, and diversified product offerings to stimulate demand during shoulder and off-peak seasons. Empirical evidence from the yield management literature supports the capacity of hotels to shift demand across the seasonal distribution through differential pricing and package design (Turrión-Prats & Duro, 2018). On the demand side, hotel accommodation is more likely to attract business travellers, conference participants, and cultural tourists whose travel timing is less constrained by climatic and institutional factors than that of leisure-oriented beach tourists who constitute the primary clientele of private rental accommodation.

The disproportionately high share of holiday home and private rental accommodation in Croatia, Greece, and southern Italy—precisely the destinations with the highest

Gini values—is thus not merely a symptom of seasonality but an active structural driver of it. From a policy perspective, these findings suggest—tentatively, given the observational nature of the analysis—that structural interventions targeting the accommodation composition of highly seasonal regions may be more effective in reducing seasonal concentration than demand-side promotional campaigns for off-peak travel alone. Policies that support hotel development, facilitate the upgrading of private rental properties toward professionally managed accommodation, or encourage year-round tourism products compatible with hotel distribution channels could plausibly contribute to reductions in Gini-measured seasonality over medium-term horizons. Three qualifications are essential, however. First, the analysis identifies associations within an observational panel and does not evaluate specific policy instruments; the estimated coefficient should not be read as the causal effect of any particular intervention. Second, expanding hotel capacity in already tourism-intensive coastal regions carries well documented trade-offs, including land-use and landscape pressures, potential intensification of overtourism dynamics in peak months, increased resource consumption, and possible displacement effects in local housing markets. Third, accommodation-composition policy interacts with local planning regimes, property structures and community preferences that differ substantially across the five countries studied. Deseasonalisation objectives should therefore be pursued as one element of integrated destination management rather than as a stand-alone rationale for capacity expansion. Recent empirical work on overtourism vulnerability reinforces this integrated framing. Bergantino et al. (2026) show that the Mediterranean destinations most exposed to overtourism risk combine pronounced seasonal peaks with tourism-dependent local economies and high shares of platform-based short-term rentals, and correspondingly recommend product diversification, temporal redistribution of demand and resilience-oriented governance. These are precisely the structural margins identified by the present analysis, suggesting that deseasonalisation policy and overtourism mitigation should be designed as complementary components of the same destination management agenda rather than as separate policy tracks.

Situating these findings within the destination management frameworks introduced in Section 2 clarifies their theoretical import. The robust negative effect of hotel share gives econometric expression to the supply-side diversification logic of Benur and Bramwell (2015): professionally managed accommodation is the infrastructure through which shoulder-season products are developed, distributed and revenue-managed, which is precisely why its share in the accommodation mix—rather than promotional effort alone—emerges as the operative structural lever. The stability of seasonal patterns across the pandemic shock is consistent with Cochrane's (2010) account of tourism systems as resilient structures that reorganise around their pre-existing configuration after disturbance, and with the corollary in Sharma et al. (2021) that shock severity does not by itself produce structural transformation.

5.3. *Interpreting the Unsupported Hypotheses: International Dependency and Island Geography*

The FE estimator identifies the effect of changes in INT within a given region over the five-year observation period. Given the relative stability of international tourism dependency within regions over such a short temporal window, the within-region variation in INT is limited, reducing statistical power and potentially rendering the coefficient insignificant even if the underlying relationship is genuine. The cross-sectional association between high internationalization and high seasonality is well-established and visible in the descriptive results—the most international destinations (HR03, EL42, EL41) are also among the most seasonal—but this between-region relationship is absorbed by the regional fixed effects and cannot be estimated within the FE framework. The insignificance of INT under FE therefore reflects the estimator's mechanics rather than the absence of a

substantive relationship, and should not be interpreted as evidence against the hypothesis in a broader conceptual sense.

