21. Financial integration and European tourism stocks

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1 INTRODUCTION

The investigation of time–varying (dynamic) cross–country sectoral linkages is a highly topical and policy–relevant area of research, with important implications for investments and risk analysis. In particular, investors, risk managers, and financial managers analyze financial assets and sectoral co–movements for asset allocation, portfolio diversification, and hedging purposes (Engle and Colacito, 2006; Engle and Figlewski, 2015). The dynamic interdependence and integration of asset markets are most commonly examined and quantified using multivariate GARCH (MGARCH) models (Christodoulakis and Satchell, 2002; Engle, 2002). Despite the sizeable body of empirical evidence on the dynamic nature of sectoral interlinkages, research on the drivers of the cross–border correlations between industries, such as the tourism sector, is still limited. Understanding the determinants of the integration of tourism equity markets, which were among the most heavily hit sectors during the recent COVID–19 pandemic, is of interest to both tourism agents and policymakers (see, for example, Gogstad et al., 2018, for the European sovereign debt crisis effects on the Greek travel and leisure industry). Higher correlations in economic downturns (with increased volatility and falling returns) lead to systemic risk build–ups and contagion (Martínez–Jaramillo et al., 2010; Ahrend and Goujard, 2014; Caporin et al., 2018). Therefore, tourism managers, investors, and regulators should assess and try to reduce contagious risk spillovers in the travel and leisure industry. In particular, identifying the macro factors affecting sectoral integration can result in more effective tools for reliable risk assessments and prudential policy intervention.

In this context, our study aims to investigate financial integration in the European tourism sector through the dynamic correlations between 11 European tourism industries and to examine the macroeconomic drivers of tourism correlation dynamics at a daily frequency. Specifically, we choose the most advanced MGARCH model for time–varying conditional correlations, namely the Dynamic Equicorrelations (DECO) model of Engle and Kelly (2012), to measure the co–movement of the Travel & Leisure (T&L) sectoral equity indices of Germany, France, Austria, Benelux (Belgium, Netherlands, Luxembourg), United Kingdom, Ireland, Italy, Spain, Greece, Switzerland, and Scandinavia over the two most recent decades (2001–2020). These indices are used as proxies for the tourism market performance in each country and are widely applied as investment benchmarks in the industry. Their correlation patterns can be attributed to common factors related to the macroeconomic environment, alongside cross–border integration, which has become a well–established legacy in globalized markets (Song et al., 2018). Hence, the main novelty and contribution of this study is its thorough analysis of cross–country tourism integration dynamics: first, by unveiling the macro drivers of those correlations and, second, by focusing on the significant role of the uncertainty channel and on the crisis impact on cross–border tourism connectedness.

Motivated by the literature gap on sectoral correlation determinants, our analysis of tourism equicorrelations addresses the issue of the drivers of their time–varying behaviour, mostly associated with economic fluctuations. The economic fundamentals underlying cross–country sectoral dependence are studied at a daily frequency. Such a high frequency of economic news affecting the trajectory of the correlations provides robust evidence on their drivers. Daily correlations, informed by high–frequency shocks from the constantly developing macro context, provide the key instruments for market players monitoring day–to–day correlation dynamics, trading in the financial markets, or supervising and controlling the whole system. By contrast, monitoring market co–movements on the basis of macro shocks with one– or three–month lags (see, for example, the mixed–frequency correlation models in Colacito et al., 2011, 2014) would not be informative about the prompt impact of macro fundamentals on markets. Correlations modeling in the high–frequency macro domain is even more critical during crisis times when the macro environment evolves very quickly.

More specifically, our study provides evidence on the significant impact on tourism correlations of seven factors, that is: (i) economic policy, (ii) financial market uncertainty, (iii) credit (corporate and sovereign), (iv) liquidity conditions, (v) geopolitical risk, (vi) economic activity, and (vii) real estate activity. We find that common European or global macro proxies drive the cross–border sectoral equity correlations, and thus we confirm the presence of integration between tourism stocks. Further, we perform a conditional correlations sensitivity analysis which sheds light on the economic uncertainty effect on the other six macro drivers and on the impact of the three crises included in our 20–year sample. Our results show that policy uncertainty has a direct positive impact on all correlations, and an indirect one through its effect on the other six macro factors. Since recessions are closely connected with the adverse effect of uncertainty concerning economic activity and almost every aspect of the macro environment (Colombo, 2013; Caggiano et al., 2017), it is not surprising that uncertainty should magnify correlations both directly and indirectly. Besides economic uncertainty, higher financial uncertainty, tighter credit and liquidity conditions, and geopolitical turbulence also increase correlations, whereas stronger economic and real estate activity drive correlations down. Therefore there is evidence of counter–cyclical behaviour in the co–movement between tourism markets. The fundamentals corresponding to a real growth effect (activity factors) are estimated to have a negative impact, and the contractionary factors (such as higher uncertainty, tighter credit, shallow liquidity, and geopolitical tensions) to have a positive one instead. Finally, the three crises considered (the 2008 financial turmoil, the European sovereign debt crisis, and the recent COVID–19 pandemic) mostly intensify the macro impact on the evolution of correlations.

To sum up, our contribution to the literature is threefold. Firstly, we are the first to explore European tourism markets correlations with multiple countries at a daily frequency by identifying the common drivers of cross–border interdependence and contagion during crisis periods (most studies on sectoral dependence analyze lower–frequency datasets without investigating the drivers of this dependence – e.g., Balli and Tsui, 2016, estimate monthly volatility spillovers in tourism demand with a bivariate

GARCH model). Secondly, our results on the impact of macro factors and crisis periods on the connectedness of tourism markets extend the academic literature on financial markets' co–movement (Creti et al., 2013; Kalotychou et al., 2014; Karanasos et al., 2016; Karanasos et al., 2018) and on the tourism–economic growth linkages (Wang, 2009; Chen and Chiou–Wei, 2009; Guizzardi and Mazzocchi, 2010; Martins et al., 2017; Perles–Ribes et al., 2017; Brida et al., 2020; Pulido–Fernández and Cárdenas–García, 2021). Thirdly, we shed light on the magnifying effect of uncertainty on tourism sectoral correlations, which had been overlooked by the literature on the tourism–uncertainty link (Dragouni et al., 2016; Demir and Gozgor, 2018; Balli et al., 2018; Tiwari et al., 2019; Madanoglu and Ozdemir, 2019; Demiralay and Kilincarslan, 2019; Wu and Wu, 2019, 2021). We unveil the economic forces that tighten the linkages of tourism markets by applying daily macro variables, and our novel evidence is of interest to both market practitioners and policymakers. Market players mostly monitor daily correlations in investment analysis, portfolio management, and risk assessment, while policymakers will also benefit from a knowledge of high–frequency macro–financial linkages in designing macro– or sector–specific prudential regulation policies during times of market turbulence and systemic risk threats.

The study is structured as follows. The next section reviews the relevant tourism and correlations literature and develops the theoretical hypotheses we test in the empirical part. Section 3 describes the data and methodology. Section 4 presents the main empirical results for the correlation models. Section 5 discusses the sensitivity of the correlation drivers to policy uncertainty and crisis effects. Finally, Section 6 concludes offers some concluding remarks.

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Our literature review focuses on the three main research areas to which we contribute: the relationship between the tourism industry and the economic environment, the tourism–uncertainty link, and cross–border interdependence and integration between markets. The hypotheses tested in the correlations analysis are developed on the basis of the business cycle dynamics, which heavily affect the performance of the tourism industry.

2.1 Literature review

2.1.1 Tourism and the macroeconomy

Tourism research has widely explored the bidirectional relationship between tourism growth and economic growth and development through the well–established hypotheses of tourism–led economic growth and economy–driven tourism growth, mostly using lower than daily–frequency data (monthly/quarterly/annual). Numerous studies have provided evidence on the way tourism growth boosts the economy and on how economic growth contributes to the tourism industry expansion (see, for example, Chatziantoniou et al., 2013; Brida et al., 2020; Pulido–Fernández and Cárdenas–García, 2021, and the literature therein). Goh et al. (2008) forecast tourism demand using macroeconomic variables (see also Gounopoulos et al., 2012). Dogru et al. (2020) study the Airbnb phenomenon and conclude that the Airbnb industry growth is explained by macroeconomic factors such as GDP growth, unemployment, and house prices. Guizzardi and Mazzocchi (2010), using Italian data, show that tourism cycles are mostly determined by lagged effects of the business cycle. Martins et al. (2017) study world tourism demand with data from 218 countries and show that it can be attributed to higher GDP per capita, domestic currency depreciation, and decreases in relative domestic prices (see also Dogru et al., 2017). Becken and Lennox (2012) and Chatziantoniou et al. (2013) investigate the effect of oil price shocks on tourism, while Khan et al. (2005) uncover the trade flows–tourist arrivals link.

Rather interestingly, a considerable number of studies focus on the detrimental effect on tourism of economic/financial crises (e.g., Wang, 2009; Smeral, 2010; Cró and Martins, 2017; Perles–Ribes et al., 2017) and terrorism (e.g., Arana and León, 2008; Corbet et al., 2019). Most recently, Sigala (2020), Higgins–Desbiolles (2021), Gallego and Font (2021), and Ozdemir et al. (2022), among others, discuss the COVID–19 pandemic effects on the travel and tourism industry, and Farzanegan et al. (2021) show how higher tourism flows increase the spread of the virus (and thus the number of cases and the death toll). Barrows and Naka (1994) were the first to explain tourism sectoral stock returns with macro aggregates focusing on hospitality stocks in a monthly–frequency context. Thereafter, a large literature followed using mostly monthly data for returns and macro variables (Chen et al., 2005; Singal, 2012; Chen, 2015). To the best of our knowledge, although researchers have explored the relationship between tourism and macro aggregates, there are no studies connecting cross–country co–movement of tourism metrics (tourism demand, supply, or industry performance) with economic fundamentals.

2.1.2 Tourism and uncertainty

Given the widely examined interaction of tourism with the macro environment and crisis events (economic/health/terrorist), a significant number of studies focus on the uncertainty affecting the tourism industry. This has normally been proxied by macro variables dispersion (e.g., GARCH conditional variance), financial uncertainty (financial markets implied volatility, e.g., VIX), economic policy uncertainty (EPU), and geopolitical risk (GPR). Chen and Chiou–Wei (2009) were the first to measure the influence of the uncertainty factor (estimated as the conditional variance of tourism and economic growth) on both tourism and economic growth through an EGARCH–M model. More recent studies, including the present one, use the news–based EPU index, which is the only daily uncertainty metric provided by Baker et al. (2016) and is also the most comprehensive one, including both economic and policy–related aspects of uncertainty. GPR is a news–based metric for geopolitical uncertainty developed by Caldara and Iacoviello (2018). Tiwari et al. (2019) investigate simultaneously the EPU and GPR effects on tourist arrivals, while Demiralay and Kilincarslan (2019) regress T&L sectoral index returns on GPR and VIX (financial uncertainty) alongside oil and crisis factors In a monthly context with quantile regressions. The EPU's damaging impact on the performance of the tourism industry (measured by arrivals/demand, hotel occupancy, income/receipts, investments, or sectoral stocks) is estimated using monthly and annual datasets for single or multiple countries/areas/continents by Dragouni et al. (2016), Demir and Gozgor (2018), Balli et al. (2018), Madanoglu and Ozdemir (2019), Wu and Wu (2019, 2021), Akron et al. (2020), and Kuok et al. (2023), among others. However, the EPU influence on tourism correlations is not addressed by the literature for any country combination, frequency, or tourism metric.

2.1.3 Market interdependence

Starting from the nineties, the globalization process has rapidly evolved, with markets becoming tightly interdependent and integrated. The investigation of market returns and volatility linkages is crucial for managers and regulators for risk assessment purposes. The MGARCH family of models contributes to our understanding of the time–varying volatility co–movement among markets (see, for example, the dynamic correlations models of Christodoulakis and Satchell, 2002; Engle, 2002; Cappiello et al., 2006; Engle and Kelly, 2012). The correlations computed can be used to quantify the interconnectedness of stock markets (Karanasos et al., 2016), bond markets (Blatt et al., 2015), commodities (Karanasos et al., 2018), different asset classes (Creti et al., 2013), and sectoral indices (Kalotychou et al., 2014). The literature has estimated correlations across regions or sectors for single or multiple asset classes and industries, but the evidence on the drivers of the dynamic correlations is still scant. One of the few relevant studies is due to Kocaarslan and Soytas (2019), who investigate cross–asset dynamic conditional correlations (oil–sectoral stocks), regressing the pairwise dynamic conditional correlation (DCC) series on relevant macro–financial variables. The correlation drivers considered are the default, term, and TED spread, foreign exchange rates, policy rates, and crisis dummies with positive and significant estimated coefficients in most cases, except for the term spread, which is mostly insignificant. More recently, Karanasos and Yfanti (2021) examine the macro drivers of cross–asset (equities–commodities–real estate) equicorrelations using the DECO model and provide a systematic analysis of both low– (monthly) and high– (daily) frequency economic fundamentals which influence the correlations. Regarding tourism sectoral dependence, Balli and Tsui (2016) estimate monthly tourism demand spillovers among Australia and New Zealand with a bivariate GARCH specification. Our analysis complements the tourism sectoral correlations research by using the daily T&L index series as proxies for the tourism industry performance in different countries, and by attributing their counter–cyclical correlation dynamics to high–frequency macro fundamentals.

2.2 Hypotheses development

Following the few studies on high–frequency (daily) financial connectedness determinants (Kocaarslan and Soytas, 2019; Karanasos and Yfanti, 2021), we select the daily macro–financial variables which thoroughly nowcast the business cycle dynamics (see Section 3.2 for a detailed description of the macro–financial variables used). Accordingly, we test three theoretical hypotheses (*H1*, *H2*, *H3*) on the influence of the macro proxies on dynamic cross–border tourism equicorrelations.

H1 *Cross–border tourism correlations are higher during business cycle downturns.*

On the basis of the empirical evidence of higher financial correlations during economic slowdowns, we expect contractionary macro forces to drive tourism correlations higher. We choose eight daily macro variables that best characterize the global economic context of the European T&L sector. The chosen variables are proxies for macro fundamentals similar to the ones widely used by studies on the relationship between tourism with macro aggregates and uncertainty (see Sections 2.1.1 and 2.1.2). Our tourism correlation determinants cover most aspects of the macro environment where the T&L industries operate, that is, typical features of the business cycle such as uncertainty, credit, liquidity, and activity dynamics. The significant regressors explaining the evolution of the T&L correlations include the uncertainty factor, given its well–known detrimental effect on the macro environment (Bloom 2009, 2014). Two types of uncertainty are considered: economic policy (Baker et al., 2016) and financial market (Bekaert et al., 2013) uncertainty. The credit channel is captured by the corporate (corporate bond yields) and sovereign (treasury bond yield volatility) credit stance, while the liquidity conditions are proxied by the TED spread (the difference between short–term money market and treasury rates). Higher corporate credit risk pricing, proxied by higher bond yields, and increased sovereign credit market turbulence, captured by the implied volatility of treasuries, are observed during economic slowdowns (see, for example, Gilchrist and Zakrajšek, 2012). Higher TED spreads indicate lower market liquidity, a common characteristic of contraction periods (Ng, 2012). We also incorporate the geopolitics effect since geopolitical tensions can slow down economic growth (Caldara and Iacoviello, 2018). Lastly, activity dynamics driving economic fluctuations are proxied by the aggregate activity predictor (the term spread) and the real estate index (Hotel and Lodging real estate activity), which is more specific to the tourism sector development. A lower slope of the Treasury yield curve (the so–called term spread calculated as the difference between the yield on ten–year and three–month government bonds) denotes an economic slowdown (see Estrella and Mishkin, 1997), similarly to a low real estate activity indicator. The first hypothesis predicts that higher uncertainty, tighter credit and liquidity, geopolitical threats, and lower activity will raise tourism correlations since they represent economic contractionary forces. Hence, under *H1*, the sign of the macro impact on sectoral markets' interdependence should be positive for regressors that increase during weaker economic periods (uncertainty, tight credit and liquidity, geopolitics) and negative for the factors that decrease during economic slowdowns (activity).

