Corrected GARCH-DCC-MIDAS Models in Economics and Finance

A Thesis Submitted for the degree of Doctor of Philosophy

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Abstract

The aim of this thesis is to investigate the dynamic correlation of cross-assets via multivariate GARCH frameworks, we further examine the recent crisis shock impact on these dynamic correlations. Moreover, our analysis discovers how macroeconomic factors influence the cross-assets connectedness and also connect to the corresponding crisis. This thesis contributes to the time-varying correlation of cross-assets in the economy and finance.

Firstly, we study the macro drivers of the time-varying (dynamic) connectedness between eleven European tourism industries. We examine the dynamic co-movement of travel and leisure markets via GJR-MGARCH-DECO specification. Our empirical evidence provides new evidence of correlations' counter-cyclical behaviour such as the weak economy can cause higher cross-country interdependence; the main factors can be characterised by elevated uncertainty and geopolitical risk, tighter credit and liquidity conditions, and sluggish economic and real estate activity.

Secondly, we investigate the cross-country interdependence among six countries' sustainability benchmarks via DCC-MIDAS; in this chapter, we identify the hedging properties and interdependence types in the short- and long-run dynamic correlation across the business cycle. Furthermore, we study how the corresponding crisis shock influences the co-movements. In addition, our study suggests that the sustainability correlation pattern's significant macro- and crisis-sensitivity reveal strong countercyclical cross-country sustainability interlinkages for the majority of index pairs and crisis periods.

In the last two chapters, we study the dynamic interdependence between financial and 'financialised' assets. We purpose the corrected DCC-GARCH-MIDAS setting to analyse the short- and long-run time-varying correlation dynamics among these assets. Both chapters' evidence provides that most cases are strong countercyclical cross-asset interlinkages which are highly dependent on the economic environment; some cross-assets are weak procyclical condition which is safe-haven properties. We also relate the dynamic correlation to the macro-determinants and the corresponding crisis shocks.

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Declaration

Chapter 1 was written in collaboration with Professor Menelaos Karanasos, Professor Guglielmo Maria Caporale and Dr Stavroula Yfanti and will be submitted to the Handbook of Financial Integration.

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Contents

Tables

List of Figures

1 Introduction

The purpose of this thesis is to study the multivariate GARCH framework in the dynamic correlation of cross-assets in the economic and financial markets. This thesis focuses on three types of multivariate GARCH models: GJR-MGARCH-DECO, DCC-MIDAS and corrected DCC-MIDAS. We apply them to the following data: cross-countries tourism industries, cross-countries stock market indexes and cross-assets financial benchmark indexes. Meanwhile, we relate them to the macroeconomic fundamentals and the responding crisis shocks (the 2008 global financial crisis, the European sovereign debt crisis, and the recent Coronavirus pandemic). In addition, our analysis suggests the crises magnify the macro impact on the cross-assets co-movement. This thesis aims to provide advice to investors and policymakers to re-consider their investment portfolio and re-construct the macroeconomic policy for the future and also the crisis period.

The first chapter aims to examine the eleven European tourism industries (Germany, France, Austria, Benelux (Belgium, Netherlands, Luxembourg - BNL), United Kingdom Ireland, Italy, Spain, Greece, Switzerland and Scandinavia) time-varying co-movement via the dynamic equicorrelations (DECO) model from Engle & Kelly (2012); the correlation pattern of these indices brings our attention to the macroeconomic factors. Hence, this chapter further studies the macroeconomic factors and the crisis shocks on the daily tourism correlation. Based on our evidence from this chapter, we notice the uncertainty channel and the responding crisis shocks have a significant role in the dynamic correlation of the tourism industries. The contribution of this chapter is four parts. Firstly, this chapter investigates the European tourism markets' co-movement with multiple countries on the daily frequency data. Meanwhile, our correlation analysis identifies the interdependence between the cross-countries tourism industries and the contagion effect during the several crisis periods. The second contribution is to extend the academic literature on the financial markets co-movement which connects to the macro environment and the crisis period. Thirdly, this chapter also discusses the connection between the tourism sector and the uncertainty channel. Overall, this chapter provides strong evidence for the dynamic correlation of tourism industries and the significant role of macroeconomic factors in the correlation.