Future research employing longer time series or exploiting more pronounced within-region variation in internationalization could provide a more definitive test of the H1 proposition. The assessment of H3 requires methodological care. Since island geography is a time-invariant characteristic of each EU NUTS-2 region, its effect is completely absorbed by the regional fixed effects and cannot be identified in the preferred FE specification. Under the random effects specification with cluster-robust inference, the ISLAND coefficient is positive but insignificant (Tables 3 and 4), and this estimate in any case rests on an orthogonality assumption rejected by the Hausman test. The correlated random effects (Mundlak) specification introduced precisely to address this problem—permitting correlation between regional effects and the regressors while identifying time-invariant variables—likewise yields a small and statistically insignificant ISLAND coefficient ($\beta = 0.035$, $p = 0.499$). H3 is therefore not supported in the formal framework: once structural covariates and their regional means are controlled for, island status per se does not exert a statistically distinguishable effect on seasonal concentration.

Agius and Briguglio (2021) demonstrate in the Maltese context that ecotourism development can contribute to reducing island seasonality by attracting nature-oriented visitors whose travel timing is less constrained by summer peak demand, while Ruggieri et al. (2022) show in a panel analysis of Mediterranean island destinations that community-based tourism models are associated with lower seasonal concentration than industrial tourism models. The descriptive island–mainland gap of 0.066 Gini units (Section 4.4) is directionally consistent with H3, but the CRE results indicate that it is accounted for by the structural composition of island regions—their international dependency, accommodation mix, economic development and tourism intensity—rather than by island status as such. This reading carries its own policy relevance, consistent with the evidence of Agius and Briguglio (2021) and Ruggieri et al. (2022): the seasonal disadvantage of island destinations is not geographically immutable but reflects modifiable structural characteristics.

The Canary Islands (ES70) constitute the principal exception: their year-round climate and high share of international charter tourists from Northern European markets whose holiday calendars are more evenly distributed produce a mean Gini of 0.221—the lowest among island regions in the sample—despite their island geography. This exception highlights that island geography per se does not mechanically generate high seasonality; rather, it creates conditions of transport dependency and product specialization that tend toward seasonal concentration in the absence of countervailing factors such as climate differentiation or market diversification. The findings of Ruggieri and Platania (2024), who document significantly higher seasonality in Mediterranean island destinations using a different methodological approach over an earlier observation period, are broadly consistent with this interpretation.

5.4. Economic Development and Post-Pandemic Recovery

The negative and highly significant coefficient on regional GDP per capita (log) under both FE and RE (Table 3) specifications indicates that more economically developed regions exhibit lower seasonal concentration, net of other covariates. This finding is consistent with the theoretical proposition that higher regional economic development is associated with greater diversification of tourism product supply, stronger institutional capacity for year-round destination management, more developed infrastructure for non-beach tourism (cultural, gastronomy, conference, wellness), and a higher proportion of domestic visitors whose travel patterns are less tightly constrained by summer calendars. The larger FE coefficient relative to RE suggests that within-region economic development trajectories—reflecting improvements in regional GDP over time—have a particularly

strong association with reductions in seasonal concentration, which is an encouraging finding from a long-term policy perspective: regions that successfully develop their economies may also simultaneously reduce their seasonality as a secondary benefit of diversification.

The positive and highly significant COVID-19 dummy coefficient (Table 3) confirms that the pandemic years 2020–2021 were associated with substantially elevated Gini values across all regions in the sample. This is consistent with Duro et al. (2021), who demonstrate that Mediterranean coastal and island destinations exhibited the highest vulnerability to the COVID-19 shock due to their extreme dependence on international tourism and concentrated seasonal demand structures, all else equal. This finding is mechanically consistent with the near-complete collapse of international tourism demand during these years: since international visitors are concentrated in summer, their absence disproportionately affected non-summer months, paradoxically increasing the relative concentration of the remaining (predominantly domestic) demand in the summer period.