H2 *The economic uncertainty channel intensifies the macro impact on cross–border tourism correlations.*

Our second hypothesis is based on the important role of EPU for the whole macro environment. Pastor and Veronesi (2013) were the first to demonstrate the indirect EPU impact on financial correlations by providing evidence that the negative activity effect on stock co–movements is partly driven by higher EPU. Thus, we anticipate that the positive and negative macro influences are magnified or partly explained by higher EPU levels. The economic uncertainty channel amplifies economic forces associated with business cycle downturns (Pastor and Veronesi, 2013; Colombo, 2013; Caggiano et al., 2017). Therefore, *H2* tests the indirect magnifying EPU impact on tourism correlations through the other seven macro–financial variables (financial uncertainty, corporate and sovereign credit, liquidity, geopolitics, aggregate, and real estate activity).

H3 *The macro impact on cross–border tourism correlations is magnified during crisis periods.*

The third hypothesis postulates that crisis shocks increase sectoral correlations by increasing the macro effects on interdependence between markets. As argued in the contagion literature (Forbes and Rigobon, 2002; Akay et al., 2013; Karanasos et al., 2016; Caporin et al., 2018), during crisis periods, economic fundamentals, acting as contagion transmitters, exert a stronger influence on correlations. Hence, under *H3*, we expect that financial and health crises should enhance the positive effects of macro drivers on tourism correlations.

In brief, all three theoretical hypotheses we test are consistent with the available evidence on tighter market linkages under weaker economic conditions (counter–cyclicality) which are associated with business cycle downturns (*H1*), higher EPU levels (*H2*) and crisis shocks (*H3*).

3 METHODOLOGY AND DATASET

The aim of the analysis is to unveil the determinants of cross–border correlations in the European tourism sector and to explore the impact of economic uncertainty and crisis shocks on the trajectory of the correlations. First, we estimate the time–varying correlations, and, second, we regress them on the macro variables. Following Karanasos and Yfanti (2021), we apply the GJR–MGARCH–DECO model. Our multivariate specification consists of the GJR–GARCH with leverage of Glosten et al. (1993) for the conditional variance of daily T&L sectoral index returns and the Dynamic Equicorrelations of Engle and Kelly (2012), which is used to calculate the pairwise correlations among the 11 index returns (see the discussion on the superiority of this approach relative to other DCC and GARCH variants in Karanasos and Yfanti, 2021). In this section, first we present the GJR–MGARCH–DECO specification estimated for all combinations of the 11 European sectoral index returns under investigation. Next, we provide details of the regression analysis of the correlations against uncertainty, credit and liquidity, activity, real estate, and geopolitics (DECO–X), and describe the dataset.

3.1 The econometric specification

3.1.1 The dynamic correlation model

Following Karanasos and Yfanti (2021) and Yfanti et al. (2023), the first estimation step consists of computing the dynamic pairwise equicorrelations between the T&L sectoral index returns of the 11 countries/country groups. The corresponding pairs of daily returns are modeled through the GJR–MGARCH–DECO bivariate specification. In line with Karanasos et al. (2016), we define the N–dimensional column vector of returns $\boldsymbol{r_t}$ as $\boldsymbol{r_t} = [r_{it}]_{i=1,\dots,N}$ (in what follows, we will drop the subscript) and the respective residual vector $\boldsymbol{\varepsilon_t}$ as $\boldsymbol{\varepsilon_t} = [\varepsilon_{it}]$. The mean equation is estimated as follows:

$$r_{it} = \phi_i + \varepsilon_{it}, \; i = 1,\dots,N \tag{1}$$

where $\boldsymbol{\phi} = [\phi_i]$ is the $N \times 1$ vector of constants. The bivariate combination is given by

$$\begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix} = \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

The cDCC–GARCH model can be thought of as a *double* MGARCH type of model. To see this explicitly, we will consider two sets of errors, that is: ε_{it} in eq. (1) and e_{it} (see eq. (5) below).

The conditional variances

Regarding ε_{it} in eq. (1), we assume that it is conditionally (on the information at time $t-1$, set $\mathcal{F}_{t-1}$) normally distributed with mean zero and conditional covariances $h_{ij,t}$, that is $h_{ij,t} = \mathbb{E}\left(\varepsilon_{it}\varepsilon_{jt} \mid \mathcal{F}_{t-1}\right)$. It follows that the corresponding conditional correlations, $\rho_{ij,t}, \mid \rho_{ij,t} \mid \leq 1 \mid (i,j = 1,\ldots,N)\ \forall\ t$, are given by:[1]

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}}. \tag{2}$$

Note that ε_{it} can be expressed as: $\varepsilon_{it} = \sqrt{h_{it}}\,\tilde{\varepsilon}_{it}$, where $h_{it} \stackrel{\text{def}}{=} h_{ii,t}$. In other words, the $\tilde{\varepsilon}_{it}$ are the *devolatilized* errors: $\tilde{\varepsilon}_{it} = \varepsilon_{it}/\sqrt{h_{it}}$. It is straightforward to show that the conditional correlations of $\tilde{\varepsilon}_{it}$'s are also $\rho_{ij,t}$, that is $\rho_{ij,t} = \mathbb{E}\left(\tilde{\varepsilon}_{it}\tilde{\varepsilon}_{jt} \mid \mathcal{F}_{t-1}\right)$.

Next, the structure of the conditional variance is specified as in Glosten et al. (1993). That is, each conditional variance follows a GJR–GARCH(1,1) model:

$$(1-\beta_i L)\sigma_{ii,t} = \omega_i + (\alpha_i + \gamma_i s_{i,t-1})L\left(\varepsilon_{it}^2\right),\ i = 1,\ldots,N, \tag{3}$$

where $\omega_i \in (0,\infty)$ and $s_{it} = 0.5\left[1-\text{sign}\left(\varepsilon_{it}\right)\right]$, that is, $s_{it} = 1$ if $\varepsilon_{it} < 0$ and 0 otherwise for all i. Therefore, a positive γ_i indicates a larger contribution of negative shocks to the volatility process.

The conditional correlations

To estimate the conditional correlations, we introduce a new set of errors, e_{it}, that i) are conditionally normally distributed with mean zero and conditional covariances $q_{ij,t}$, that is $q_{ij,t} = \mathbb{E}\left(e_{it}e_{jt} \mid \mathcal{F}_{t-1}\right)$, and ii) can be expressed as $e_{it} = \sqrt{q_{ii,t}}\,\tilde{\varepsilon}_{it}$. It is straightforward to show that the conditional correlations of e_{it}'s are also $\rho_{ij,t}$:[2]

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}. \tag{4}$$

Moreover, according to the corrected DCC(1,1) model of Engle (2002) – that is, the cDCC of Aielli (2013) – the structure of $q_{ij,t}$ is given by

$$q_{ij,t} = (1-a-b)\,q_{ij} + a\,e_{i,t-1}\,e_{j,t-1} + b\,q_{ij,t-1}, \tag{5}$$

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[1] Most importantly, we allow for time–varying correlations, $\rho_{ij,t}$, instead of the constant ones, ρ_{ij}, defined by Bollerslev (1990). In particular, $\boldsymbol{R_t} = \left[\rho_{ij,t}\right]_{i,j=1,\ldots,N}$ (in what follows we will drop the subscript) is the $N \times N$ symmetric positive semi–definite time–varying correlation matrix with ones on the diagonal ($\rho_{ii,t} = 1$) and the off–diagonal elements less than one in absolute value.

[2] In particular, we have:

$$q_{ij\cdot t} = \mathbb{E}\left(e_{it}e_{jt} \mid \mathcal{F}_{t-1}\right) = \sqrt{q_{ii\cdot t}}\sqrt{q_{jj\cdot t}}\,\mathbb{E}\left(\tilde{\varepsilon}_{it}\tilde{\varepsilon}_{jt} \mid \mathcal{F}_{t-1}\right) = \sqrt{q_{ii\cdot t}}\sqrt{q_{jj\cdot t}}\,\rho_{ij\cdot t} \Rightarrow \rho_{ij\cdot t} = \frac{q_{ij\cdot t}}{\sqrt{q_{ii\cdot t}}\sqrt{q_{jj\cdot t}}}.$$

where $q_{ij} = \mathbb{E}\left(q_{ij,t}\right)$, a and b are nonnegative scalar parameters satisfying $a + b < 1$. Engle (2002) specifies the conditional correlations as a weighted sum of past correlations since the $q_{ij,t}$'s are written as GARCH processes and then transformed into correlations.

In the bivariate case, the cDCC(1,1) conditional correlation coefficient $\rho_{12,t}$ is expressed as follows:

$$\rho_{12,t}^{DCC} = \frac{q_{12,t}}{\sqrt{q_{11,t}}\sqrt{q_{22,t}}}, \tag{6}$$

$$\begin{aligned} q_{12,t} &= (1 - a - b)\, q_{12} + a\, e_{1,t-1} e_{2,t-1} + b q_{12,t-1}, \\ q_{11,t} &= (1 - a - b)\, q_{ij} + a e_{1,t-1}^2 + b q_{11,t-1}, \\ q_{22,t} &= (1 - a - b)\, q_{ij} + a e_{2,t-1}^2 + b q_{22,t-1}. \end{aligned}$$

To summarize, the model in the first step estimates the vector of the errors, $\boldsymbol{\varepsilon_t} = \left[\varepsilon_{it}\right]$, and the vector of the conditional variances, $\boldsymbol{h_t} = \left[h_{it}\right]$, using a GJR–GARCH, and the corresponding vector of the devolatilized errors $\boldsymbol{\tilde{e}_t} = \left[\tilde{e}_{it}\right]$, since $\tilde{e}_{it} = \varepsilon_{it}/\sqrt{h_{it}}$. In the second step, it estimates the matrix of the conditional covariances of the vector of the errors $\boldsymbol{e_t} = \left[e_{it}\right]$, that is $\boldsymbol{Q_t} = \left[q_{ij,t}\right]$, using a cDDC–GARCH process. Once $\boldsymbol{h_t}$ and $\boldsymbol{Q_t}$ are estimated, then estimates of the elements of $\boldsymbol{R_t}$ (the conditional correlations of the errors, either $\boldsymbol{e_t}$ or $\boldsymbol{\tilde{e}_t}$ or $\boldsymbol{\varepsilon_t}$) are obtained using eq. (4), and then the estimated non–diagonal elements of $\boldsymbol{H_t} = \left[h_{ij,t}\right]$ are obtained using eq. (2).[3]

For computational ease, Engle and Kelly (2012) impose a critical assumption on the calculation of $\boldsymbol{R_t^{DCC}} = \left[\rho_{ij,t}^{DCC}\right]$ model in order to estimate dynamic equicorrelation matrices. Each pair of returns should have the same correlation, that is ρ_t^{DECO}. In the DECO model, the $q_{ij,t}$ are computed by the cDCC of Aielli (2013). In general, for $N > 2$, the DECO(1,1) correlation matrix is defined as follows:

$$\boldsymbol{R_t^{DECO}} = \left(1 - \rho_t^{DECO}\right) \boldsymbol{I_N} + \rho_t^{DECO} \boldsymbol{J_N}, \tag{7}$$

$$\rho_t^{DECO} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}, \tag{8}$$

where $\boldsymbol{J_N}$ the $N \times N$ matrix of ones.

Finally, in the special case of a bivariate specification with assets $N = 2$, the dynamic equicorrelation, ρ_t^{DECO}, equals the cDCC–computed dynamic correlations.

3.1.2 The correlations regression specification

The second step of our empirical analysis consists of the regression of the daily dynamic equicorrelations (computed through the DECO model of the first step) on the macro drivers of the cross–country sectoral correlations evolution (DECO–X). The Fisher transformation of correlations is first applied to unbind the correlations from the $[-1,1]$ interval. The resulting daily time series $Corr_t$ is calculated as follows: $Corr_t = \log\left(\frac{1+\rho_t^{DECO}}{1-\rho_t^{DECO}}\right)$. For each sectoral index, we compute the average pairwise equicorrelation series of the particular index with the other ten indices. For example, the DECO

[3] A heuristic proof of the consistency of the cDCC estimator is provided in Aielli (2013); see the discussion in its section 3.2.

model for Germany yields ten pairwise correlation series with the other ten countries/country groups. Therefore, we calculate the average dynamic correlation time series from the ten bivariate combinations of each index with the others, which results in 11 equicorrelations as dependent variables in the DECO–X equation ($Corr_t$). Apart from the bivariate specifications, we run the multivariate model with all 11 indices, where the DECO specification calculates the dynamic equicorrelations series considering all pairwise cross–country sectoral correlations.

Moreover, each country's/country group's daily correlations $Corr_t$ with the other ten indices are regressed on the daily proxies for economic policy (EPU_t) and financial (FU_t) uncertainty, corporate (CCR_t) and sovereign (SCR_t) credit conditions, liquidity conditions (LIQ_t), geopolitical risk (GPR_t), economic activity (EC_t), and real estate activity (RE_t). The selected regressors are tested for their first–lag effect on the correlations. In the time series regression context, we apply a stepwise algorithm that tests all causal effects and selects the best model according to the significance of the coefficients, the adjusted R^2 ($\overline{R}^2$) and the information criteria (IC: AIC and BIC are the Akaike and the Schwartz Information Criteria, respectively). Furthermore, the first autoregressive lag, $Corr_{t-1}$, is used to remove any serial correlation from the model. To sum up, we address our main research question on the macro determinants of cross–country tourism correlations' evolution and test *H1* by estimating the following equation for each correlation series:

$$\begin{aligned} Corr_t = {} & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} + c_3 FU_{t-1} + c_4 CCR_{t-1} + c_5 SCR_{t-1} \\ & + c_6 LIQ_{t-1} + c_7 GPR_{t-1} + c_8 EC_{t-1} + c_9 RE_{t-1} + u_t, \end{aligned} \tag{9}$$

where c_0 is a constant, and u_t the standard stochastic error term.

3.1.3 Equicorrelations sensitivity analysis

After exploring the macro drivers of the time–varying connectedness between European tourism industries, we investigate the uncertainty (*H2*) and crisis (*H3*) impact on the determinants of the correlation dynamics. The sensitivity of the macro–financial regressors to EPU levels is measured by adding the EPU interaction terms (multiplying the EPU variable with each macro regressor other than policy uncertainty) in the correlation regression model (eq. (9)). Thus, we estimate the following regression equation, eq. (10), where the superscript^{EPU} denotes the coefficients of the EPU interaction terms:

$$\begin{aligned} Corr_t = {} & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} + c_3 FU_{t-1} + c_3^{EPU} EPU_{t-1} FU_{t-1} \\ & + c_4 CCR_{t-1} + c_4^{EPU} EPU_{t-1} CCR_{t-1} + c_5 SCR_{t-1} + c_5^{EPU} EPU_{t-1} SCR_{t-1} \\ & + c_6 LIQ_{t-1} + c_6^{EPU} EPU_{t-1} LIQ_{t-1} + c_7 GPR_{t-1} + c_7^{EPU} EPU_{t-1} GPR_{t-1} \\ & + c_8 EC_{t-1} + c_8^{EPU} EPU_{t-1} EC_{t-1} + c_9 RE_{t-1} + c_9^{EPU} EPU_{t-1} RE_{t-1} + u_t, \end{aligned} \tag{10}$$

Then, we focus on the financial and health crisis impact on the tourism industry interdependence. We distinguish between three crisis periods: the Global Financial crisis (GFC), the European Sovereign Debt crisis (ESDC, ESDC_A, and ESDC_B), and the COVID–19 pandemic (COVID) and expand eq. (9) by adding slope dummies corresponding to each crisis period. the GFC, Given ESDC, and COVID timelines, we construct the corresponding crisis dummies $d_{CRISIS,t}$, with $CRISIS = GFC, ESDC, ESDC\_A, ESDC\_B, COVID$, as follows:

- $d_{GFC,t} = 1$, if t in the GFC period, else $d_{GFC,t} = 0$
- $d_{ESDC,t} = 1$, if t in the ESDC period, else $d_{ESDC,t} = 0$
- $d_{ESDC\_A,t} = 1$, if t in the first ESDC period, else $d_{ESDC\_A,t} = 0$
- $d_{ESDC\_B,t} = 1$, if t in the second ESDC period, else $d_{ESDC\_B,t} = 0$
- $d_{COVID,t} = 1$, if t in the COVID period, else $d_{COVID,t} = 0$.