The second chapter studies the cross-countries stock markets' connection during the crisis period and relates to the macroeconomic fundamentals. In this chapter, we apply 6 countries' stock market indexes (European, Australia, Brazil, Japan, US, and Canada) to the bivariate DCC-MIDAS (Dynamic Conditional Correlations - Mixed Data Sampling) specification from Colacito et al. (2011), we can estimate the short- and long-run correlation together based on this model's framework. Our correlation analysis indicates a stronger connection between European and North American indices but a weaker connection between Europe and Japan, Australia and Brazil. In addition, our evidence shows most correlations increase due to the crisis. Meanwhile, this chapter also identifies high- and low-frequency contagion transmitters, as well as interdependence drivers, in the macroenvironment. The contribution of this chapter focuses on filling up the gap in ESG (environmental, social, governance). Also, the second contribution is studying the short- and long-run correlations and discussing the macroeconomic factors and crisis vulnerability on these correlations. To summarise, this chapter provides a picture of cross-countries connection to the investors and market particulars. Also, it alarms the regulatory authorities to devise stabilising policies to reduce the contagion effect.

The third chapter investigates the connection between the financial and 'financialised' assets via the corrected DCC-MIDAS model. The third chapter focuses on studying the relationship between three benchmark indexes which is global equities, real estate and aggregate commodities. The last chapter is interested in the two benchmark indexes (global equities and real estate) with five commodity types (energy commodities, precious metals, industrial metals, agriculture and livestock). Meanwhile, we purposes the cDCC-GARCH-MIDAS setting to apply these indexes to indicate the short- and long-run co-movement between these indexes. After the estimation of cDCC-GARCH-MIDAS, we base on the short- and long-run correlation to identify the cross-assets hedging properties and interdependence types. Then, we relate cross-asset correlations to the macroeconomic factors and corresponding crises in the three indexes. Our results indicate the combination of equities and the real estate market is the strongest connection among these assets. Meanwhile, the contagion effect appears during three crisis periods. The main contribution of these two chapters is to examine the short and long-run connection between different cross-assets; the second contribution studies these cross-asset dependences to three crises and concludes the hedging property for all pairs in these two chapters. The third contribution is based on the mean difference test to examine the difference between short- and long-run correlation. The fourth contribution conducts the macro sensitivity investigation with economic fundamentals. The last contribution of this chapter purposes the modification of the DCC-MIDAS with Aielli's correction on the estimation of the correlation.

The last section of this thesis is the conclusion.

2 The connection between Financial Integration and European tourism stocks

2.1 Introduction

The investigation of time-varying (dynamic) cross-country sectoral linkages constitutes a highly topical and policy-relevant field of business studies, including empirical economics, finance, and management research with important implications for investments and risk analytics. Investors, risk and financial managers analyze financial assets and sectoral co-movements under the scope of asset allocation, portfolio diversification and hedging (Engle & Colacito 2006, Engle & Figlewski 2015). The dynamic interdependence and integration of asset markets are most commonly examined and quantified by multivariate GARCH (MGARCH) models (Christodoulakis & Satchell 2002, Engle 2002). Despite the sample empirical evidence on the dynamic nature of sectoral interlinkages, research on the drivers of the cross-border correlations' evolution among industries, such as the tourism sector, is still silent. The economic forces associated with the integration of tourism equity markets, among the most heavily hit sectors during the recent pandemic-induced crisis, concern both tourism practitioners and policymakers (see, for example, Gogstad et al. (2018), for the European sovereign debt crisis effects on the Greek travel and leisure industry). Elevated correlations in economic downturns (with increased volatility and falling returns) lead the way to systemic risk build-ups and contagion (Ahrend & Goujard 2014, Caporin et al. 2018, Martínez-Jaramillo et al. 2010). Tourism managers, investors, and regulators should proactively evaluate and try to alleviate contagious risk spillovers in the travel and leisure industry. Thus, identifying the macro factors of sectoral integration adds to the tools for reliable risk assessments and prudential policy intervention.

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

Motivated by the literature gap on sectoral correlation determinants, the analysis of tourism equicorrelations responds to our main research question about the drivers of their time-varying behaviour mostly associated with economic fluctuations. The economic fundamentals underlying the cross-country sectoral dependence are studied on a daily frequency. Such a high frequency of economic news affecting the correlations trajectory ensures the robust identification of 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. Otherwise, when we monitor the markets' co-movement based on macro shocks with one- or three-month lags (see, for example, mixed-frequency correlation models in Colacito et al. (2011), Conrad et al. (2014)), this cannot reflect the up-to-date impact of macro fundamentals on markets. Correlations modelling with the high-frequency macro domain is even more critical during crisis times when the macro environment evolves very fast.