The result thus reflects a disruption-induced increase in apparent seasonality rather than a genuine structural shift toward more seasonal behavior. The rapid decline of Gini values from 2022 onwards and their stability through 2023 and 2024 support a bounded answer to RQ2: within the observation window, the pandemic disruption did not translate into a persistent shift in regional seasonality patterns across Mediterranean EU destinations. This finding is consistent with the theoretical prediction derived from the inertia literature (Turrión-Prats & Duro, 2019) that deeply embedded institutional and structural factors driving seasonal concentration are resistant to even substantial external shocks.

5.5. Policy Implications

For governance, the implication follows Ruhanen et al. (2010): deseasonalisation policy must target the structural composition of supply—a domain in which public authorities hold concrete instruments through planning, licensing and investment incentives—rather than relying on promotional coordination alone, and must calibrate expectations to the destination's position in its development cycle (Butler, 1980), since mature coastal destinations face the strongest structural lock-in. Within the competitiveness framework of Ritchie and Crouch (2003), the within-country heterogeneity documented in Section 4.2 indicates that year-round resource deployment is achievable within every national context in the sample, but only where the underlying supply structure supports it.

This conclusion is consistent with recommendations emerging from the broader Mediterranean tourism sustainability literature (Zvaigzne et al., 2022; Ruggieri & Platania, 2024). The failure to confirm H1 under the fixed effects specification—the hypothesis that higher international tourist shares drive higher seasonal concentration—represents a substantively important finding that warrants careful interpretation. At first glance, this result appears to contradict the established literature, in which the share of international visitors has been consistently identified as a positive determinant of seasonality (Rosselló et al., 2004; Turrión-Prats & Duro, 2019). The key to reconciling this apparent contradiction lies in the distinction between within-region and between-region variation that characterizes fixed effects estimation.

With respect to the pandemic specifically, the implication is cautionary rather than conclusive: the recovery-phase trajectory suggests that a severe external disruption did not, by itself, generate durable deseasonalisation, which underlines the argument that structural change in seasonal patterns is unlikely to occur without deliberate supply-side intervention. A definitive assessment of whether the post-2022 configuration constitutes a full return to the pre-pandemic equilibrium requires a panel extending into the pre-pandemic period, which is beyond the scope of the present study.

6. Conclusions

This study examined the level, spatial distribution, and structural determinants of tourism seasonality across 61 Mediterranean EU NUTS-2 regions from Croatia, Spain, Greece, Portugal and Italy during the 2020–2024 period. Using harmonised Eurostat data and a balanced panel framework, the analysis operationalised the Gini coefficient as the dependent variable in a regional panel regression to identify the structural factors driving cross-regional variation in seasonal concentration.

The findings make two principal contributions to the tourism seasonality literature. Methodologically, the study demonstrates that the Gini coefficient—previously used mainly as a descriptive measure—can be operationalised as a dependent variable within a multi-country EU NUTS-2 panel framework, providing a replicable analytical template for future comparative destination research. Empirically, the analysis generates the first systematic regional comparison of Mediterranean EU tourism seasonality covering the post-pandemic recovery period, with three central findings: hotel accommodation share emerges as a robust negative determinant of seasonal concentration (supporting H2), international tourism dependency does not predict within-region changes in seasonality under fixed effects estimation (H1 not supported), and island geography effects remain inconclusive due to methodological constraints associated with time-invariant variables (H3 inconclusive).

The COVID-19 pandemic temporarily elevated seasonal concentration during 2020–2021; within the observation window, concentration returned to stable recovery-phase levels from 2022 onwards, with no evidence of a lasting pandemic-induced structural shift, although a direct comparison with pre-pandemic equilibria lies beyond the panel's temporal coverage. For destination management and EU regional policy, the implications are direct. The robust hotel share effect indicates that structural interventions targeting accommodation composition—incentives for hotel development, support for upgrading private rental capacity, and product diversification programs—are likely to produce more durable seasonality reductions than demand-side promotional campaigns alone. The recovery-phase trajectory further suggests that external shocks, however severe, do not by themselves appear to drive durable structural change within the horizon observed here, underlining the role of deliberate policy intervention—subject to the trade-offs discussed above.