Next, we multiply the crisis dummies with the macro variables to obtain the slope dummies for the respective macro effect and include them in eq. (9). The correlations regression with the crisis influence is estimated as follows:

$$\begin{aligned}Corr_t = {} & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} + c_2^{CRISIS} d_{CRISIS,t-1} EPU_{t-1} \\ & + c_3 FU_{t-1} + c_3^{CRISIS} d_{CRISIS,t-1} FU_{t-1} + c_4 CCR_{t-1} + c_4^{CRISIS} d_{CRISIS,t-1} CCR_{t-1} \\ & + c_5 SCR_{t-1} + c_5^{CRISIS} d_{CRISIS,t-1} SCR_{t-1} + c_6 LIQ_{t-1} + c_6^{CRISIS} d_{CRISIS,t-1} LIQ_{t-1} \\ & + c_7 GPR_{t-1} + c_7^{CRISIS} d_{CRISIS,t-1} GPR_{t-1} + c_8 EC_{t-1} + c_8^{CRISIS} d_{CRISIS,t-1} EC_{t-1} \\ & + c_9 RE_{t-1} + c_9^{CRISIS} d_{CRISIS,t-1} RE_{t-1} + u_t, \end{aligned} \tag{11}$$

where $CRISIS = GFC, ESDC, ESDC\_A, ESDC\_B, COVID$ and the superscript^{CRISIS} denotes the coefficients of the crisis slope dummies.

Finally, we combine the EPU index with the crisis impact to estimate the uncertainty effect on each macro regressor during crisis periods separately. The in–crisis EPU impact on the correlation dynamics is captured by the coefficients with the superscript $^{EPU\_CR}(CR = GFC, ESDC, ESDC\_A, ESDC\_B, COVID)$ in the following equation:

$$\begin{aligned}Corr_t = {} & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} \\ & + c_3 FU_{t-1} + c_3^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} FU_{t-1} \\ & + c_4 CCR_{t-1} + c_4^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} CCR_{t-1} \\ & + c_5 SCR_{t-1} + c_5^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} SCR_{t-1} \\ & + c_6 LIQ_{t-1} + c_6^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} LIQ_{t-1} \\ & + c_7 GPR_{t-1} + c_7^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} GPR_{t-1} \\ & + c_8 EC_{t-1} + c_8^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} EC_{t-1} \\ & + c_9 RE_{t-1} + c_8^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} RE_{t-1} + u_t. \end{aligned} \tag{12}$$

3.2 Data description

Next, we describe the data used for the European tourism industry performance and the macro–financial variables driving the cross–country sectoral correlations. We analyze daily index prices from 11 European Travel & Leisure sectoral equity indices considered as benchmarks for the performance of the tourism industry in each country/country group. Our tourism benchmarks, obtained from Refinitiv Eikon Datastream, cover the T&L stock market sectors of Germany (DE), France (FR), Austria (AT), Benelux (Belgium, Netherlands, Luxembourg – BNL), United Kingdom (UK), Ireland (IRE), Italy (IT), Spain (ES), Greece (GR), Switzerland (SW), and Scandinavia (SC).[4] Our sample covers the period from 01/01/2001 to 20/05/2020, that is, it includes 5,057 daily observations. For each sectoral index, we calculate the continuously compounded return as follows: $r_{it} = \left[\ln\left(P_{it}^{C}\right) - \ln\left(P_{i,t-1}^{C}\right)\right] \times 100$, with P_{it}^{C} being the daily closing price of day t.

The summary statistics and unit root tests of the return series are reported in the Appendix, Table A21.1. The Augmented Dickey–Fuller (ADF) test rejects the unit root hypothesis. Thus, our dependent variables, given their leptokurtic characteristics (skewness and kurtosis values) as well, are suitable for the GJR–GARCH variance specification used in this study. The pairwise correlation coefficients of all bivariate combinations of returns (Table 21.1) are positive, which indicates strong co–movement of the European tourism sectors. The highest correlation value (0.731) is calculated for the France–United Kingdom pair and the lowest (0.141) for Greece–Austria. The DECO model will reveal the time–varying feature of conditional correlations and the macro influence on the correlation dynamics.

The daily macro factors used as regressors in the equicorrelations regressions (equations (9), (10), (11), and (12)) provide evidence of the global macro effects on the evolution of the European tourism correlations:

Table 21.1 Correlation coefficients of T&L index returns

	DE	FR	AT	BNL	UK	IRE	IT	ES	GR	SW	SC
DE	1										
FR	0.611	1									
AT	0.196	0.239	1								
BNL	0.257	0.302	0.141	1							
UK	0.591	0.731	0.277	0.390	1						
IRE	0.430	0.462	0.174	0.226	0.564	1					
IT	0.464	0.563	0.215	0.267	0.530	0.366	1				
ES	0.527	0.621	0.232	0.312	0.611	0.416	0.495	1			
GR	0.240	0.291	0.141	0.169	0.293	0.163	0.254	0.268	1		
SW	0.321	0.359	0.150	0.201	0.350	0.222	0.282	0.327	0.159	1	
SC	0.349	0.417	0.186	0.319	0.452	0.309	0.329	0.373	0.193	0.262	1

Note: The table reports the pairwise correlation coefficients for each pair of T&L index returns series.

[4] The T&L equity indices are constructed by Refinitiv Eikon Datastream as benchmarks of the sector. They include the T&L listed companies on each country's stock exchange. The country selection is based on data availability, as T&L equity index data are not available for all European countries for a long period covering all three crises under consideration in the current study.

- Economic policy uncertainty (EPU_t) is proxied by the daily US EPU index in its log–level form. Baker, Bloom, and Davis (www.policyuncertainty.com) construct EPU indices with a daily frequency for the US and the UK. We consider the US index as a global factor for our European cross–country sectoral correlation study.
- Financial uncertainty (FU_t) is proxied by the Euro Stoxx 50 implied volatility index VSTOXX ($VSTOXX_t$) included in the first difference of its log–levels.
- Corporate credit conditions (CCR_t) are proxied by the first difference of Moody's BAA global corporate bond yields levels (BAA_t).
- Sovereign credit conditions (SCR_t) are proxied by the log–level of the Merrill Lynch MOVE 1–month index ($MOVE_t$), which quantifies the Option Implied Volatility of US Treasury bonds. It captures the sovereign credit market stance. Higher sovereign bond volatility denotes increased turbulence in the credit channel for sovereigns with a direct pass–through to the credit conditions of financial and non–financial corporations.
- Liquidity conditions (LIQ_t) are measured by the TED spread (TED_t), a proxy for liquidity conditions and perceived credit risk in the financial system, calculated as the daily difference between the 3–month Euribor and the 3–month German Treasury bill.
- Geopolitical risk (GPR_t) is measured using the daily global Geopolitical Risk index (log–level) of Caldara and Iacoviello (2018) downloaded from Iacoviello's website (www.matteoiacoviello.com/gpr).
- Economic activity (EC_t) is proxied by the first difference of the German Yield Curve slope (or term spread), computed as the difference between the ten–year and the three–month German Treasury bond yields ($YCsl_t$). This variable has been shown to be a powerful predictor of economic activity (Estrella and Mishkin, 1997).
- Real estate activity (RE_t) in the tourism sector is proxied by the European Hotel and Lodging REITs index ($REIT_t$), calculated by Datastream and included in the first difference of its log–levels.

The regressors used cover all major aspects of the macro environment in which the tourism industry operates: economic agents' uncertainty, credit and liquidity conditions, geopolitics, and aggregate activity indicators. The macro–financial variables data (except for EPU_t and GPR_t) are also obtained from Refinitiv Eikon Datastream for the same sample as the dependent variables (T&L data). Only the GPR index sample is shorter, from 01/01/2001 to 11/03/2020, being available only for that period on Iacoviello's website. Therefore, first we run the DECO–X regressions with seven out of eight macro regressors, excluding the GPR variable, and report the correlation regression results for the full sample up to May 2020. Second, we estimate the same equations with all eight macro factors and report only the GPR coefficient for the shorter sample separately. The exogenous macro variables are included in their level (TED_t), log–level (EPU_t, $MOVE_t$, GPR_t), first difference of the levels (BAA_t, $YCsl_t$) or first difference of the log–levels ($VSTOXX_t$, $REIT_t$) as indicated above in order to ensure that there are no multicollinearity or unit roots in the regressors, and also to select the form with the most significant effect on equicorrelations. Table A21.2 (in the Appendix) reports the summary statistics of the independent variables in the DECO–X equations, with the ADF test rejecting the unit root hypothesis for all regressors.

Finally, in the sensitivity analysis of the cross–country tourism sectoral correlations, we use the GFC, ESDC, and COVID crisis timelines as defined by the Bank for International Settlements and the Federal Reserve Bank of St. Louis (for GFC), the European Central Bank (for ESDC), and the World Health Organization (for COVID). The crisis periods are as follows:

- GFC: 9/8/2007–31/3/2009. The GFC starts with the suspension of major BNP Paribas investment funds and finishes in 2009 with a gradual return to "calm" in the markets.
- ESDC: 9/5/2010–31/7/2015. The ESDC starts with the Greek state default and bailout in 2010. For most of the Euro–zone the ESDC finished at the end of 2012 (ESDC_A, first ESDC subperiod), while for Greece sovereign debt turbulence persisted until July 2015 (ESDC_B, second ESDC subperiod). Therefore, we distinguish between two ESDC subperiods: the first (ESDC_A): 09/05/2010–31/12/2012 and the second (ESDC_B): 01/01/2013–31/07/2015.
- COVID: 9/1/2020–20/5/2020. The COVID period begins with the first death in China in January 2020 and it continues until the end of the sample.

During crisis times, the whole macro environment weakens, with uncertainty increasing, credit and liquidity conditions tightening, economic and real estate activity contracting, or even slumping sharply. Table 21.2 shows the time variation of the mean value for each macro variable used across the crisis subsamples. The EPU index log–level is higher on average during all crises, apart from the second ESDC period, and jumps sharply during the recent pandemic. Financial uncertainty growth is at its highest in the GFC period and also jumps sharply during the recent COVID period. Credit conditions tightening is mostly observed during the global financial turmoil of 2008, with higher growth of corporate lending cost and higher treasury volatility on average. The German TED spread is significantly higher during the GFC, the first ESDC period, and the COVID period, which indicates lower liquidity in financial markets. Economic and real estate activity growth decreases during crises, while geopolitical risk is highest during the recent

Table 21.2 Time series mean of macro regressors across the crisis subsamples

Macro effects	Macro variables	total sample	GFC	ESDC	ESDC_A	ESDC_B	COVID
EPU_t	EPU_t	1.930	2.054	2.002	2.142	1.858	2.375
FU_t	$VSTOXX_t$	0.000	0.002	–0.001	–0.001	0.000	0.008
CCR_t	BAA_t	–0.001	0.004	–0.001	–0.002	0.001	0.000
SCR_t	$MOVE_t$	1.921	2.146	1.883	1.923	1.842	1.864
LIQ_t	TED_t	0.305	0.932	0.391	0.599	0.178	0.258
GPR_t	GPR_t	1.940	1.782	1.828	1.728	1.930	2.096
EC_t	$YCsl_t$	0.000	–0.005	–0.001	–0.002	–0.001	–0.003
RE_t	$REIT_t$	0.000	–0.002	0.000	0.000	0.000	–0.005

Note: The table reports the mean value of each macro variable time series across the crisis subsamples vs. the total sample mean.

pandemic. We provide below further evidence that during crises cross–country tourism correlations are higher and the effects of macro drivers become more intense, being partly driven by uncertainty.

4 ESTIMATION RESULTS

4.1 The DECO estimation

MGARCH models with time–varying correlations provide the necessary tools for understanding the linkages between financial volatilities. Hence, we explore the dynamic cross–country sectoral correlations for the 11 European tourism industries through the GJR–MGARCH(1,1)–DECO(1,1) model. In particular, we estimate all bivariate combinations of the daily index returns and the multivariate specification with all 11 indices included. Moreover, we regress the correlations (average per country/country group) computed by the DECO model on daily macro factors.

Table 21.3 reports the univariate mean and variance models estimated for each country. The DECO estimation is a two–step procedure where, in the first step, the mean and variance equations are estimated, while the second step consists of estimating the conditional equicorrelations. Therefore, the mean and conditional variance equations of each index are identical in all bivariate specifications where the index is included. In the conditional variance GJR specification, the asymmetry coefficient (γ_i) is always positive and significant, which denotes the larger contribution of negative shocks to the volatility process, with the highest γ_i estimated for the UK. The variance of the Greek T&L sector exhibits the highest persistence, which is computed as $\left(\alpha_i + \beta_i + \frac{\gamma_i}{2}\right)$. The correlation equation, estimated with all 11 T&L indices included, gives an average overall conditional

Table 21.3 GJR–MGARCH–DECO estimation results

Panel A. Mean and Variance equations

	Mean equation	Variance equation					
	ϕ_i	ω_i	α_i	β_i	γ_i	$logL$	Q_{12}
DE	0.0042	0.0676***	0.0379***	0.9175***	0.0488***	–9930.55	10.84
	(0.18)	(2.97)	(3.03)	(46.90)	(3.70)		[0.54]
FR	0.0154	0.0307***	0.0069	0.9184***	0.1105***	–8133.41	13.81
	(1.00)	(4.93)	(0.88)	(74.95)	(6.91)		[0.31]
AT	0.0476	0.2873***	0.0807***	0.8446***	0.0731***	–11396.6	9.96
	(1.49)	(3.00)	(4.48)	(24.02)	(2.61)		[0.62]
BNL	0.0531***	0.1306***	0.0664***	0.8559***	0.0502***	–9041.21	15.49
	(2.71)	(2.40)	(2.63)	(23.22)	(2.42)		[0.22]
UK	0.0365***	0.0301***	0.0183**	0.8873***	0.1405***	–7240.83	17.76
	(2.81)	(4.31)	(2.05)	(51.69)	(5.59)		[0.12]
IRE	0.0717***	0.0223***	0.0163*	0.9521***	0.0477***	–9190.12	16.11
	(3.78)	(2.13)	(1.85)	(79.23)	(3.26)		[0.19]

Table 21.3 (continued)

Panel A. Mean and Variance equations							
	Mean equation	Variance equation					
	ϕ_i	ω_i	α_i	β_i	γ_i	*logL*	Q_{12}
IT	0.0128	0.0499***	0.0267***	0.9038***	0.0908***	–8572.94	10.46
	(0.75)	(2.89)	(2.68)	(41.47)	(4.30)		[0.58]
ES	0.0178	0.0602***	0.0443***	0.8817***	0.1176***	–9283.28	17.42
	(0.94)	(2.95)	(3.30)	(36.37)	(3.44)		[0.14]
GR	0.0178	0.0213*	0.0404**	0.9404***	0.0295***	–9577.19	8.60
	(0.87)	(1.68)	(2.37)	(47.13)	(2.62)		[0.74]
SW	0.0190	0.0275*	0.0205	0.9345***	0.0798***	–9320.45	18.29
	(0.98)	(1.79)	(1.02)	(36.19)	(3.00)		[0.11]
SC	0.0315	0.1007**	0.0320**	0.9036***	0.0660***	–9709.74	11.43
	(1.40)	(2.40)	(2.35)	(31.36)	(3.65)		[0.49]
Panel B. Equicorrelation equation with all 11 index returns							
a	0.0296***						
	(6.32)						
b	0.9596***						
	(148.2)						
logL	–96622.8						

Note: The table reports the estimation results of the GJR–MGARCH–DECO model for each T&L index return. The numbers in parentheses are t–statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. The numbers in square brackets are p–values. Q_{12} is the Box–Pierce Q–statistics on the standardized residuals with 12 lags. *logL* denotes the log–likelihood.

equicorrelation close to 30% (see the last graph – "all 11 indices" – in Figure 21.1 and the last line – "ALL" – in Table 21.4) for the whole sample and high persistence ($a + b$) in its time–varying pattern.