Therefore, our study reveals the significant impact of seven factors on tourism correlations, that is i) economic policy and ii) financial market uncertainty, iii) credit (corporate and sovereign) and iv) liquidity conditions, v) geopolitical risk, vi) economic and vii) real estate activity. Since common European or global macro proxies drive the cross-border sectoral equity correlations, we confirm the tourism stock markets' integration. Further, we perform conditional correlations sensitivity analysis which indicates the economic uncertainty effect on the other six macro effects and the crisis periods' ramifications (two financial and one health crisis during the twenty-year sample period applied). Against this backdrop, our results underline the policy uncertainty channel's inflating impact on all correlations (directly) and on the other six macro factors as well (indirectly).

From an economic perspective, since recessions are closely connected with the adverse effect of uncertainty on activity and almost every aspect of the whole macro environment (Caggiano et al. (2017), Colombo (2013)), we reasonably conclude on uncertainty's intensifying role for correlations both directly and indirectly. Besides economic uncertainty, higher financial uncertainty, tighter credit and liquidity conditions, and geopolitical turbulence increase correlations, whereas stronger economic and real estate activity drive correlation levels lower. The economic interpretation of our findings on the macro determinants of cross-country tourism correlations points to the counter-cyclicality of tourism markets' co-movement, that is the observed correlation's upturn during economic slowdowns. The fundamentals signifying a real growth effect (activity factors) are estimated with a negative signed coefficient and the contractive forces (elevated uncertainty, tighter credit, shallow liquidity, and geopolitical tensions) with a positive sign. Finally, the three crises considered (the 2008 financial turmoil, the European sovereign debt crisis, and the recent Covid-19 pandemic crash) mostly exacerbate the macro impact on correlations' evolution.

In this framework, our contribution to the empirical literature is threefold. Firstly, we are the first to explore European tourism markets correlations with multiple countries on a daily frequency by identifying the common drivers of cross-border interdependence and contagion during crisis periods (most studies on sectoral dependence apply lower-frequency datasets without investigating the drivers of this dependence such as Balli & Tsui (2016), estimate monthly volatility spillovers in tourism demand with a bivariate GARCH model). Secondly, our results on the macro-relevance and crisis-vulnerability of tourism markets' connectedness extend the academic literature on financial markets' co-movement (Creti et al. 2013, Kalotychou et al. 2014, Karanasos et al. 2018, 2016) and the tourism-economic growth linkages bibliography, as well (Brida et al. 2020, Chen & Chiou-Wei 2009, Guizzardi & Mazzocchi 2010, Martins et al. 2017, Perles-Ribes et al. 2017, Pulido-Fernández & Cárdenas-García 2021, Wang 2009). Thirdly, we shed light on the uncertainty magnifying effect on tourism sectoral correlations, which is currently ignored by the literature of the tourism-uncertainty link (Balli et al. 2018, Demir & Gözgör 2018, Demiralay & Kilincarslan 2019, Dragouni et al. 2016, Madanoglu & Ozdemir 2018, Tiwari et al. 2019, Wu & Wu 2019, 2021). We unveil the economic forces that tighten the linkages of tourism markets by applying daily macro variables and our novel conclusions can support market practitioners' and policymakers' practice and decision-making. Market players mostly monitor daily correlations in investment analysis, portfolio management, and risk assessments, while policymakers should also benefit from high-frequency macro-financial linkages in policy design for macro- or sector-specific prudential regulation in times of market turbulence and systemic risk threats.

The chapter is structured as follows. The next Section 2.2 reviews the relevant tourism and correlations literature and develops the theoretical hypotheses we intend to test in the empirical part of the study. In Section 2.3, we describe our methodological approach and our data input. Section 2.4 presents the main empirical analysis of the equicorrelation models' estimates. Moreover, Section 2.5 includes the sensitivity analysis of correlations' drivers to policy uncertainty and crisis effects. Finally, the last section 2.6 concludes the empirical study.