The case of Jadranska Hrvatska, recording the highest seasonal concentration among all non-island regions in the sample, illustrates the magnitude of the challenge facing destinations dominated by private accommodation and international leisure demand. Several limitations should be acknowledged, together with their implications for measurement, estimation and interpretation. First, the temporal scope constrains causal interpretation in two distinct ways. The five-year window limits the within-region variation available to the fixed effects estimator, which is the most plausible explanation for the non-significance of the international dependency variable: characteristics that change slowly over five years contribute little identifying variation, so the FE non-result for H1 should be read as “not identifiable within the window” rather than “absent”. More critically, because the panel contains no pre-pandemic baseline years, the COVID coefficient identifies only the contrast between the pandemic phase (2020–2021) and the recovery phase (2022–2024) within the observation window; it cannot distinguish a full return to the pre-pandemic equilibrium from convergence to a marginally different post-pandemic baseline. All pandemic-related conclusions in this study are therefore bounded statements about the observation window, with pre-pandemic levels reported in the literature serving only as external context.

Second, the exclusion of platform-intermediated short-term rentals from Eurostat accommodation statistics affects both the dependent and a key explanatory variable. On the

dependent variable side, because platform supply is itself strongly seasonal, the Gini coefficient computed from registered establishments likely understates true seasonal concentration, and this understatement is largest precisely in regions with high platform penetration—coastal Croatia, the Greek islands and parts of southern Italy—implying that the reported cross-regional differences in seasonality are, if anything, conservative. On the explanatory side, the HOT variable measures the hotel share of registered accommodation only; where unregistered platform supply is substantial, the true hotel share of total capacity is lower than measured, which would tend to attenuate the estimated coefficient toward zero. The robust negative effect of HOT despite this attenuation strengthens rather than weakens the substantive conclusion, but the precise magnitude of the effect should be interpreted with corresponding caution.

Third, the geographic scope bounds generalisability. The sample covers the complete EU NUTS-2 structure of five EU member states with harmonised statistical systems; extending the findings to non-EU Mediterranean destinations—where registration practices, accommodation structures and source-market compositions differ substantially—or to high-seasonality contexts outside the Mediterranean basin would require independent verification. Within the EU Mediterranean itself, the sample was designed to capture the largest Mediterranean tourism systems in which seasonality constitutes a defining structural challenge of the national tourism economy—Croatia, Spain, Greece, Portugal and Italy. The remaining Mediterranean member states fall outside this criterion for complementary reasons: Malta and Cyprus are small tourism systems that each constitute a single EU NUTS-2 region and thus offer no within-country regional variation; Slovenia's Mediterranean segment accounts for a marginal share of its regional structure; and France, while a major tourism economy, spans several distinct basins in which Mediterranean seasonality is not the defining structural feature, so that the whole-country inclusion principle adopted here would have added a large number of predominantly non-Mediterranean regions. The results therefore characterize the five-country system analyzed rather than the Mediterranean EU in its entirety. Future research should extend the temporal scope as longer post-pandemic time series become available, allowing more definitive testing of whether 2020–2024 represents a return to the prior equilibrium or the establishment of a new structural baseline. Incorporating platform-based accommodation data—once harmonized statistics become available at the regional level—would substantially improve the precision of seasonality measurement in regions where short-term rentals dominate. Finally, complementing the panel approach with case-study evidence from specific high-seasonality destinations such as Jadranska Hrvatska could illuminate the institutional and behavioral mechanisms through which structural determinants operate, providing finer-grained insights to inform regionally tailored policy interventions.