Figure 21.1 shows all pairwise cross–country sectoral correlation patterns (averaged per country from the bivariate DECO specifications) and the overall correlation dynamics with the 11 European tourism industries included in the multivariate DECO model (bivariate correlations of each country with the others [not averaged] are available upon request). They increase significantly during the GFC and the first ESDC period, which suggests probable contagion effects. Higher correlations are also observed during the Brexit referendum turbulence (June 2016) while, in the recent pandemic era, the correlations experience an unprecedented jump in levels even beyond the GFC period's peaks. Moreover, we observe that post–crisis dynamic correlations return to higher than the pre–crisis levels of the early 2000s for most countries, which confirms the higher degree of sectoral integration. In what follows, we attempt to explain this integration process with the common economic factors that drive the dynamic cross–country correlations and show a similar pattern during crises with uncertainties soaring, credit and liquidity squeezing, activity contracting, and geopolitical risks mostly rising (Figure 21.2).

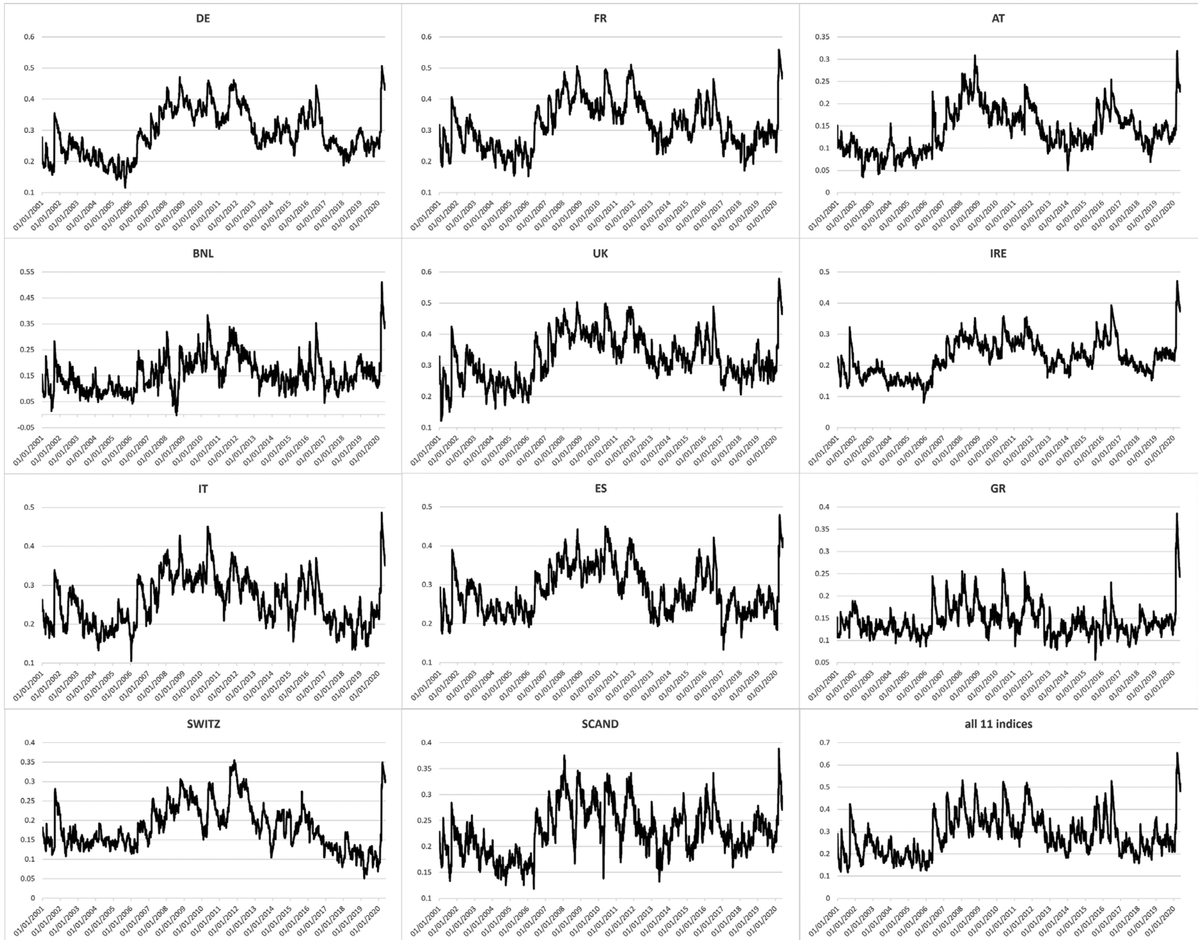

Figure 21.1 *Cross–border T&L sectoral dynamic conditional equicorrelations graphs*

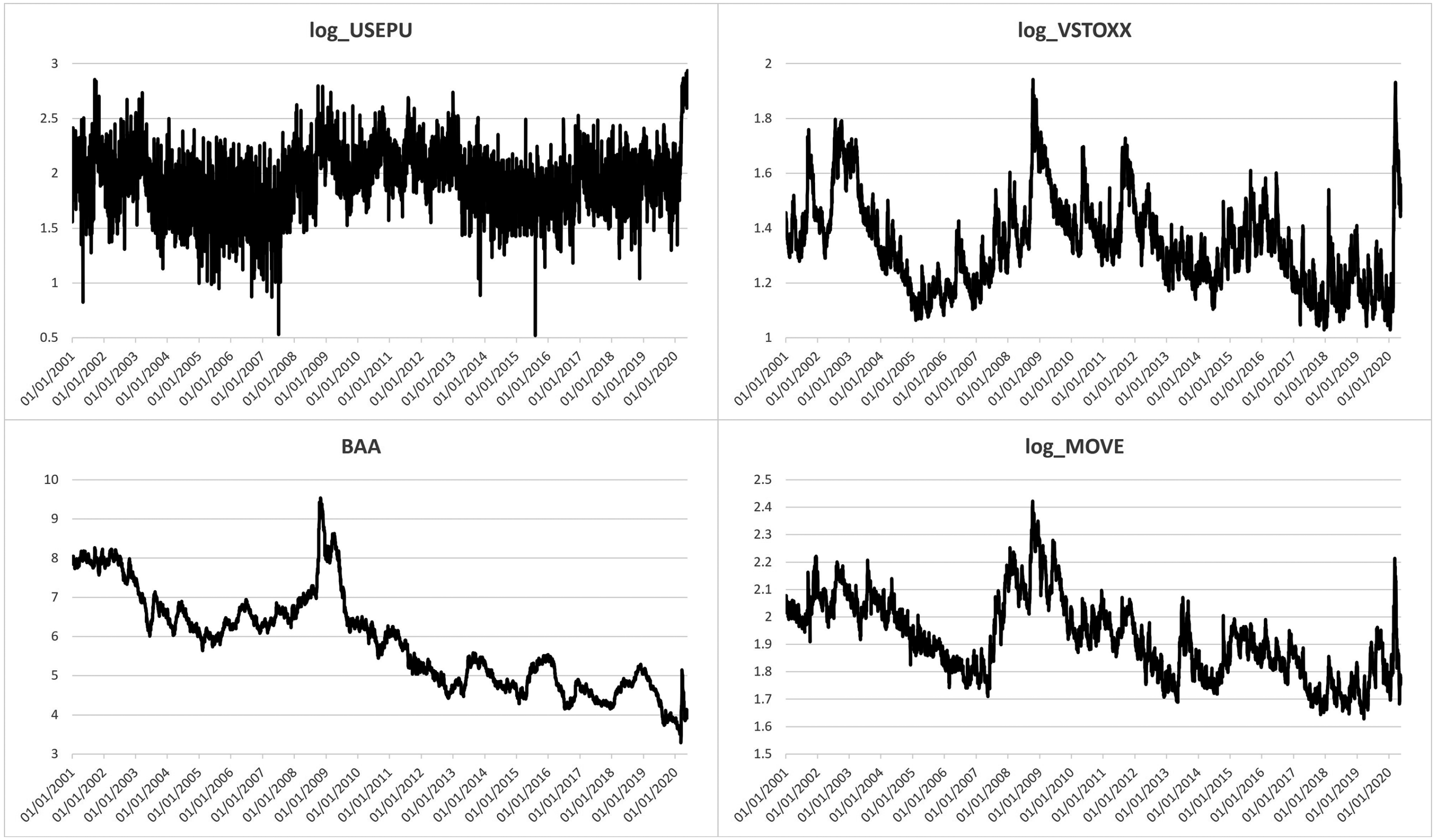

Figure 21.2 Macro–financial variables graphs

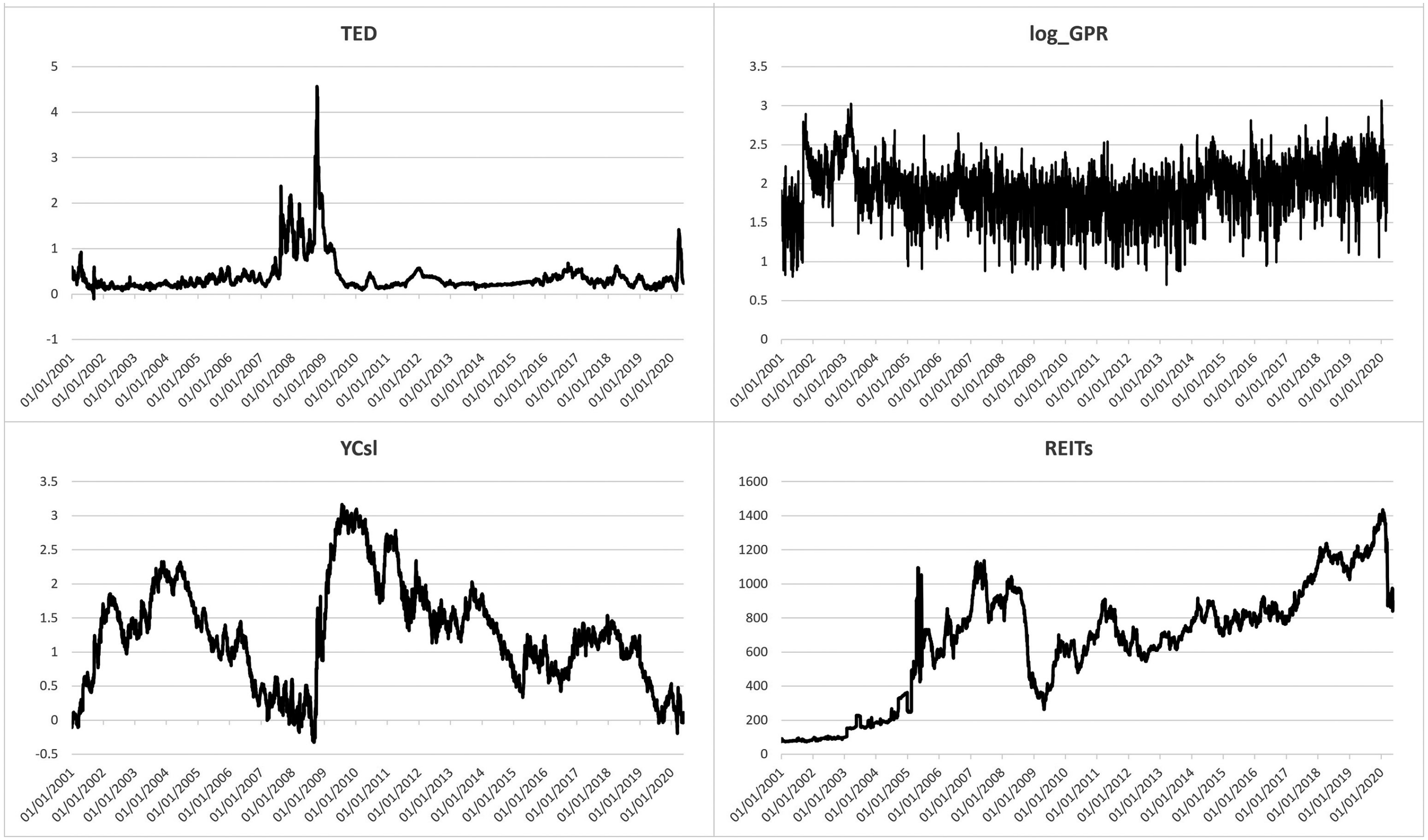

Figure 21.2 *(continued)*

Table 21.4 Time series mean of DECOs across the crisis subsamples

	total sample	GFC	ESDC	ESDC_A	ESDC_B	COVID
DE	0.291	0.385	0.329	0.375	0.282	0.396
FR	0.319	0.423	0.349	0.396	0.302	0.427
AT	0.140	0.222	0.142	0.166	0.118	0.213
BNL	0.156	0.163	0.185	0.228	0.141	0.317
UK	0.325	0.419	0.357	0.391	0.322	0.454
IRE	0.226	0.283	0.246	0.272	0.219	0.352
IT	0.259	0.338	0.285	0.319	0.250	0.362
ES	0.285	0.357	0.297	0.338	0.256	0.356
GR	0.145	0.183	0.145	0.164	0.126	0.251
SW	0.183	0.240	0.222	0.257	0.186	0.248
SC	0.229	0.292	0.240	0.260	0.219	0.289
ALL	0.289	0.381	0.315	0.360	0.269	0.466

Note: The table reports the mean value of each equicorrelation series (computed by the GJR–MGARCH–DECO model) across the crisis subsamples vs. the total sample mean.

4.2 Equicorrelations regressions

Next we regress the dynamic equicorrelation time series computed through the multivariate DECO specification (and averaged per country) on global macro–financial variables in order to identify the drivers of the cross–country European tourism sectoral co–movement. Table A21.3 (in the Appendix) shows the summary statistics of the time–varying correlations. The highest mean value is observed again in the case of the UK correlation with the other ten countries/country groups, while the lowest value is calculated for Austria. All correlations are positive for the whole sample apart from the Benelux series, where a minimum close to zero (–0.003) is computed for one day only (06/08/2008). Table 21.4 summarizes the mean values of each correlation series for the crisis subsamples rather than the full sample, and provides evidence consistent with the graphical analysis (Figure 21.1). Specifically, we observe significantly higher interdependence during the global turmoil of 2008 and the first subperiod of the European debt crisis, while the means for the second ESDC are generally lower than for the full sample. During the pandemic period, most sectoral co–movements peaked at higher levels than during the GFC, with correlation values being twice the those for the full sample. This indicates a significantly higher degree of financial integration among tourism stock markets in the most recent years of the last two decades under investigation.