2.2 Literature Review and Theoretical Framework

Our review of the bibliography is based on the three main pillars of research we contribute to the relationship between the tourism industry and the economic environment, the tourism-uncertainty link, and the cross-border markets' interdependence and integration. Moreover, the hypotheses tested in the correlations analysis are mainly developed on the basis of the business cycle dynamics, which heavily affect the tourism industry's performance.

2.2.1 Literature Review

2.2.1.1 Tourism and Macro-economy

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, overall using lower- than daily-frequency data (monthly/quarterly/annual). Numerous studies have provided evidence on the way tourism growth boosts economic expansion and on how economic growth contributes to the tourism industry expansion (see, for example, Brida et al. (2020), Chatziantoniou et al. (2013), Pulido-Fernández & Cárdenas-García (2021), and the literature therein). Goh et al. (2008) forecast tourism demand with the use of macroeconomic variables (see also Gounopoulos et al. (2012)). Suess 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 & Mazzocchi (2010), using Italian data, demonstrate that tourism cycles are mostly determined by lagged effects of the business cycle. Martins et al. (2017) study the world tourism demand with data from 218 countries and show that tourism demand is attributed to higher GDP per capita, domestic currency depreciation, and relative domestic prices decrease (see also Dogru et al. (2017)). Becken & Lennox (2012) and Chatziantoniou et al. (2013) investigate the effect of oil price shocks on tourism, while Khan et al. (2005) reveal the trade flows-tourist arrivals link.

More intriguingly, a considerable number of researchers focus on economic/financial crises (e.g. Cró & Martins (2017), Smeral (2010), Wang (2009)) and terrorism (e.g. Araña & León (2008), Corbet et al. (2019)) detrimental impact on tourism. Recently, Gallego & Font (2021), Higgins-Desbiolles (2020), Ozdemir et al. (2022), Sigala (2020),among others, discuss the Coronavirus pandemic effect on the travel and tourism industry, and Farzanegan et al. (2021) show how higher tourism flows increase the virus spread (increase in cases and death toll). Lastly, Barrows & 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 voluminous literature followed using mostly monthly data for returns and macro regressors (Chen 2015, Chen et al. 2005, Singal 2012). To the best of our knowledge, although researchers have explored the relationship between tourism and macro aggregates, there is no literature connecting cross-country co-movement of tourism metrics (tourism demand, supply, or industry performance) with economic fundamentals.

2.2.1.2 Tourism and Uncertainty

Given the widely-examined interaction of tourism with the macro environment and crisis events (economic / health/terrorist), a significant amount of studies further focus on the uncertainty injected into the tourism industry's performance. In this vein, uncertainty in tourism research has 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 & Chiou-Wei (2009) are the first to measure the influence of the significant uncertainty factor (estimated as the conditional variance of tourism and economic growth) for both tourism and economic growth through an EGARCH-M model. More recent studies, use the news-based EPU index, which we also focus on in the present study since it is the sole daily uncertainty metric provided by Baker et al. (2016) and which is perceived as the most comprehensive one, including both economic and policy-related aspects of uncertainty. GPR is a news-based metric, as well, for geopolitical uncertainty developed by Caldara & Iacoviello (2022). Tiwari et al. (2019) investigate the EPU and GPR effect simultaneously on tourist arrivals, while Demiralay & 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 damaging impact on tourism industry performance (measured by arrivals/demand, hotel occupancy, income/receipts, investments, or sectoral stocks) is estimated mostly on monthly and annual datasets for single or multiple countries/areas/continents by Akron et al. (2020), Balli et al. (2018), Demir & Gözgör (2018), Dragouni et al. (2016), Kuok et al. (2022), Madanoglu & Ozdemir (2018), Wu & Wu (2019, 2021), among others. Still, the EPU influence on tourism correlations is not addressed by the literature for any country combination, any frequency, or any tourism metric.