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Abbreviations

The following abbreviations are used in this manuscript:

EU	European Union
GDP	Gross Domestic Product
Gini	Gini Coefficient
NUTS	Nomenclature of Territorial Units for Statistics
PPS	Purchasing Power Standard
Q3	Third Quarter (July–September)
RE	Random Effects
FE	Fixed Effects
VIF	Variance Inflation Factor
COVID-19	Coronavirus Disease 2019

Appendix A

This appendix provides the complete list of EU NUTS–2 regions included in the analytical sample together with the coding of the ISLAND variable (Table A1), descriptive statistics by region for the 2020–2024 period (Table A2), the complete region-year Gini coefficient dataset (Table A3), and a sensitivity re-estimation of the fixed effects model excluding the urban and special-status reference regions (Table A4).

Table A1. EU NUTS–2 regions included in the sample: classification and ISLAND coding.

Code	Region (Eurostat Name)	Country	Category	ISLAND
HR02	Panonska Hrvatska	Croatia	Mainland	0
HR03	Jadranska Hrvatska	Croatia	Mainland	0
HR05	Grad Zagreb	Croatia	Urban/special-status reference	0
HR06	Sjeverna Hrvatska	Croatia	Mainland	0
ES11	Galicia	Spain	Mainland	0
ES12	Principado de Asturias	Spain	Mainland	0
ES13	Cantabria	Spain	Mainland	0
ES21	País Vasco	Spain	Mainland	0
ES22	Comunidad Foral de Navarra	Spain	Mainland	0
ES23	La Rioja	Spain	Mainland	0
ES24	Aragón	Spain	Mainland	0
ES30	Comunidad de Madrid	Spain	Urban/special-status reference	0
ES41	Castilla y León	Spain	Mainland	0
ES42	Castilla-La Mancha	Spain	Mainland	0
ES43	Extremadura	Spain	Mainland	0
ES51	Cataluña	Spain	Mainland	0
ES52	Comunitat Valenciana	Spain	Mainland	0
ES53	Illes Balears	Spain	Island	1
ES61	Andalucía	Spain	Mainland	0
ES62	Región de Murcia	Spain	Mainland	0
ES63	Ciudad de Ceuta	Spain	Urban/special-status reference	0
ES64	Ciudad de Melilla	Spain	Urban/special-status reference	0
ES70	Canarias	Spain	Island	1
EL30	Attiki	Greece	Mainland	0
EL41	Voreio Aigaio	Greece	Island	1

EL42	Notio Aigaio	Greece	Island	1
EL43	Kriti	Greece	Island	1
EL51	Anatoliki Makedonia, Thraki	Greece	Mainland	0
EL52	Kentriki Makedonia	Greece	Mainland	0
EL53	Dytiki Makedonia	Greece	Mainland	0
EL54	Ipeiros	Greece	Mainland	0
EL61	Thessalia	Greece	Mainland	0
EL62	Ionia Nisia	Greece	Mainland	0
EL63	Dytiki Elláda	Greece	Mainland	0
EL64	Stereia Elláda	Greece	Mainland	0
EL65	Peloponnisos	Greece	Mainland	0
PT11	Norte	Portugal	Mainland	0
PT15	Algarve	Portugal	Mainland	0
PT20	Região Autónoma dos Açores	Portugal	Island	1
PT30	Região Autónoma da Madeira	Portugal	Island	1
ITC1	Piemonte	Italy	Mainland	0
ITC2	Valle d'Aosta/Vallée d'Aoste	Italy	Mainland	0
ITC3	Liguria	Italy	Mainland	0
ITC4	Lombardia	Italy	Mainland	0
ITF1	Abruzzo	Italy	Mainland	0
ITF2	Molise	Italy	Mainland	0
ITF3	Campania	Italy	Mainland	0
ITF4	Puglia	Italy	Mainland	0
ITF5	Basilicata	Italy	Mainland	0
ITF6	Calabria	Italy	Mainland	0
ITG1	Sicilia	Italy	Island	1
ITG2	Sardegna	Italy	Island	1
ITH1	Provincia Autonoma di Bolzano/Bozen	Italy	Mainland	0
ITH2	Provincia Autonoma di Trento	Italy	Mainland	0
ITH3	Veneto	Italy	Mainland	0
ITH4	Friuli-Venezia Giulia	Italy	Mainland	0
ITH5	Emilia-Romagna	Italy	Mainland	0
ITI1	Toscana	Italy	Mainland	0
ITI2	Umbria	Italy	Mainland	0
ITI3	Marche	Italy	Mainland	0
ITI4	Lazio	Italy	Mainland	0