Table 21.5 presents the estimation results of the correlation regressions on the macro–financial variables showing the impact of the global macro factors on correlation dynamics. These are chosen according to their significance and model selection criteria (AIC, BIC, $\bar{R}^2$). Specifically, for EPU the US index was selected, for financial uncertainty the European proxy, for sovereign and corporate credit conditions the US treasury volatility and the global BAA yield respectively, for the liquidity effect the German TED, for geopolitics the global GPR index, for economic activity the German yield curve slope, and for real estate activity the global sectoral REITs index. As a robustness check, we also ran the equicorrelation regressions replacing the US EPU index with the UK EPU, the Euro Stoxx 50

Table 21.5 Tourism equicorrelations regressions on daily macro factors (eq. (9))

↓Macro effects	↓Macro variables	DE	FR	AT	BNL	UK	IRE
	c_0	0.2976***	0.2487***	0.1189***	0.0786***	0.2946***	0.1517***
		(10.72)	(10.07)	(8.45)	(3.26)	(11.16)	(7.79)
	$Corr_{t-1}$	0.9968***	0.9950***	0.9932***	0.9854***	0.9919***	0.9950***
		(858.0)	(743.0)	(579.4)	(394.5)	(520.6)	(613.5)
EPU_{t-1}	EPU_{t-1}	0.0006*	0.0010**	0.0001	0.0012**	0.0013**	0.0007***
		(1.74)	(2.15)	(0.51)	(2.12)	(2.02)	(2.50)
FU_{t-1}	$VSTOXX_{t-1}$	0.0036**	0.0027*	0.0015*	0.0064**	0.0060**	0.0229***
		(2.31)	(1.70)	(1.66)	(2.10)	(2.21)	(2.85)
CCR_{t-1}	BAA_{t-1}	0.0051*	0.0046**	0.0033*	0.0061*	0.0065*	0.0074**
		(1.74)	(2.27)	(1.73)	(1.84)	(1.73)	(2.39)
SCR_{t-1}	$MOVE_{t-1}$	0.0289***	0.0478***	0.0030***	0.0358***	0.0059**	0.0028*
		(4.30)	(4.60)	(2.16)	(2.48)	(1.99)	(1.65)
LIQ_{t-1}	TED_{t-1}	0.0107***	0.0159***	0.0113***	0.0187***	0.0207***	0.0097***
		(3.14)	(3.91)	(3.16)	(3.10)	(3.23)	(2.51)
$GPR^{\oplus}_{t-1}$	GPR_{t-1}	0.0006*	0.0003*	0.0002	0.0008*	0.0003	0.0001
		(1.81)	(1.69)	(0.64)	(1.71)	(0.70)	(0.10)
EC_{t-1}	$YCsl_{t-1}$	–0.0075***	–0.0140***	–0.0077***	–0.0160***	–0.0189***	–0.0074**
		(–2.69)	(–3.79)	(–2.68)	(–3.25)	(–3.26)	(–2.21)
RE_{t-1}	$REIT_{t-1}$	–0.0241***	–0.0223***	–0.0024*	–0.0097	–0.0038	–0.0049
		(–2.81)	(–2.43)	(–1.69)	(–0.59)	(–1.08)	(–0.55)
AIC		–7.2907	–6.8855	–7.7700	–6.3352	–6.2353	–7.3453
BIC		–7.2777	–6.8725	–7.7500	–6.3222	–6.2223	–7.3322
DW		1.9219	1.9496	2.0590	2.0284	1.9790	1.9431
$\bar{R}^2$		0.9928	0.9894	0.9870	0.9675	0.9832	0.9876

Table 21.5 (continued)

↓Macro effects	↓Macro variables	IT	ES	GR	SWITZ	SCAND	ALL
	c_0	0.1112***	0.2310***	0.1118***	0.0807***	0.1402***	0.1341***
		(4.53)	(12.34)	(9.02)	(3.81)	(8.14)	(8.67)
	$Corr_{t-1}$	0.9925***	0.9907***	0.9826***	0.9959***	0.9880***	0.9955***
		(570.4)	(478.9)	(279.7)	(730.1)	(444.3)	(648.0)
EPU_{t-1}	EPU_{t-1}	0.0008*	0.0011**	0.0007**	0.0005*	0.0002***	0.0007***
		(1.85)	(2.16)	(2.01)	(1.77)	(2.55)	(2.59)
FU_{t-1}	$VSTOXX_{t-1}$	0.0295***	0.0053***	0.0032*	0.0191***	0.0230***	0.0065***
		(3.25)	(2.88)	(1.86)	(4.29)	(4.08)	(4.11)
CCR_{t-1}	BAA_{t-1}	0.0051**	0.0083***	0.0042**	0.0076***	0.0033*	0.0032***
		(2.11)	(2.80)	(1.97)	(2.64)	(1.69)	(2.46)
SCR_{t-1}	$MOVE_{t-1}$	0.0377***	0.0043**	0.0043***	0.0135***	0.0140**	0.0332***
		(4.11)	(1.94)	(2.64)	(2.54)	(2.11)	(4.63)
LIQ_{t-1}	TED_{t-1}	0.0114***	0.0190***	0.0110***	0.0064**	0.0077**	0.0048**
		(2.45)	(3.71)	(3.01)	(2.19)	(1.98)	(1.95)
$GPR^{\oplus}_{t-1}$	GPR_{t-1}	0.0003	0.0005	0.0002	0.0004*	0.0004	0.0003*
		(0.76)	(1.24)	(0.83)	(1.87)	(1.28)	(1.80)
EC_{t-1}	$YCsl_{t-1}$	–0.0100***	–0.0167***	–0.0096***	–0.0068***	–0.0081**	–0.0066***
		(–2.53)	(–3.59)	(–2.93)	(–2.69)	(–2.32)	(–3.37)
RE_{t-1}	$REIT_{t-1}$	–0.0140*	–0.0293***	–0.0049**	–0.0008	–0.0151*	–0.0024*
		(–1.66)	(–2.53)	(–2.32)	(–0.69)	(–1.85)	(–1.79)
AIC		–6.8518	–6.7191	–7.4541	–7.8279	–7.1856	–7.9556
BIC		–6.8388	–6.706	–7.4424	–7.8149	–7.1726	–7.9439
DW		2.0150	1.9951	2.0752	1.9212	2.0097	1.9654
$\overline{R}^2$		0.9855	0.9822	0.9646	0.9916	0.9787	0.9906

Note: The table reports the estimation results of the dynamic equicorrelations regressions on daily macro factors (eq. (9)). The numbers in parentheses are t–statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. AIC and BIC are the Akaike and the Schwartz Information Criteria, respectively. DW is the Durbin–Watson statistic. R^2 is the adjusted $\overline{R}^2$. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

implied volatility index (VSTOXX) with its S&P 500 counterpart (VIX), and the German TED and term (yield curve slope) spreads with their US counterparts calculated from the US treasury yields and money market rates (USD libor). All estimated coefficients have the same signs but are insignificant in more cases than those reported in Table 21.5.

The uncertainty effect on correlations is always positive. Specifically, the economic policy uncertainty variable is found to be significant in all cases except for Austria, and the financial uncertainty growth is always significant. Higher uncertainty levels and growth rates associated with economic downturns lead to higher cross–country tourism correlations. Moreover, both credit proxies (corporate and sovereign credit) drive correlations upwards, which implies that tighter credit conditions boost tourism sectoral interdependence. Similarly, liquidity tightening exerts a positive impact, with the coefficient on the TED spread always being positive and highly significant. Geopolitics have a positive and significant effect in five out of 12 cases, while the coefficients on the activity variables are always negative. A lower growth rate of economic and real estate activity is associated with higher cross–country dependence. Finally, we run an additional robustness check by regressing the growth rate of the correlation ($\Delta Corr_t = \frac{Corr_t}{s\,Corr_{t-1}} - 1$) on that of the same macro factors (Table A21.4 in the Appendix). Our conclusions are similar to those for the empirical analysis of the correlation levels. Uncertainty, credit, and liquidity growth proxies have a positive effect on sectoral interconnectedness while activity has a negative one. However, the GPR growth effect is positive and significant in most cases (while it is weak in the case of the level regressions).

To sum up, our analysis of the effects of macro variables on cross–country tourism integration suggests the following. Higher tourism correlations are associated with higher uncertainty and tighter credit and liquidity conditions, while lower correlations correspond to higher economic and real estate activity growth. These findings support our first theoretical hypothesis (*H1*) and highlight the counter–cyclicality of tourism correlations, that is, economic variables associated with weak economic conditions increase correlations, while activity growth indicators mostly reduce cross–border tourism interdependence. Accordingly, the magnifying EPU and crisis effects on the macro factors, investigated in the following parts of our empirical analysis (Section 5), are economically plausible since increased uncertainty and crisis periods are linked to economic downturns. Our results also contribute to the contagion literature. Specifically, Forbes and Rigobon (2002) define contagion as being characterized by increased spillovers between different markets after a crisis shock in one market, while interdependence stands for high interlinkages among markets during all states of the economy. Therefore our evidence that higher correlations are mainly caused by economic fundamentals suggests the existence of cross–country contagion effects.

5 SENSITIVITY ANALYSIS

Following our investigation of the economic forces driving integration in the tourism industry of the main European countries, we carry out some sensitivity analysis over the business cycle. First, we focus on the uncertainty channel for the transmission of the macro effects, given that higher uncertainty is associated with economic downturns. Second, we examine the crisis periods, which lead to recessions, to measure the macro effects during economic turmoil. Lastly, we consider the uncertainty channel in crisis periods separately to estimate the magnifying EPU impact on the macro drivers during crises.

5.1 The EPU effect on tourism correlations

We investigate further the role of EPU in driving correlation dynamics by analyzing its indirect impact on cross–country tourism sectoral interdependence through the macro factors that drive it. In other words, we examine the issue of whether EPU affects the evolution of correlations not only directly but also indirectly through the economic forces that explain their time–varying pattern. Our empirical results have important implications for investors in the tourism industry and policymakers concerned with stability and systemic risk oversight. More specifically, cross–country sectoral integration dynamics are of interest to investors for asset allocation, portfolio optimization, and risk management (diversification and hedging) purposes, and to regulators for their market intervention activities (stabilization and proactive macro–prudential policies). However, the previous literature had not thoroughly explored the role of EPU as a driver of tourism sectoral correlations and in particular its enhancing of the impact of financial uncertainty, credit and liquidity channel, geopolitics and activity revealed by our DECO analysis.

Above we have already highlighted the direct positive impact of EPU on correlations. In this section, we investigate its effect on the macro drivers of dynamic equicorrelations. Table 21.6 reports the coefficients of the interaction terms estimated in equation (10). We present estimates of the uncertainty effect on each macro determinant from alternative restricted forms of equation (10), including each EPU effect separately (each coefficient with the superscript^{EPU} is estimated separately). All significant interaction terms are found to have the same sign as the corresponding macro effect (similar results were obtained from regressing $\Delta Corr_t$ on the growth rate of the macro factors, see Table A21.5 in the Appendix). Interestingly, we show that higher policy uncertainty results in stronger effects of financial uncertainty, credit and liquidity conditions, geopolitical risk, economic and real estate activity on cross–border tourism integration. In other words, EPU enhances the impact of the macro determinants of the equicorrelations, which confirms the validity of our second hypothesis (*H2*). In particular, in Table 21.6 we observe that the financial uncertainty, credit, and liquidity EPU interaction terms are always positive and mostly significant, while the activity terms are negative. VSTOXX, BAA bond yields growth, MOVE, and TED spread exert considerable influence on correlations, which is partly explained by EPU. The EPU impact on the geopolitical risk factor is positive and significant in five out of 12 cases for the equicorrelation levels. Moreover, lower activity, proxied by the term spread and REITs associated with higher policy uncertainty, increases all correlations.

On the whole, our evidence shows that EPU has both a direct and an indirect effect on the cross–country correlations, the latter through amplifying the influence of the other macro drivers (and thus it implies that both should be taken into account by policy makers). More specifically, the DECO analysis shows the positive effect of EPU on the correlations (direct link). Further, the macro effects on the correlations are state–dependent and are magnified by uncertainty (indirect link). In particular, the positive effects of tighter credit and liquidity conditions and of a weaker economy are enhanced by EPU. These new findings represent an important contribution to the literature on the integration of the tourism sector.

Table 21.6 The EPU effect on the macro drivers of tourism equicorrelations (eq. (10))

Macro effect→	FU_{t-1}	CCR_{t-1}	SCR_{t-1}	LIQ_{t-1}	$GPR^{\oplus}_{t-1}$	EC_{t-1}	RE_{t-1}
Macro variables→	EPU_{t-1} $VSTOXX_{t-1}$	EPU_{t-1} BAA_{t-1}	EPU_{t-1} $MOVE_{t-1}$	EPU_{t-1} TED_{t-1}	EPU_{t-1} GPR_{t-1}	EPU_{t-1} $YCsl_{t-1}$	EPU_{t-1} $REIT_{t-1}$
DE	0.0020***	0.0002***	0.0023***	0.0047***	0.0004***	–0.0004*	–0.0127***
	(2.84)	(2.80)	(2.88)	(4.10)	(3.16)	(–1.82)	(–2.63)
FR	0.0016*	0.0025**	0.0016***	0.0028***	0.0003*		–0.0127**
	(1.89)	(2.38)	(3.43)	(2.43)	(1.66)		(–2.17)
AT	0.0007**	0.0001	0.0010*	0.0019**	0.0001	–0.0002	–0.0012*
	(2.03)	(0.57)	(1.70)	(2.41)	(0.67)	(–1.08)	(–1.66)
BNL	0.0117***	0.0001	0.0078**	0.0040***	0.0001*	–0.0013	–0.0092
	(3.44)	(0.10)	(2.34)	(2.51)	(1.66)	(–1.28)	(–1.31)
UK	0.0025**	0.0009*	0.0026**	0.0050***	0.0004	–0.0021**	–0.0026*
	(2.32)	(1.65)	(2.10)	(3.28)	(1.28)	(–2.00)	(–1.70)
IRE	0.0014***	0.0002**	0.0010*	0.0023***	0.0001	–0.0003*	–0.0047
	(3.24)	(2.33)	(1.69)	(3.11)	(1.14)	(–1.70)	(–1.07)
IT	0.0115***	0.0010**	0.0108***	0.0034***	0.0001	–0.0009	–0.0071*
	(4.37)	(2.15)	(4.52)	(3.00)	(0.39)	(–1.23)	(–1.74)
ES	0.0024***	0.0016**	0.0017**	0.0046***	0.0001	–0.0023***	–0.0150***
	(3.05)	(2.02)	(1.92)	(3.59)	(0.88)	(–2.63)	(–2.50)
GR	0.0006*	0.0009*	0.0011*	0.0023***	0.0001	–0.0001	–0.0021**
	(1.89)	(1.67)	(1.67)	(2.84)	(0.60)	(–0.65)	(–2.25)
SW	0.0008***	0.0001*	0.0003*	0.0011*	0.0002***	–0.0002*	–0.0008
	(3.11)	(1.75)	(1.89)	(1.85)	(2.49)	(–1.69)	(–1.25)
SC	0.0020***	0.0001	0.0005*	0.0026***	0.0002	–0.0001**	–0.0071*
	(3.79)	(1.12)	(1.69)	(2.85)	(1.35)	(–2.36)	(–1.72)
ALL	0.0026***	0.0012**	0.0007***	0.0014*	0.0001*		–0.0013*
	(4.03)	(2.27)	(3.27)	(1.70)	(1.65)		(–1.76)

Note: The table reports the EPU effect on the macro factors' impact on dynamic equicorrelations (eq. (10)). The coefficients of each EPU interaction term estimated separately are displayed. The numbers in parentheses are t–statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. ⊕ denotes that the GPR coefficient is estimated separately with a shorter sample.