2.2.1.3 Markets 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' risk assessments. The MGARCH family of models contributes to our understanding of the time-varying volatilities co-movement among markets (see, for example, the dynamic correlations models of Cappiello et al. (2006), Christodoulakis & Satchell (2002), Engle (2002), Engle & Kelly (2012)). The correlations computed are 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 delved into estimating correlations across regions or sectors for single or multiple asset classes and industries but with evidence still scant on the drivers of the correlations' evolution. Kocaarslan & Soytas (2019) belong to very few studies on correlation determinants. They 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 applied are the default, term, and TED spread, foreign exchange rates, policy rates, and crisis dummies with estimated coefficients positive and significant in most cases, except for the term spread, which is mostly insignificant. More recently, Karanasos & Yfanti (2021) reveal 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' evolution. Regarding tourism sectoral dependence, Balli & Tsui (2016) have estimated monthly tourism demand spillovers among Australia and New Zealand with a bivariate GARCH specification. We, hereby, complement the tourism sectoral correlations research by using the daily T&L index series as proxies of the tourism industry performance in different countries and by attributing their counter-cyclical correlation dynamics to high-frequency macro fundamentals.

2.2.2 Hypotheses Development

Motivated by the few studies on high-frequency (daily) financial connectedness determinants (Karanasos & Yfanti 2021, Kocaarslan & Soytas 2019), we select the daily macro-financial variables which thoroughly nowcast the business cycle dynamics (see Section 2.3.2 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.

Based on the empirical evidence of elevated financial correlations during economic slowdowns, we expect that contractive macro forces 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 of macro fundamentals similar to the ones widely used by studies on the relationship between tourism with macro aggregates and uncertainty (see Sections 2.2.1.1 & 2.2.1.2). 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. Thereupon, the regressors, which are estimated significant in explaining the T&L correlations' evolution, include the uncertainty factor, given its well-known detrimental effect on the macro deterioration (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 of the economic system 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 treasuries' implied volatility, are observed during economic slowdowns (see, for example, Gilchrist & Zakrajšek (2012). Elevated TED spreads mean lower market liquidity, a common characteristic of contraction periods Ng (2012). We further incorporate the geopolitics effect since geopolitical tensions can heavily harm and decelerate economic expansion (Caldara & Iacoviello 2022). Lastly, activity dynamics lie at the core of economic fluctuations and are proxied by two activity variables: 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. Lower treasury yield curve slope (the so-called term spread calculated as the difference of ten-year minus three-month government bond yields) denotes the economy's slowdown (see Estrella & Mishkin (1997)), similarly to a weak performance of the 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 constitute economic contraction 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 EPU role in the whole macro environment. Pástor & Veronesi (2013) are the pioneers in demonstrating the indirect EPU impact on financial correlations with sound evidence that the negative activity effect on stock co-movements is partly driven by higher EPU. Along these lines, we anticipate that the positive and negative macro influences are magnified or partly explained by elevated EPU levels. The economic uncertainty channel amplifies economic forces associated with business cycle downturns (Caggiano et al. 2017, Colombo 2013, Pástor & Veronesi 2013). Therefore, *H2* tests the indirect exacerbating 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 anticipates that crisis shocks increase sectoral correlations by escalating the macro effects on markets' interdependence. Following the contagion literature (Akay et al. 2013, Caporin et al. 2018, Forbes & Rigobon 2002, Karanasos et al. 2016), during crisis periods the economic fundamentals, acting as contagion transmitters, exert a stronger influence on correlations. Hence, under *H3*, we expect that financial and health crises add an inflammatory macro impact on upraising tourism correlations.

To sum up, all three theoretical hypotheses we test are in line with the well-established evidence on tighter market linkages in weaker economic conditions (counter-cyclicality) which are associated with the business cycle downturns (*H1*), higher EPU levels (*H2*), and crisis shocks (*H3*).

2.3 Methodology and Data description

The present empirical analysis' objective and contribution are to unveil the determinants of cross-border correlations in the European tourism sector and explore the role of economic uncertainty and crisis shocks on the correlation trajectory. First, we estimate the time-varying correlations and, second, we regress the correlations on the macro regressors. Following Karanasos & 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 & Kelly (2012), which calculates the pairwise correlations among the eleven index returns. The selection of using DECO instead of the DCC model is because we consider that the first progress is using GJR-GARCH to estimate conditional variance, this model involves asymmetric effect from negative returns. Meanwhile, according to Engle & Kelly (2012), they stated that the estimation of DCC becomes cumbersome if the size of assets increases. Especially, they pointed out that sometimes DCC's estimation will break down due to the large size of systems. Additionally, Aielli (2013) also indicates that DCC will lose efficiency when it involves large system estimation. Therefore, we use the GJR-MGARCH-DECO instead of DCC model. [1].