Note: ISLAND = 1 denotes regions whose territory consists entirely or predominantly of islands (Section 3.5); shaded rows. "Urban/special-status reference" denotes non-coastal metropolitan regions and autonomous cities retained as year-round reference cases (Section 3.2): Comunidad de Madrid (ES30), Ciudad de Ceuta (ES63), Ciudad de Melilla (ES64) and Grad Zagreb (HR05). Source: Eurostat NUTS 2021 classification.

Table A2. Descriptive statistics by region, 2020–2024 means.

Code	Gini Mean	Gini SD	Q3 (%)	INT (%)	HOT (%)	GDP (PPS)	TI
EL30	0.297	0.103	40.6	69.3	91.0	92	2330
EL41	0.555	0.051	67.7	65.3	70.5	41	10,613
EL42	0.578	0.062	64.1	89.6	79.9	64	89,181
EL43	0.567	0.066	63.0	94.1	85.0	55	40,760
EL51	0.542	0.026	66.7	64.4	66.1	43	4859
EL52	0.546	0.037	65.1	72.3	66.2	53	7108
EL53	0.227	0.093	31.4	13.4	89.0	52	1034
EL54	0.491	0.079	60.7	47.6	57.0	43	7224
EL61	0.490	0.058	61.0	48.4	65.1	51	4530
EL62	0.632	0.065	72.1	91.8	72.0	58	69,619
EL63	0.412	0.080	53.1	45.3	88.0	47	2724
EL64	0.472	0.070	60.2	35.0	72.8	60	4412
EL65	0.490	0.084	60.0	42.9	70.9	56	7974
ES11	0.402	0.088	53.2	21.8	72.4	81	3943
ES12	0.478	0.115	61.4	13.6	57.9	79	5551
ES13	0.504	0.110	62.9	15.9	49.4	81	8422
ES21	0.280	0.105	42.2	37.1	71.2	110	3433
ES22	0.321	0.093	45.8	20.7	48.2	105	4832
ES23	0.348	0.133	47.2	15.0	57.1	92	4217
ES24	0.294	0.132	43.9	18.2	64.4	99	5367
ES30	0.169	0.163	26.1	46.7	82.6	120	3325
ES41	0.286	0.137	42.2	16.5	66.7	83	4255
ES42	0.226	0.113	37.0	12.0	66.7	72	2304
ES43	0.237	0.112	37.8	12.6	66.2	67	2966
ES51	0.398	0.091	51.3	54.0	63.1	101	8219
ES52	0.298	0.114	43.0	46.7	53.2	75	7929
ES53	0.540	0.083	60.7	83.2	83.5	91	40,898
ES61	0.312	0.135	43.4	44.0	72.3	66	6669
ES62	0.254	0.105	40.2	32.6	55.2	73	2901
ES63	0.201	0.083	32.3	22.9	100.0	64	1401
ES64	0.160	0.122	29.4	17.3	95.3	59	1258
ES70	0.221	0.241	27.6	83.7	71.8	67	32,227
HR02	0.334	0.048	47.2	56.2	32.2	50	1017
HR03	0.664	0.055	76.6	91.2	22.4	68	56,376
HR05	0.190	0.076	32.6	77.1	59.1	124	2472
HR06	0.243	0.085	40.0	50.2	57.7	60	1208
ITC1	0.263	0.100	41.9	44.0	57.9	99	2743
ITC2	0.453	0.133	48.2	34.5	70.5	123	23,969
ITC3	0.423	0.094	54.7	38.1	58.8	101	8998
ITC4	0.259	0.107	40.5	55.6	66.0	131	3336
ITF1	0.523	0.097	65.7	11.9	64.6	82	4633
ITF2	0.478	0.084	62.3	7.6	57.5	72	1471
ITF3	0.426	0.114	53.8	39.4	78.9	62	2769
ITF4	0.563	0.067	68.4	23.9	54.0	63	3821
ITF5	0.518	0.084	64.3	12.2	70.5	73	3862
ITF6	0.652	0.036	77.8	14.4	78.3	56	3665
ITG1	0.447	0.102	56.7	38.5	72.9	60	2691
ITG2	0.605	0.064	71.4	41.0	65.2	70	7762
ITH1	0.368	0.159	48.8	66.4	73.9	158	57,230
ITH2	0.431	0.135	52.1	37.7	69.4	124	29,524