5.2 The crisis effect on tourism correlations

Following the regression analysis with the macro determinants of the evolution of cross–country tourism correlations, in this section we investigate the crisis impact on the macro regressors. In particular, we focus on the repercussion of the GFC, ESDC, and COVID crises and examine time variation in the model parameters. For this purpose we incorporate crisis slope dummies in the DECO–X regression (eq. (9)) and estimate equation (11) for each crisis period/subperiod. The crisis impact on the time–varying macro effects is captured by the coefficients of the slope dummies with the ^{CRISIS} superscript. In Table 21.7, we show the estimated crisis effect on each macro regressor from alternative restricted forms of equation (11) by including each slope dummy separately (similar results from the $\Delta Corr_t$ regressions with the crisis impact are not reported to save space but are available upon request). We choose to report the GFC, the first ESDC period, and the COVID

Table 21.7 The crisis effect on the macro drivers of tourism equicorrelations (eq. (11))

↓Macro effects	↓Macro variables	DE	FR	AT	BNL	UK	IRE
Panel A. The GFC effect							
EPU_{t-1}	$d_{GFC,t-1}EPU_{t-1}$	0.0043***	0.0041**	0.0015	0.0009	0.0037*	0.0018*
		(2.45)	(2.32)	(0.99)	(0.27)	(1.83)	(1.71)
FU_{t-1}	$d_{GFC,t-1}VSTOXX_{t-1}$	0.0030	0.0036	0.0028	0.0025	0.0066*	0.0004
		(0.89)	(0.89)	(1.13)	(0.35)	(1.63)	(0.31)
CCR_{t-1}	$d_{GFC,t-1}BAA_{t-1}$	0.0013**	0.0068*	0.0033	0.0002	0.0011***	0.0002
		(2.10)	(1.64)	(1.18)	(0.10)	(2.79)	(1.24)
SCR_{t-1}	$d_{GFC,t-1}MOVE_{t-1}$	0.0047***	0.0048*	0.0050	0.0011	0.0043	0.0091*
		(2.51)	(1.76)	(0.98)	(0.21)	(0.40)	(1.70)
LIQ_{t-1}	$d_{GFC,t-1}TED_{t-1}$	0.0127***	0.0068*	0.0049*	0.0147***	0.0146***	0.0050**
		(3.45)	(1.73)	(1.71)	(2.78)	(3.38)	(2.13)
$GPR^{\oplus}_{t-1}$	$d_{GFC,t-1}GPR_{t-1}$	0.0014	0.0016	0.0020	0.0043	0.0013	0.0004
		(0.75)	(0.68)	(1.21)	(0.53)	(1.00)	(0.51)
EC_{t-1}	$d_{GFC,t-1}YCsl_{t-1}$	–0.0045*	–0.0045*	–0.0013	–0.0035	–0.0016	–0.0008
		(–1.72)	(–1.66)	(–0.87)	(–1.06)	(–0.61)	(–0.58)
RE_{t-1}	$d_{GFC,t-1}REIT_{t-1}$	–0.0146	–0.0066	–0.0040	–0.0129	–0.0024	–0.0121
		(–1.10)	(–0.41)	(–0.38)	(–0.59)	(–0.12)	(–1.05)
Panel B. The first ESDC period effect							
EPU_{t-1}	$d_{ESDC\_A,t-1}EPU_{t-1}$	0.0026*	0.0049**	0.0019***	0.0057*	0.0042**	0.0020*
		(1.87)	(2.15)	(2.90)	(1.63)	(2.05)	(1.71)
FU_{t-1}	$d_{ESDC\_A,t-1}VSTOXX_{t-1}$	0.0033	0.0015	0.0088**	0.0243**	0.0050	0.0065*
		(0.99)	(0.36)	(2.09)	(2.06)	(1.12)	(1.70)
CCR_{t-1}	$d_{ESDC\_A,t-1}BAA_{t-1}$	0.0025**	0.0040	0.0018**	0.0067**	0.0036**	0.0019**
		(2.20)	(0.91)	(2.09)	(2.26)	(2.29)	(1.95)
SCR_{t-1}	$d_{ESDC\_A,t-1}MOVE_{t-1}$	0.0077**	0.0126**	0.0097***	0.0190**	0.0068	0.0032
		(2.15)	(2.00)	(2.44)	(2.01)	(0.73)	(0.73)
LIQ_{t-1}	$d_{ESDC\_A,t-1}TED_{t-1}$	0.0280	0.0635*	0.0045	0.0164	0.0554*	0.0189
		(1.28)	(1.83)	(0.81)	(1.31)	(1.85)	(1.01)
$GPR^{\oplus}_{t-1}$	$d_{ESDC\_A,t-1}GPR_{t-1}$	0.0001	0.0001	0.0002	0.0017	0.0007	0.0005
		(0.17)	(0.05)	(0.68)	(1.00)	(1.06)	(1.15)

EC_{t-1}	$d_{ESDC\_A,t-1}YCsl_{t-1}$	–0.0040**	–0.0062*	–0.0025	–0.0108*	–0.0051*	–0.0032*
		(–1.90)	(–1.67)	(–1.23)	(–1.65)	(–1.69)	(–1.91)
RE_{t-1}	$d_{ESDC\_A,t-1}REIT_{t-1}$	–0.0018	–0.0003	–0.0016	–0.0459*	–0.0202	–0.0031
		(–0.10)	(–0.16)	(–0.13)	(–1.69)	(–0.87)	(–0.17)
Panel C. The COVID effect							
EPU_{t-1}	$d_{COVID,t-1}EPU_{t-1}$	0.0055***	0.0010**	0.0045**	0.0022**	0.0056*	0.0089*
		(2.58)	(2.18)	(2.17)	(2.35)	(1.81)	(1.85)
FU_{t-1}	$d_{COVID,t-1}VSTOXX_{t-1}$	0.0251*	0.0280*	0.0152***	0.0504	0.0404*	0.0297
		(1.75)	(1.66)	(2.68)	(0.99)	(1.65)	(0.94)
CCR_{t-1}	$d_{COVID,t-1}BAA_{t-1}$	0.0005	0.0321***	0.0021**	0.0027	0.0003	0.0010**
		(0.35)	(2.45)	(2.26)	(0.79)	(0.13)	(0.66)
SCR_{t-1}	$d_{COVID,t-1}MOVE_{t-1}$	0.0045	0.0236**	0.0183**	0.0126	0.0427*	0.0213*
		(0.71)	(2.15)	(2.36)	(0.87)	(1.86)	(1.68)
LIQ_{t-1}	$d_{COVID,t-1}TED_{t-1}$	0.0055	0.0335	0.0222	0.0715	0.0038	0.0078
		(0.68)	(0.94)	(1.00)	(0.97)	(0.28)	(0.80)
$GPR^{\oplus}_{t-1}$	$d_{COVID,t-1}GPR_{t-1}$	0.0011*	0.0088*	0.0013*	0.0021*	0.0023**	0.0009
		(1.70)	(1.67)	(1.64)	(1.73)	(2.08)	(0.72)
EC_{t-1}	$d_{COVID,t-1}YCsl_{t-1}$	–0.0037	–0.0154	–0.0053	–0.0050	–0.0083	–0.0034
		(–0.25)	(–0.47)	(–0.48)	(–0.17)	(–0.31)	(–0.20)
RE_{t-1}	$d_{COVID,t-1}REIT_{t-1}$	–0.0773**	–0.0779	–0.0298	–0.1350*	–0.1349*	–0.0799*
		(–1.98)	(–1.16)	(–1.07)	(–1.63)	(–1.67)	(–1.67)

Table 21.7 (continued)

↓Macro effects	↓Macro variables	IT	ES	GR	SWITZ	SCAND	ALL
Panel A. The GFC effect							
EPU_{t-1}	$d_{GFC,t-1}EPU_{t-1}$	0.0016	0.0020	0.0023**	0.0035*	0.0019*	0.0021*
		(0.60)	(1.12)	(1.92)	(1.84)	(1.72)	(1.76)
FU_{t-1}	$d_{GFC,t-1}VSTOXX_{t-1}$	0.0007	0.0060*	0.0084***	0.0082*	0.0040*	0.0116***
		(0.11)	(1.67)	(4.23)	(1.65)	(1.68)	(2.45)
CCR_{t-1}	$d_{GFC,t-1}BAA_{t-1}$	0.0005	0.0001	0.0018***	0.0018*	0.0008*	0.0025
		(0.39)	(0.27)	(4.09)	(1.77)	(1.80)	(0.88)
SCR_{t-1}	$d_{GFC,t-1}MOVE_{t-1}$	0.0018	0.0025	0.0048	0.0071*	0.0031*	0.0028***
		(0.46)	(0.31)	(0.89)	(1.67)	(1.70)	(5.03)
LIQ_{t-1}	$d_{GFC,t-1}TED_{t-1}$	0.0065*	0.0076*	0.0060**	0.0042	0.0040*	0.0048**
		(1.67)	(1.82)	(2.35)	(1.28)	(1.81)	(1.90)
$GPR^{\oplus}_{t-1}$	$d_{GFC,t-1}GPR_{t-1}$	0.0009	0.0004	0.0009	0.0017	0.0019	0.0009
		(0.86)	(0.69)	(1.03)	(0.66)	(1.09)	(1.11)
EC_{t-1}	$d_{GFC,t-1}YCsl_{t-1}$	–0.0009	–0.0039*	–0.0017	–0.0004	–0.0015	–0.0017
		(–0.32)	(–1.71)	(–0.88)	(–0.33)	(–0.95)	(–0.99)
RE_{t-1}	$d_{GFC,t-1}REIT_{t-1}$	–0.0236*	–0.0148	–0.0055	–0.0062	–0.0136	–0.0033
		(–1.64)	(–0.92)	(–0.48)	(–0.65)	(–0.93)	(–0.34)
Panel B. The first ESDC period effect							
EPU_{t-1}	$d_{ESDC\_A,t-1}EPU_{t-1}$	0.0049**	0.0039**	0.0034**	0.0026***	0.0039**	0.0020**
		(2.14)	(2.23)	(2.04)	(2.96)	(2.13)	(2.16)
FU_{t-1}	$d_{ESDC\_A,t-1}VSTOXX_{t-1}$	0.0152**	0.0009	0.0115**	0.0079**	0.0148**	0.0046*
		(1.95)	(0.21)	(2.00)	(2.21)	(2.42)	(1.62)
CCR_{t-1}	$d_{ESDC\_A,t-1}BAA_{t-1}$	0.0042**	0.0031**	0.0029**	0.0015*	0.0031**	0.0015
		(2.06)	(2.14)	(1.93)	(1.86)	(1.94)	(0.59)
SCR_{t-1}	$d_{ESDC\_A,t-1}MOVE_{t-1}$	0.0119*	0.0048	0.0020	0.0047*	0.0097**	0.0076**
		(1.84)	(0.68)	(0.37)	(1.83)	(1.96)	(1.93)
LIQ_{t-1}	$d_{ESDC\_A,t-1}TED_{t-1}$	0.0198**	0.0161**	0.0095*	0.0195	0.0112*	0.0293
		(2.22)	(2.29)	(1.66)	(1.18)	(1.73)	(1.28)
$GPR^{\oplus}_{t-1}$	$d_{ESDC\_A,t-1}GPR_{t-1}$	0.0005	0.0005	0.0004	0.0009	0.0008	0.0001
		(1.17)	(1.03)	(1.01)	(0.82)	(0.78)	(0.16)

EC_{t-1}	$d_{ESDC\_A,t-1}YCsl_{t-1}$	–0.0077*	–0.0042	–0.0045	–0.0020	–0.0046	–0.0034
		(–1.83)	(–1.15)	(–1.24)	(–1.12)	(–1.16)	(–1.37)
RE_{t-1}	$d_{ESDC\_A,t-1}REIT_{t-1}$	–0.0244	–0.0048	–0.0037	–0.0104	–0.0028	–0.0098
		(–1.05)	(–0.19)	(–0.27)	(–0.85)	(–0.13)	(–0.82)
Panel C. The COVID effect							
EPU_{t-1}	$d_{COVID,t-1}EPU_{t-1}$	0.0043*	0.0010**	0.0109**	0.0094**	0.0025***	0.0007***
		(1.71)	(2.20)	(2.14)	(2.26)	(2.91)	(2.87)
FU_{t-1}	$d_{COVID,t-1}VSTOXX_{t-1}$	0.0281	0.0322*	0.0328	0.0205	0.0156	0.0277**
		(0.83)	(1.75)	(1.08)	(0.92)	(0.96)	(2.02)
CCR_{t-1}	$d_{COVID,t-1}BAA_{t-1}$	0.0005	0.0015	0.0018	0.0001	0.0020	0.0146*
		(0.34)	(0.52)	(1.32)	(0.05)	(0.80)	(1.66)
SCR_{t-1}	$d_{COVID,t-1}MOVE_{t-1}$	0.0065	0.0264*	0.0223*	0.0033	0.0046	0.0035
		(0.73)	(1.64)	(1.84)	(0.63)	(0.88)	(0.56)
LIQ_{t-1}	$d_{COVID,t-1}TED_{t-1}$	0.0415	0.0588	0.0460*	0.0028	0.0417	0.0026
		(0.99)	(0.95)	(1.81)	(0.40)	(0.83)	(0.29)
$GPR^{\oplus}_{t-1}$	$d_{COVID,t-1}GPR_{t-1}$	0.0014*	0.0023*	0.0030*	0.0012	0.0005	0.0002**
		(1.75)	(1.77)	(1.64)	(0.84)	(0.48)	(2.17)
EC_{t-1}	$d_{COVID,t-1}YCsl_{t-1}$	–0.0249	–0.0052	–0.001	–0.0064	–0.0005	–0.0009
		(–1.12)	(–0.22)	(–0.06)	(–0.58)	(–0.27)	(–0.10)
RE_{t-1}	$d_{COVID,t-1}REIT_{t-1}$	–0.0597	–0.1124*	–0.0725**	–0.0694**	–0.0461	–0.0755*
		(–1.30)	(–1.66)	(–1.98)	(–2.30)	(–0.74)	(–1.65)

Notes: The table reports the crisis effect on the macro factors' impact on dynamic equicorrelations (eq. (11)). The coefficients of each crisis slope dummy estimated separately are displayed. The numbers in parentheses are t-statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. ⊕ denotes that the GPR coefficient is estimated separately with a shorter sample.

effect on the economic transmission mechanism on correlations since the second ESDC period effect is weak or insignificant in most cases.

Our crisis analysis reveals that most macro factors exert a more profound influence on dynamic correlations during crisis periods, in line with the third theoretical hypothesis (*H3*). In the GFC case (Table 21.7, Panel A), the positive impact of economic and financial uncertainty, credit and liquidity conditions is enhanced, with the slope dummies coefficients being significant for most correlation series. The negative economic activity effect is greater but insignificant in most cases. As for the first ESDC period (Table 21.7, Panel B), we draw similar conclusions. Higher uncertainty, tighter credit and liquidity conditions increase correlations across all countries during the crisis. Moreover, lower economic activity increases further in–crisis cross–country sectoral interdependence, that is, the yield curve slope dummies are significant for most countries, whereas REITs is still insignificant in all cases but one. The incremental effect of geopolitics is not significant in either the GFC or ESDC periods. During the recent COVID–19 pandemic (Table 21.7, Panel C), the effect of uncertainty, credit, and geopolitics is intensified, while the liquidity slope dummies are insignificant. The negative impact of real estate activity becomes stronger in contrast to that of economic activity (see Table 21.9, Panel A, for the number of significant crisis effects out of 12 cases).