This Section proceeds as follows. We present the GJR-MGARCH-DECO specification estimated for all combinations of the eleven European sectoral index returns under investigation. Next, we detail the regression analysis of the correlation time series on the independent variables of uncertainty, credit and liquidity, activity, real estate, and geopolitics (DECO-X) and describe our dataset.

2.3.1 Econometric Methodology

2.3.1.1 Dynamic Correlation model

Following Karanasos & 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 eleven 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 $\mathbf{r}_t$ as $\mathbf{r}_t = [r_{it}]_{i=1,\dots,N}$ (in what follows we will drop the subscript) and the respective residual vector ε_t as $\varepsilon_t = [\varepsilon_{it}]$. The mean equation is estimated as follows:

$$r_{it}{=}\phi_i{+}\varepsilon_{it},\ i = 1, \dots, N, \tag{2.1}$$

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

$$\begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix} = \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}. \tag{2.2}$$

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. (2.1) and e_{it} (see

[1] In this chapter, we want to focus on monthly data for tourism sectors,see also the discussion on the superiority of the particular combination compared to other DCC and GARCH variants in Karanasos & Yfanti (2021)

Eq. (2.6) below).

The Conditional Variances

Regarding ε_{it} in Eq. (2.1), we assume that it is conditionally (on the information at time $t-1$, set $_{t-1}$) normally distributed with mean zero and conditional covariances $h_{ij,t}$, that is $h_{ij,t} = \mathbb{E}(\varepsilon_{it}\varepsilon_{jt}|_{t-1})$. It follows that the corresponding conditional correlations, $\rho_{ij,t}$, $|\rho_{ij,t}| \leq 1$ $(i, j = 1, \ldots, N)$ $\forall$ t, are given by:[2]

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}}. \tag{2.3}$$

Notice that ε_{it} can be expressed as: $\varepsilon_{it} = \sqrt{h_{it}}\widetilde{e}_{it}$, where $h_{it} \overset{\text{def}}{=} h_{ii,t}$. In other words, the $\widetilde{e}_{it}$ are the *devolatilized* errors: $\widetilde{e}_{it} = \varepsilon_{it}/\sqrt{h_{it}}$. It is straightforward to show that the conditional correlations of $\widetilde{e}_{it}$'s are also $\rho_{ij,t}$, that is $\rho_{ij,t} = \mathbb{E}(\widetilde{e}_{it}\widetilde{e}_{jt}|_{t-1})$.

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:

$$(1 - \beta_i L)\sigma_{ii,t} = \omega_i + (\alpha_i + \gamma_i s_{it-1})L(\varepsilon_{it}^2),\ i = 1, \ldots, N, \tag{2.4}$$

where $\omega_i \in (0, \infty)$ and $s_{it} = 0.5[1 - sign(\varepsilon_{it})]$, that is, $s_{it} = 1$ if $\varepsilon_{it} < 0$ and 0 otherwise for all i. Therefore, positive γ_i means 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 $q_{ij,t} = \mathbb{E}(e_{it}e_{jt}|_{t-1})$, and ii) can be expressed as $e_{it} = \sqrt{q_{ii,t}}\widetilde{e}_{it}$. It straightforward to

[2]Most importantly, we allow for time-varying correlations, $\rho_{ij,t}$,instead of the constant ones, ρ_{ij}, defined by Bollerslev (1990). In particular, $\mathbf{R}_t = [\rho_{ij,t}]_{i,j=1,\ldots,N}$ (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.

show that the conditional correlations of e_{it}'s are also $\rho_{ij,t}$:[3]

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}. \tag{2.5}$$

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:

$$q_{ij,t} = (1-a-b)q_{ij} + ae_{i,t-1}e_{j,t-1} + bq_{ij,t-1}, \tag{2.6}$$

where q_{ij}=$\mathbb{E}(q_{ij,t})$, a and b are nonnegative scalar parameters satisfying $a+b<1$. It is clear that 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 to correlations. In the bivariate case, the cDCC$(1,1)$ conditional correlation coefficient $\rho_{12,t}$ is expressed as follows:

$$\rho_{12,t}^{DCC} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}, \tag{2.7}$$