ITH3	0.456	0.086	57.2	61.9	41.5	108	12,125
ITH4	0.464	0.082	58.7	52.2	51.9	102	6927
ITH5	0.477	0.075	58.9	23.2	74.8	117	7706
ITI1	0.450	0.096	56.9	45.5	43.0	101	10,262
ITI2	0.370	0.137	50.0	27.8	49.9	83	6194
ITI3	0.501	0.051	62.7	13.9	44.0	89	6575
ITI4	0.239	0.147	32.5	51.4	68.4	112	5446
PT11	0.270	0.097	40.2	51.3	70.2	67	2956
PT15	0.367	0.099	47.9	65.6	80.8	80	37,129
PT20	0.329	0.068	42.7	49.1	78.2	68	8760
PT30	0.239	0.180	32.5	80.7	89.4	79	26,840

Note: Period means over 2020–2024 (N = 5 per region). Q3 = share of annual overnight stays in July–September. INT = share of international overnight stays. HOT = share of hotel overnight stays. GDP = regional GDP per capita in PPS (% of EU average). TI = overnight stays per 1000 inhabitants. Island regions shaded. Source: Authors' calculations based on Eurostat data.

Table A3. Gini coefficient by region and year (complete dataset).

Code	2020	2021	2022	2023	2024	Mean
EL30	0.424	0.388	0.258	0.205	0.208	0.297
EL41	0.466	0.591	0.578	0.565	0.573	0.555
EL42	0.666	0.619	0.543	0.529	0.532	0.578
EL43	0.656	0.620	0.528	0.519	0.512	0.567
EL51	0.516	0.581	0.555	0.537	0.522	0.542
EL52	0.549	0.605	0.550	0.514	0.513	0.546
EL53	0.381	0.246	0.178	0.157	0.171	0.227
EL54	0.592	0.551	0.476	0.422	0.413	0.491
EL61	0.564	0.540	0.457	0.451	0.438	0.490
EL62	0.724	0.679	0.592	0.583	0.584	0.632
EL63	0.523	0.472	0.362	0.353	0.350	0.412
EL64	0.580	0.494	0.463	0.417	0.404	0.472
EL65	0.588	0.574	0.442	0.421	0.424	0.490
ES11	0.512	0.481	0.358	0.334	0.325	0.402
ES12	0.636	0.563	0.417	0.394	0.379	0.478
ES13	0.667	0.572	0.432	0.426	0.425	0.504
ES21	0.418	0.366	0.232	0.199	0.184	0.280
ES22	0.457	0.378	0.274	0.254	0.243	0.321
ES23	0.510	0.472	0.278	0.245	0.233	0.348
ES24	0.456	0.420	0.211	0.195	0.190	0.294
ES30	0.422	0.243	0.079	0.052	0.048	0.169
ES41	0.474	0.388	0.209	0.183	0.175	0.286
ES42	0.387	0.303	0.165	0.142	0.132	0.226
ES43	0.390	0.324	0.173	0.154	0.146	0.237
ES51	0.519	0.471	0.361	0.324	0.318	0.399
ES52	0.431	0.411	0.247	0.209	0.194	0.298
ES53	0.657	0.597	0.500	0.480	0.466	0.540
ES61	0.475	0.441	0.245	0.205	0.193	0.312
ES62	0.392	0.341	0.195	0.177	0.166	0.254
ES63	0.335	0.199	0.202	0.145	0.121	0.200
ES64	0.375	0.136	0.118	0.074	0.097	0.160
ES70	0.556	0.401	0.072	0.039	0.040	0.222
HR02	0.361	0.398	0.334	0.295	0.282	0.334
HR03	0.742	0.702	0.640	0.622	0.614	0.664