To sum up, crises (such as the GFC, ESDC, and COVID ones) generally magnify the effects of the macro drivers, with EPU having an enhancing impact on financial uncertainty, credit, liquidity, GPR, and activity (see Section 5.1). Higher uncertainty and GPR (during the COVID crisis only), tighter credit and liquidity conditions and lower activity have a greater effect on correlations during crises (especially during the ESDC and COVID periods). Further, there is clear evidence of contagion between tourism industries. Specifically, the estimated crisis slope dummy coefficients imply a more sizeable impact of the macro drivers during the period of turmoil following the onset of a crisis. In addition to a contagion effect during crises (*H3*), there is also evidence of an intensified EPU effect during periods of turmoil (*H2*) (see the EPU analysis in Section 5.1), in line with previous empirical results on VIX as a contagion driver (see Akay et al., 2013, among others). Finally, most macro, EPU, and crisis effects on tourism interlinkages are similar (in terms of magnitude and significance) across the various country pairs.

The final part of our sensitivity analysis investigates the EPU impact on the effects of the correlation drivers during crises by estimating equation (12) for each crisis period. The crisis impact on the EPU interaction term is captured by the coefficients with the $^{EPU\_CR}$ superscript. Table 21.8 reports the estimated interaction terms from alternative restricted forms of equation (12) by including each term separately (the corresponding results from the $\Delta Corr_t$ regressions including the crisis impact are not reported but are available upon request).[5] We focus again on the GFC, the first ESDC period and the COVID periods, given the fact that the effect of the second ESDC period is weak or insignificant in most cases. As in the case of the crisis analysis of the macro effects (Table 21.7), we find that all EPU interaction terms have a magnified effect during crises (Table 21.8, Panel A for the GFC impact, Panel B for the ESDC_A impact, and Panel C for the COVID impact), with

[5] The estimation results of the whole equations (10), (11), and (12), when each EPU, crisis, and EPU under crisis effect is incorporated separately, are not reported for space considerations. They are available upon request to the authors.

Table 21.8 The EPU effect on the macro drivers of tourism equicorrelations during crises (eq. (12))

↓Macro variables Macro effects	DE	FR	AT	BNL	UK	IRE
Panel A. The GFC effect						
$d_{GFC,t-1}EPU_{t-1}VSTOXX_{t-1}$	0.0012^{**}	0.0014^{*}	0.0012	0.0007	0.0026^{*}	0.0013^{*}
FU_{t-1}	(1.99)	(1.87)	(1.32)	(0.33)	(1.81)	(1.70)
$d_{GFC,t-1}EPU_{t-1}BAA_{t-1}$	0.0007^{***}	0.0030^{*}	0.0001	0.0001	0.0005^{**}	0.0003^{*}
CCR_{t-1}	(2.62)	(1.67)	(0.44)	(0.12)	(1.94)	(1.83)
$d_{GFC,t-1}EPU_{t-1}MOVE_{t-1}$	0.0023^{***}	0.0022^{***}	0.0018	0.0003	0.0012	0.0033^{*}
SCR_{t-1}	(2.65)	(2.50)	(0.98)	(0.19)	(0.31)	(1.65)
$d_{GFC,t-1}EPU_{t-1}TED_{t-1}$	0.0044^{***}	0.0029^{**}	0.0014^{*}	0.0033^{*}	0.0040^{***}	0.0020^{**}
LIQ_{t-1}	(3.26)	(2.33)	(1.73)	(1.83)	(2.55)	(2.40)
$d_{GFC,t-1}EPU_{t-1}GPR_{t-1}$	0.0009^{***}	0.0009^{**}	0.0004^{*}	0.0002^{*}	0.0008^{*}	0.0002
$GPR^{\oplus}_{t-1}$	(2.85)	(2.35)	(1.65)	(1.69)	(1.71)	(0.70)
$d_{GFC,t-1}EPU_{t-1}YCsl_{t-1}$	-0.0021^{***}	-0.0015^{*}	–0.0005	–0.0012	–0.0010	–0.0004
EC_{t-1}	(–2.53)	(–1.73)	(–0.98)	(–0.96)	(–1.12)	(–0.79)
$d_{GFC,t-1}EPU_{t-1}REIT_{t-1}$	–0.0047	–0.0017	–0.0014	–0.004	–0.0009	–0.0053
RE_{t-1}	(–0.91)	(–0.26)	(–0.35)	(–0.47)	(–0.12)	(–1.21)
Panel B. The first ESDC period effect						
$d_{ESDC\_A,t-1}EPU_{t-1}VSTOXX_{t-1}$	0.0013	0.0006	0.0018^{**}	0.0044^{*}	0.0020	0.0018^{**}
FU_{t-1}	(1.00)	(0.37)	(2.11)	(1.69)	(1.13)	(2.20)
$d_{ESDC\_A,t-1}EPU_{t-1}BAA_{t-1}$	0.0005^{**}	0.0014	0.0004^{*}	0.0011^{*}	0.0007^{*}	0.0004^{**}
CCR_{t-1}	(2.23)	(0.82)	(1.76)	(1.71)	(1.69)	(2.27)
$d_{ESDC\_A,t-1}EPU_{t-1}MOVE_{t-1}$	0.0017^{***}	0.0025^{**}	0.0038^{**}	0.0030^{*}	0.0028	0.0014
SCR_{t-1}	(2.43)	(2.16)	(2.39)	(1.69)	(0.78)	(0.82)
$d_{ESDC\_A,t-1}EPU_{t-1}TED_{t-1}$	0.0075^{*}	0.0131^{**}	0.0015	0.0045^{*}	0.0095^{*}	0.0052^{*}
LIQ_{t-1}	(1.78)	(1.93)	(1.06)	(1.66)	(1.81)	(1.68)
$d_{ESDC\_A,t-1}EPU_{t-1}GPR_{t-1}$	0.0001	0.0001	0.0001^{*}	0.0006	0.0003^{**}	0.0002^{**}
$GPR^{\oplus}_{t-1}$	(0.22)	(0.27)	(1.69)	(0.97)	(2.12)	(2.23)
$d_{ESDC\_A,t-1}EPU_{t-1}YCsl_{t-1}$	-0.0011^{**}	-0.0017^{**}	-0.0007^{*}	–0.0023	-0.0012^{*}	-0.0009^{***}
EC_{t-1}	(–2.20)	(–2.05)	(–1.64)	(–1.30)	(–1.76)	(–2.46)
$d_{ESDC\_A,t-1}EPU_{t-1}REIT_{t-1}$	–0.0008	–0.0002	–0.0010	-0.0178^{*}	–0.0075	–0.0012
RE_{t-1}	(–0.11)	(–0.10)	(–0.20)	(–1.72)	(–0.84)	(–0.16)

Table 21.8 (continued)

↓Macro variables Macro effects	DE	FR	AT	BNL	UK	IRE
Panel C. The COVID effect						
$d_{COVID,t-1}EPU_{t-1}VSTOXX_{t-1}$	0.0087^{**}	0.0090^{*}	0.0059^{***}	0.0135^{*}	0.0135^{*}	0.0075^{*}
FU_{t-1}	(1.90)	(1.71)	(2.89)	(1.71)	(1.73)	(1.68)
$d_{COVID,t-1}EPU_{t-1}BAA_{t-1}$	0.0001	0.0114^{***}	0.0009^{*}	0.0003	0.0006	0.0001
CCR_{t-1}	(0.94)	(2.53)	(1.71)	(0.15)	(0.30)	(0.10)
$d_{COVID,t-1}EPU_{t-1}MOVE_{t-1}$	0.0008	0.0091^{*}	0.0070^{***}	0.0024	0.0143^{**}	0.0069^{*}
SCR_{t-1}	(0.40)	(1.71)	(2.47)	(0.73)	(1.99)	(1.68)
$d_{COVID,t-1}EPU_{t-1}TED_{t-1}$	0.0022	0.0090	0.0082	0.0225	0.0013	0.0021
LIQ_{t-1}	(0.46)	(0.86)	(0.96)	(0.86)	(0.27)	(0.59)
$d_{COVID,t-1}EPU_{t-1}GPR_{t-1}$	0.0001^{**}	0.0041^{*}	0.0005^{**}	0.0010^{***}	0.0008^{*}	0.0002^{*}
$GPR^{\oplus}$	(2.21)	(1.63)	(2.03)	(2.50)	(1.70)	(1.65)
$d_{COVID,t-1}EPU_{t-1}YCsl_{t-1}$	–0.0012	–0.0006	–0.0018	–0.0016	–0.0020	–0.0010
EC_{t-1}	(–0.23)	(–0.06)	(–0.38)	(–0.14)	(–0.23)	(–0.18)
$d_{COVID,t-1}EPU_{t-1}REIT_{t-1}$	$–0.0232^{*}$	–0.0212	–0.0087	$–0.0397^{*}$	$–0.0379^{*}$	$–0.0234^{*}$
RE_{t-1}	(–1.78)	(–0.97)	(–0.88)	(–1.68)	(–1.66)	(–1.67)

↓Macro variables Macro effects	IT	ES	GR	SWITZ	SCAND	ALL
Panel A. The GFC effect						
$d_{GFC,t-1}EPU_{t-1}VSTOXX_{t-1}$	0.0013	0.0023*	0.0020***	0.0022*	0.0012*	0.0042**
FU_{t-1}	(0.76)	(1.73)	(2.54)	(1.71)	(1.76)	(2.30)
$d_{GFC,t-1}EPU_{t-1}BAA_{t-1}$	0.0002	0.0002	0.0004***	0.0005*	0.0003*	0.0011
CCR_{t-1}	(0.63)	(0.87)	(2.82)	(1.81)	(1.77)	(1.00)
$d_{GFC,t-1}EPU_{t-1}MOVE_{t-1}$	0.0008	0.0005	0.0019	0.0017*	0.0008	0.0010**
SCR_{t-1}	(0.64)	(0.19)	(0.93)	(1.82)	(1.26)	(1.91)
$d_{GFC,t-1}EPU_{t-1}TED_{t-1}$	0.0024*	0.0022*	0.0020***	0.0015*	0.0012*	0.0016*
LIQ_{t-1}	(1.86)	(1.71)	(2.51)	(1.68)	(1.74)	(1.64)
$d_{GFC,t-1}EPU_{t-1}GPR_{t-1}$	0.0002	0.0002*	0.0004	0.0008**	0.0007**	0.0006***
$GPR^{\oplus}_{t-1}$	(0.42)	(1.77)	(1.11)	(1.95)	(2.20)	(2.56)
$d_{GFC,t-1}EPU_{t-1}YCsl_{t-1}$	–0.0002	–0.0015*	–0.0010**	–0.0001	–0.0001	–0.0006
EC_{t-1}	(–0.20)	(–1.78)	(–1.98)	(–0.09)	(–0.12)	(–0.97)
$d_{GFC,t-1}EPU_{t-1}REIT_{t-1}$	–0.0084*	–0.0049	–0.0018	–0.0024	–0.0043	–0.0014
RE_{t-1}	(–1.70)	(–0.77)	(–0.40)	(–0.53)	(–0.75)	(–0.37)
Panel B. The first ESDC period effect						
$d_{ESDC\_A,t-1}EPU_{t-1}VSTOXX_{t-1}$	0.0037**	0.0004	0.0029***	0.0024***	0.0032***	0.0018*
FU_{t-1}	(2.35)	(0.25)	(2.49)	(3.57)	(2.66)	(1.62)
$d_{ESDC\_A,t-1}EPU_{t-1}BAA_{t-1}$	0.0009**	0.0007**	0.0007**	0.0005***	0.0006*	0.0005
CCR_{t-1}	(2.27)	(2.11)	(2.21)	(3.25)	(1.89)	(0.53)
$d_{ESDC\_A,t-1}EPU_{t-1}MOVE_{t-1}$	0.0026**	0.0018	0.0005	0.0014***	0.0020**	0.0015**
SCR_{t-1}	(2.15)	(0.65)	(0.25)	(3.18)	(2.07)	(2.13)
$d_{ESDC\_A,t-1}EPU_{t-1}TED_{t-1}$	0.0050**	0.0042**	0.0030*	0.0074***	0.0038**	0.0068*
LIQ_{t-1}	(2.11)	(2.22)	(1.82)	(2.64)	(2.15)	(1.66)
$d_{ESDC\_A,t-1}EPU_{t-1}GPR_{t-1}$	0.0002**	0.0002**	0.0002**	0.0005**	0.0004	0.0001
$GPR^{\oplus}_{t-1}$	(2.26)	(2.01)	(2.04)	(2.18)	(1.01)	(0.41)
$d_{ESDC\_A,t-1}EPU_{t-1}YCsl_{t-1}$	–0.0022**	–0.0013*	–0.0013*	–0.0009***	–0.0013*	–0.0010*
EC_{t-1}	(–2.14)	(–1.68)	(–1.76)	(–2.98)	(–1.80)	(–1.84)
$d_{ESDC\_A,t-1}EPU_{t-1}REIT_{t-1}$	–0.0091	–0.0014	–0.0017	–0.0042	–0.0010	–0.0038
RE_{t-1}	(–1.00)	(–0.15)	(–0.31)	(–0.87)	(–0.12)	(–0.79)

Table 21.8 (continued)

↓Macro variables Macro effects	IT	ES	GR	SWITZ	SCAND	ALL
Panel C. The COVID effect						
$d_{COVID,t-1}EPU_{t-1}VSTOXX_{t-1}$	0.0054	0.0109*	0.0086*	0.0069	0.0071	0.0093**
FU_{t-1}	(1.04)	(1.82)	(1.70)	(1.33)	(1.33)	(2.01)
$d_{COVID,t-1}EPU_{t-1}BAA_{t-1}$	0.0007	0.0005	0.0001	0.0001	0.0014	0.0052*
CCR_{t-1}	(0.45)	(0.32)	(0.05)	(0.14)	(1.06)	(1.71)
$d_{COVID,t-1}EPU_{t-1}MOVE_{t-1}$	0.0001	0.0090*	0.0074**	0.0014	0.0029	0.0008
SCR_{t-1}	(0.62)	(1.69)	(2.03)	(0.70)	(1.16)	(0.38)
$d_{COVID,t-1}EPU_{t-1}TED_{t-1}$	0.0116	0.0209	0.0138*	0.0008	0.0182	0.0009
LIQ_{t-1}	(0.85)	(0.95)	(1.76)	(0.34)	(0.99)	(0.27)
$d_{COVID,t-1}EPU_{t-1}GPR_{t-1}$	0.0003*	0.0010*	0.0007**	0.0004	0.0001	0.0003
$GPR^{\oplus}$	(1.69)	(1.69)	(2.33)	(0.81)	(0.31)	(0.89)
$d_{COVID,t-1}EPU_{t-1}YCsl_{t-1}$	–0.0106	–0.0012	–0.0011	–0.0013	–0.0001	–0.0017
EC_{t-1}	(–1.21)	(–0.13)	(–0.15)	(–0.35)	(–0.19)	(–0.32)
$d_{COVID,t-1}EPU_{t-1}REIT_{t-1}$	–0.0157	–0.0327	–0.0230**	–0.0226**	–0.0119	–0.0238*
RE_{t-1}	(–1.06)	(–1.33)	(–1.94)	(–2.16)	(–0.58)	(–1.71)

Note: The table reports the EPU effect during crises on the macro factors' impact on dynamic equicorrelations (eq. (12)). The coefficients of each EPU interaction term under crisis estimated separately are displayed. The numbers in parentheses are t–statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table 21.9 The significant cases (over 12 total cases) of the crisis effect and the EPU indirect effect during crisis on the macro drivers of tourism equicorrelations (sum of Tables 21.7 and 21.8)

Macro effects →	EPU	FU	CCR	SCR	LIQ	GPR	EC	RE
Panel A. The crisis effect								
GFC period	8	6	6	6	11	0	3	1
first ESDC period	12	8	10	8	6	0	6	1
COVID period	12	6	4	6	1	9	0	8
Panel B. The EPU indirect effect during crisis								
GFC period		9	7	5	12	9	4	1
first ESDC period		8	10	8	11	7	11	1
COVID period		9	3	6	1	9	0	7

Note: The table reports the number of significant coefficients for the crisis and EPU under crisis effect on each DECO macro factor displayed in Tables 21.7 and 21.8.

both the estimated positive coefficients on financial uncertainty, credit, liquidity, and geopolitics and the negative one on activity being bigger in most cases (see also Table 21.9, Panel B, for the number of significant cases out of 12).