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

To summarize, the model in the first step estimates the vector of the errors, $\varepsilon_t = [\varepsilon_{it}]$, and the vector of the conditional variances, $\mathbf{h}_t = [h_{it}]$, using a GJR-GARCH, and correspondingly the vector of the *devolatilized* errors $\widetilde{\mathbf{e}}_t = [\widetilde{e}_{it}]$, since $\widetilde{e}_{it} = \varepsilon_{it}/\sqrt{h_{it}}$. In the second step, it estimates the matrix of the conditional covariances of the vector of the errors $\mathbf{e}_t = [e_{it}]$, that is $\mathbf{Q}_t = [q_{ij,t}]$, using a cDDC-GARCH process. Once $\mathbf{h}_t$ and $\mathbf{Q}_t$ are estimated then the estimated elements of $\mathbf{R}_t$ (the conditional correlations of the errors, either $\mathbf{e}_t$ or $\widetilde{\mathbf{e}}_t$ or ε_t) are obtained using eq. (2.5), and then the estimated non-diagonal elements of $\mathbf{H}_t = [h_{ij,t}]$ are obtained using eq. (2.3).[4] For computational ease, Engle &

[3] In particular, we have:

$$\begin{aligned} q_{ij,t} &= \mathbb{E}(e_{it}e_{jt}|_{t-1}) = \sqrt{q_{ii,t}}\sqrt{q_{jj,t}}\mathbb{E}(\widetilde{e}_{it}\widetilde{e}_{jt}|_{t-1}) \\ &= \sqrt{q_{ii,t}}\sqrt{q_{jj,t}}\rho_{ij,t} \Rightarrow \\ \rho_{ij,t} &= \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}. \end{aligned}$$

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

Kelly (2012) impose a critical assumption to the calculation of $\mathbf{R}_t^{DCC} = [\rho_{ij,t}^{DCC}]$ model in order to estimate dynamic equicorrelation matrices. Each returns pair 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:

$$\mathbf{R}_t^{DECO} = (1 - \rho_t^{DECO})\mathbf{I}_N + \rho_t^{DECO}\mathbf{J}_N, \tag{2.8}$$

$$\rho_t^{DECO} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{2.9}$$

where $\mathbf{J}_N$ 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.

2.3.1.2 Correlation 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 unbound the correlations from the $[-1, 1]$ interval. The resulting daily time series $Corr_t$ is calculated as follows: $Corr_t = \log(\frac{1+\rho_t^{DECO}}{1-\rho_t^{DECO}})$. For each sectoral index, we compute the average pairwise equicorrelation series of the particular index with the other ten indices. For example, the DECO model computes for Germany 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, resulting in eleven equicorrelations as dependent variables in the DECO-X equation ($Corr_t$). Apart from the bivariate specifications, we run the multivariate model with all eleven 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 regressed on the daily proxies of 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 regressors selected are tested for their immediate lag effect (first lag) on 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 coefficients' significance, 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:

$$\begin{aligned} Corr_t \;=\; & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} + c_3 FU_{t-1} + c_4 CCR_{t-1} + c_5 SCR_{t-1} \\ & + c_6 LIQ_{t-1} + c_7 GPR_{t-1} + c_8 EC_{t-1} + c_9 RE_{t-1} + u_t, \end{aligned} \tag{2.10}$$

with c_0 the regression's constant, and u_t the standard stochastic error term.

2.3.1.3 Equicorrelation Sensitivity Analysis

After exploring the macro drivers of the time-varying European tourism industries' connectedness, 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 the policy uncertainty) in the correlation regression model (eq. (2.10)). Thus, we estimate the following regression equation, eq. (2.11), where the superscript ^{EPU} denotes the coefficients of the EPU interaction terms:

$$\begin{aligned} Corr_t \;=\; & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} + c_3 FU_{t-1} + c_3^{EPU} EPU_{t-1} FU_{t-1} \\ & + c_4 CCR_{t-1} + c_4^{EPU} EPU_{t-1} CCR_{t-1} + c_5 SCR_{t-1} + c_5^{EPU} EPU_{t-1} SCR_{t-1} \\ & + c_6 LIQ_{t-1} + c_6^{EPU} EPU_{t-1} LIQ_{t-1} + c_7 GPR_{t-1} + c_7^{EPU} EPU_{t-1} GPR_{t-1} \\ & + c_8 EC_{t-1} + c_8^{EPU} EPU_{t-1} EC_{t-1} + c_9 RE_{t-1} + c_9^{EPU} EPU_{t-1} RE_{t-1} + u_t. \end{aligned} \tag{2.11}$$