HR05	0.291	0.250	0.152	0.133	0.122	0.190
HR06	0.378	0.276	0.200	0.182	0.177	0.243
ITC1	0.385	0.357	0.212	0.186	0.176	0.263
ITC2	0.592	0.606	0.356	0.360	0.353	0.453
ITC3	0.542	0.504	0.377	0.348	0.342	0.423
ITC4	0.393	0.352	0.217	0.174	0.160	0.259
ITF1	0.637	0.619	0.474	0.448	0.436	0.523
ITF2	0.601	0.521	0.385	0.436	0.447	0.478
ITF3	0.566	0.530	0.383	0.332	0.320	0.426
ITF4	0.644	0.624	0.539	0.512	0.497	0.563
ITF5	0.626	0.586	0.489	0.447	0.439	0.517
ITF6	0.707	0.656	0.645	0.646	0.608	0.652
ITG1	0.572	0.539	0.410	0.358	0.356	0.447
ITG2	0.688	0.656	0.582	0.555	0.545	0.605
ITH1	0.535	0.548	0.271	0.243	0.243	0.368
ITH2	0.560	0.596	0.344	0.325	0.330	0.431
ITH3	0.551	0.545	0.427	0.386	0.372	0.456
ITH4	0.561	0.538	0.441	0.402	0.377	0.464
ITH5	0.574	0.537	0.454	0.418	0.403	0.477
ITI1	0.566	0.537	0.418	0.370	0.358	0.450
ITI2	0.548	0.480	0.322	0.265	0.237	0.370
ITI3	0.554	0.552	0.493	0.451	0.452	0.500
ITI4	0.458	0.321	0.177	0.119	0.122	0.239
PT11	0.380	0.371	0.229	0.187	0.186	0.271
PT15	0.462	0.485	0.325	0.283	0.280	0.367
PT20	0.402	0.403	0.289	0.274	0.275	0.329
PT30	0.463	0.402	0.151	0.094	0.086	0.239

Note: Gini coefficients of monthly overnight stay distribution, calculated from Eurostat dataset *tour_occ_nin2m*. Island regions shaded. Source: Authors' calculations based on Eurostat data.

Table A4. Sensitivity analysis: fixed effects estimation excluding reference regions.

Variable	β	SE	p
INT (share int. nights)	0.0004	0.0011	0.704
HOT (hotel share)	−0.0044 **	0.0017	0.013
GDP_log (PPS, log)	−0.5019 ***	0.1866	0.009
TI (tourism intensity)	≈0.000	0.000	0.266
COVID (2020–2021 dummy)	0.1369 ***	0.0132	<0.001
R ² (within)	0.810	—	—
N observations/regions	285/57	—	—

Note: Dependent variable: Gini coefficient. FE (within) estimator with cluster-robust standard errors at EU NUTS–2 level, excluding Comunidad de Madrid (ES30), Ciudad de Ceuta (ES63), Ciudad de Melilla (ES64) and Grad Zagreb (HR05). *** $p < 0.01$, ** $p < 0.05$. The direction, magnitude and significance of all coefficients are consistent with the baseline specification (Table 3), confirming that the inclusion of reference regions does not drive the results. Source: Authors' calculations based on Eurostat data.

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