6 CONCLUSIONS

This study provides evidence on the determinants of financial integration in the case of a specific sector, namely the tourism industry, which is particularly vulnerable to exogenous shocks such as the recent COVID–19 pandemic. Specifically, the analysis sheds light on the macro determinants of the time–varying correlations among 11 European Travel & Leisure sectoral stock indices. Our evidence shows that cross–border tourism interlinkages are significantly affected by economic policy and financial uncertainty, credit and liquidity conditions, geopolitical risk, and economic and real estate activity. These results are in line with the contagion literature and confirm the counter–cyclical dynamics of tourism sectoral correlations, namely factors causing economic contractions (such as uncertainty, tight credit, low liquidity, and geopolitical turbulence) increase cross–country connectedness while strong fundamentals (economic and real estate activity) move correlations down. Furthermore, the sensitivity analysis of the transmission mechanism highlights the detrimental impact of economic policy uncertainty and the sizeable effect of crises on tourism integration.

These findings concerning the driving forces of integration of the tourism sectors across Europe provide useful information to policymakers for policy intervention and regulation enforcement purposes, and to practitioners for investment analysis and portfolio management ones. Higher correlations during economic slowdowns increase the risk of contagion, with negative effects in terms of systemic risk and financial stability. Increased interconnectedness driven by weak fundamentals should be seen by regulatory authorities as an alarming signal and lead them to take action to alleviate sectoral systemic stress during economic downturns. Tourism managers and investors should assess the cross–border contagion risks in crisis periods when international diversification benefits fade away owing to stronger sectoral correlations. Future research could shed additional light on the macro drivers of tourism correlation dynamics by concentrating on country–specific proxies in a multi–country/continent context (e.g., bivariate tourism correlations between two countries or regions explained by global and local fundamentals). Our framework could also be used to analyze integration drivers in the case of other economic sectors and financial markets.

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APPENDIX

Summary statistics

Table A21.1 Summary statistics of T&L index returns

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	ADF
DE	–0.036	0.000	14.605	–16.592	2.002	–0.255	8.963	–67.854***
FR	–0.013	0.011	10.248	–14.135	1.493	–0.359	9.745	–67.266***
AT	0.045	0.000	16.434	–29.591	2.712	–0.874	15.865	–64.182***
BNL	0.044	0.019	20.332	–18.766	1.674	–0.033	18.676	–68.150***
UK	0.013	0.034	14.006	–20.003	1.362	–1.010	25.757	–27.469***
IRE	0.038	0.000	10.499	–19.981	1.706	–0.510	12.287	–69.017***
IT	–0.006	0.019	9.964	–21.564	1.522	–0.880	15.222	–37.613***
ES	–0.021	0.000	19.723	–21.391	1.809	–0.549	15.138	–45.599***
GR	–0.003	0.000	10.752	–22.145	1.851	–0.734	11.415	–69.483***
SW	0.001	0.000	16.720	–25.142	1.761	–0.936	20.292	–70.089***
SC	–0.002	0.000	18.057	–15.505	1.828	0.201	10.948	–67.002***

Note: The table reports the summary statistics of each T&L index returns series. The abbreviations Max, Min, and Std.Dev. denote maximum, minimum, and standard deviation. ADF stands for the Augmented Dickey–Fuller test statistic. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table A21.2 Summary statistics of macro regressors

Macro effects	Macro variables	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	ADF
EPU_t	EPU_t	1.930	1.930	2.938	0.521	0.282	–0.071	3.652	–7.476***
FU_t	$VSTOXX_t$	0.000	–0.003	0.471	–0.434	0.062	0.745	7.486	–73.006***
CCR_t	BAA_t	–0.001	0.000	0.480	–0.290	0.052	0.573	8.002	–70.409***
SCR_t	$MOVE_t$	1.921	1.907	2.423	1.628	0.142	0.364	2.653	–3.996***
LIQ_t	TED_t	0.305	0.220	2.894	–0.120	0.341	2.364	12.095	–4.121***
GPR_t	GPR_t	1.940	1.941	3.068	0.700	0.330	–0.177	3.469	–8.224***
EC_t	$YCsl_t$	0.000	–0.001	0.647	–0.680	0.060	0.117	23.294	–31.286***
RE_t	$REIT_t$	0.000	0.000	0.665	–0.565	0.030	3.049	148.218	–73.549***

Note: The table reports the summary statistics of each macro variable. The abbreviations Max, Min, and Std.Dev. denote maximum, minimum, and standard deviation. ADF stands for the Augmented Dickey–Fuller test statistic. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table A21.3 Summary statistics of dynamic equicorrelation time series

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	ADF
DE	0.291	0.280	0.507	0.115	0.076	0.267	2.303	–2.666*
FR	0.319	0.313	0.560	0.152	0.077	0.360	2.517	–3.385***
AT	0.140	0.133	0.319	0.034	0.049	0.535	2.771	–3.862***
BNL	0.156	0.147	0.511	–0.003	0.066	1.024	4.933	–5.535***
UK	0.325	0.319	0.579	0.122	0.075	0.255	2.658	–4.133***
IRE	0.226	0.223	0.471	0.079	0.058	0.462	3.395	–3.315***
IT	0.259	0.253	0.487	0.105	0.065	0.386	2.529	–4.026***
ES	0.285	0.276	0.479	0.133	0.061	0.454	2.428	–4.311***
GR	0.145	0.138	0.386	0.056	0.036	1.825	9.146	–5.961***
SW	0.183	0.171	0.355	0.051	0.058	0.585	2.805	–3.502***
SC	0.229	0.225	0.389	0.118	0.047	0.341	2.534	–5.182***
ALL	0.289	0.272	0.654	0.116	0.092	0.743	3.357	–4.329***

Note: The table reports the summary statistics of each equicorrelation time series (computed by the GJR–MGARCH–DECO model). The abbreviations Max, Min, and Std.Dev. denote maximum, minimum, and standard deviation. ADF stands for the Augmented Dickey–Fuller test statistic. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Dynamic equicorrelations growth regressions

Table A21.4 Tourism equicorrelations growth ($\Delta Corr_t$) regressions on daily macro factors

↓Macro effects	↓Macro variables	DE	FR	AT	BNL	UK	IRE
	c_0	–0.0075**	–0.0071**	–0.0137	0.0033**	–0.0091*	–0.0096**
		(–2.12)	(–1.95)	(–1.26)	(2.21)	(–1.65)	(–2.34)
	$\Delta Corr_{t-1}$	0.0446**	0.0260*	–0.0530***	–0.0535	0.0204	0.0324*
		(2.41)	(1.61)	(–2.68)	(–0.51)	(1.06)	(1.75)
EPU_{t-1}	EPU_{t-1}	0.0023*	0.0025**	0.0004	0.0021	0.0017*	0.0028**
		(1.79)	(2.01)	(1.00)	(0.86)	(1.76)	(1.92)
FU_{t-1}	$VSTOXX_{t-1}$	0.0333***	0.0254*	0.0558***	0.0477*	0.0494***	0.0267**
		(2.89)	(1.85)	(2.98)	(1.73)	(3.84)	(2.11)
CCR_{t-1}	BAA_{t-1}	0.0442***	0.0156*	0.0152	0.0308	0.0358***	0.0261**
		(3.76)	(1.87)	(1.16)	(0.83)	(2.87)	(2.14)
SCR_{t-1}	$MOVE_{t-1}$	0.0377***	0.0494***	0.0072*	0.0355	0.0473***	0.0403***
		(3.51)	(3.30)	(1.67)	(0.94)	(3.41)	(3.01)
LIQ_{t-1}	TED_{t-1}	0.0334***	0.0272***	0.0266**	0.1653**	0.0257***	0.0266***
		(2.85)	(2.79)	(2.08)	(2.36)	(2.49)	(2.57)
$GPR^{\oplus}_{t-1}$	GPR_{t-1}	0.0013*	0.0009*	0.0016	0.0002	0.0029*	0.0018*
		(1.76)	(1.70)	(0.74)	(0.05)	(1.69)	(1.66)
EC_{t-1}	$YCsl_{t-1}$	–0.0437***	–0.0450***	–0.0008	–0.0798**	–0.0392***	–0.0327***
		(–3.68)	(–4.00)	(–1.17)	(–2.00)	(–3.48)	(–2.92)
RE_{t-1}	$REIT_{t-1}$	–0.1782***	–0.0263*	–0.0504*	–0.7337***	–0.0240*	–0.1661***
		(–3.47)	(–1.73)	(–1.70)	(–3.32)	(–1.78)	(–2.80)
AIC		–4.5634	–4.3927	–3.3394	–1.5943	–4.1176	–4.2027
BIC		–4.5504	–4.3797	–3.3264	–1.5827	–4.1046	–4.1897
DW		2.0003	2.0007	2.0013	2.0019	1.9982	1.9987
$\overline{R}^2$		0.0363	0.0303	0.0101	0.0164	0.0237	0.0215

↓Macro effects	↓Macro variables	IT	ES	GR	SWITZ	SCAND	ALL
	c_0	–0.0040	–0.0024	–0.0144***	–0.0095**	–0.0097**	–0.1341
		(–1.48)	(–1.04)	(–2.62)	(–2.23)	(–2.34)	(–1.27)
	$\Delta Corr_{t-1}$	0.0137	0.0042	–0.0456**	0.0348**	–0.0030	0.0197
		(0.92)	(0.28)	(–2.26)	(1.94)	(–0.16)	(1.14)
EPU_{t-1}	EPU_{t-1}	0.0009	0.0014*	0.0045*	0.0028*	0.0031**	0.0022**
		(1.17)	(1.71)	(1.88)	(1.66)	(2.10)	(2.07)
FU_{t-1}	$VSTOXX_{t-1}$	0.0473***	0.0509***	0.0667***	0.0441***	0.0469***	0.0460***
		(3.41)	(4.24)	(2.91)	(3.28)	(4.26)	(4.02)
CCR_{t-1}	BAA_{t-1}	0.0147*	0.0286**	0.0573**	0.0352***	0.0182*	0.0341***
		(1.75)	(2.33)	(2.07)	(3.41)	(1.80)	(3.01)
SCR_{t-1}	$MOVE_{t-1}$	0.0550***	0.0446***	0.0988***	0.0300**	0.0244**	0.0463***
		(3.84)	(3.21)	(4.81)	(2.03)	(1.90)	(4.01)
LIQ_{t-1}	TED_{t-1}	0.0213**	0.0072	0.0204	0.0293*	0.0303*	0.0227**
		(2.03)	(0.68)	(0.79)	(1.83)	(1.75)	(2.25)
$GPR^{\oplus}_{t-1}$	GPR_{t-1}	0.0024*	0.0015	0.0036**	0.0025*	0.0015	0.0014*
		(1.64)	(1.29)	(2.09)	(1.88)	(1.21)	(1.83)
EC_{t-1}	$YCsl_{t-1}$	–0.0304***	–0.0238**	–0.0535**	–0.0354***	–0.0264**	–0.0351***
		(–2.75)	(–2.05)	(–2.01)	(–2.45)	(–1.94)	(–3.34)
RE_{t-1}	$REIT_{t-1}$	–0.0275**	–0.0168*	–0.0627**	–0.1812***	–0.0210*	–0.0281*
		(–2.22)	(–1.68)	(–2.18)	(–3.17)	(–1.68)	(–2.50)
AIC		–4.0944	–4.2242	–3.3985	–3.9861	–4.0769	–4.7574
BIC		–4.0814	–4.2111	–3.3855	–3.9730	–4.0639	–4.7443
DW		1.9987	2.0000	1.9999	1.9979	1.9992	1.9981
$\overline{R}^2$		0.0236	0.0243	0.0304	0.0237	0.0169	0.0409

Note: The table reports the estimation results of the dynamic equicorrelations growth regressions on daily macro factors. The numbers in parentheses are t–statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. AIC and BIC are the Akaike and the Schwartz Information Criteria, respectively. DW is the Durbin–Watson statistic. R^2 is the adjusted $\overline{R}^2$. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table A21.5 The EPU effect on the macro drivers of tourism equicorrelations growth ($\Delta Corr\ t$)

Macro effect→	FU_{t-1}	CCR_{t-1}	SCR_{t-1}	LIQ_{t-1}	$GPR^{\oplus}_{t-1}$	EC_{t-1}	RE_{t-1}
Macro variables→	EPU_{t-1} $VSTOXX_{t-1}$	EPU_{t-1} BAA_{t-1}	EPU_{t-1} $MOVE_{t-1}$	EPU_{t-1} TED_{t-1}	EPU_{t-1} GPR_{t-1}	EPU_{t-1} $YCsl_{t-1}$	EPU_{t-1} $REIT_{t-1}$
DE	0.0128***	0.0150***	0.0143***	0.0105**	0.0003*	–0.0167***	–0.0660***
	(2.92)	(3.46)	(3.53)	(2.32)	(1.67)	(–3.48)	(–3.32)
FR	0.0203***	0.0158***	0.0168***	0.0063*	0.0010*	–0.0154***	–0.0114**
	(4.65)	(3.80)	(3.29)	(1.86)	(1.80)	(–3.74)	(–1.98)
AT	0.0237***	0.0073*	0.0005	0.0094**	0.0002	–0.0004	–0.0262*
	(3.13)	(1.68)	(0.45)	(1.96)	(0.30)	(–1.29)	(–1.72)
BNL	0.0174*	0.0121	0.0140	0.0622**	0.0009	–0.0296*	–0.2705***
	(1.66)	(0.81)	(0.93)	(2.33)	(0.64)	(–1.83)	(–3.16)
UK	0.0196***	0.0135***	0.0173***	0.0074**	0.0012*	–0.0159***	–0.0119**
	(4.13)	(3.00)	(3.38)	(1.96)	(1.66)	(–3.56)	(–1.99)
IRE	0.0099**	0.0107**	0.0142***	0.0076**	0.0009	–0.0132***	–0.0691***
	(2.15)	(2.30)	(2.79)	(1.93)	(1.14)	(–2.90)	(–2.85)
IT	0.0186***	0.0102**	0.0217***	0.0061*	0.0010*	–0.0117***	–0.0136***
	(3.66)	(2.31)	(4.00)	(1.65)	(1.68)	(–2.66)	(–2.44)
ES	0.0206***	0.0121***	0.0172***	0.0014	0.0008	–0.0106**	–0.0101*
	(4.52)	(2.42)	(3.33)	(0.33)	(1.24)	(–2.21)	(–1.83)
GR	0.0279***	0.0199**	0.0399***	0.0031	0.0009*	–0.0227**	–0.0347***
	(2.92)	(2.02)	(5.22)	(0.31)	(1.68)	(–2.03)	(–3.02)
SW	0.0166***	0.0136***	0.0104*	0.0110*	0.0004*	–0.0138**	–0.0629***
	(3.31)	(3.37)	(1.91)	(1.89)	(1.87)	(–2.40)	(–2.88)
SC	0.0197***	0.0094**	0.0116**	0.0118*	0.0009*	–0.0146**	–0.0130*
	(4.41)	(2.09)	(2.22)	(1.79)	(1.65)	(–2.22)	(–1.87)
ALL	0.0191***	0.0133***	0.0185***	0.0065*	0.0009**	–0.0147***	–0.0158***
	(4.35)	(2.90)	(4.16)	(1.66)	(1.92)	(–3.30)	(–3.10)

Note: The table reports the EPU effect on the macro factors' impact on dynamic equicorrelations growth. The coefficients of each EPU interaction term estimated separately are displayed. The numbers in parentheses are t–statistics. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. ⊕ denotes that the GPR coefficient is estimated separately with a shorter sample.