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 enrich eq. (2.10) with the macro variables' slope dummies corresponding to each crisis period. Following the GFC, ESDC, and COVID timelines, we first construct the respective 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 whole ESDC period else $d_{ESDC,t} = 0$
- $d_{ESDC\_A,t} = 1$, if t in the first ESDC subperiod else $d_{ESDC\_A,t} = 0$
- $d_{ESDC\_B,t} = 1$, if t in the second ESDC subperiod 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 construct the slope dummies for the respective macro effect to include them in eq. (2.10). The correlations regression with the crisis influence is estimated as follows:

$$\begin{aligned} Corr_t \;=\; & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} + c_2^{CRISIS} d_{CRISIS,t-1} EPU_{t-1} \\ & + c_3 FU_{t-1} + c_3^{CRISIS} d_{CRISIS,t-1} FU_{t-1} + c_4 CCR_{t-1} + c_4^{CRISIS} d_{CRISIS,t-1} CCR_{t-1} \\ & + c_5 SCR_{t-1} + c_5^{CRISIS} d_{CRISIS,t-1} SCR_{t-1} + c_6 LIQ_{t-1} + c_6^{CRISIS} d_{CRISIS,t-1} LIQ_{t-1} \\ & + c_7 GPR_{t-1} + c_7^{CRISIS} d_{CRISIS,t-1} GPR_{t-1} + c_8 EC_{t-1} + c_8^{CRISIS} d_{CRISIS,t-1} EC_{t-1} \\ & + c_9 RE_{t-1} + c_9^{CRISIS} d_{CRISIS,t-1} RE_{t-1} + u_t, \end{aligned} \tag{2.12}$$

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 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:

$$\begin{aligned} Corr_t \;=\; & c_0 + c_1 Corr_{t-1} + c_2 EPU_{t-1} + \\ & + c_3 FU_{t-1} + c_3^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} FU_{t-1} \\ & + c_4 CCR_{t-1} + c_4^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} CCR_{t-1} \\ & + c_5 SCR_{t-1} + c_5^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} SCR_{t-1} \\ & + c_6 LIQ_{t-1} + c_6^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} LIQ_{t-1} \\ & + c_7 GPR_{t-1} + c_7^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} GPR_{t-1} \\ & + c_8 EC_{t-1} + c_8^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} EC_{t-1} \\ & + c_9 RE_{t-1} + c_9^{EPU\_CR} d_{CRISIS,t-1} EPU_{t-1} RE_{t-1} + u_t. \end{aligned} \tag{2.13}$$

2.3.2 Data description

Next, we present the data used for the European tourism industry performance and the macro-financial variables driving the cross-country sectoral correlations. We use daily index prices from eleven European Travel & Leisure sectoral equity indices considered as benchmarks for the performance of the tourism industry in each country/country group. Our tourism benchmarks, sourced 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)[5].

Table 2.1: 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^{***}

Notes:

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.

Our sample covers the period from 01/01/2001 to 20/05/2020, that is 5,057 daily ob-

[5]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. T&L equity index data are not available for all European continent's countries for a long period covering all three crises under consideration in the current study.

servations. For each sectoral index, we calculate the continuously compounded return as follows: $r_{it} = [\ln(P^C_{i,t}) - \ln(P^C_{i,t-1})] \times 100$, with $P^C_{i,t}$ the daily closing price of day t. The summary statistics and unit root tests of the return series are available in the table 2.1. 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 applied in this study. The pairwise correlation coefficients of all bivariate combinations of returns are all positive (table 2.2), indicating a strong co-movement of the European tourism sector. 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 (eqs. (2.10), (2.11), (2.12), and (2.13)) provide evidence of the global macro effects on the European tourism correlations' evolution:

Table 2.2: 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

Notes:

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

The economic policy uncertainty (EPU_t) is proxied by the daily US EPU index in its log-level form. Baker, Bloom, and Davis (https://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.

The financial uncertainty (FU_t) is proxied by the Euro Stoxx 50 implied volatility index VSTOXX ($VSTOXX_t$) included in its first difference of log-levels.

The corporate credit conditions (CCR_t) are proxied by the first difference of Moody's BAA global corporate bond yields levels (BAA_t).

The 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. Elevated sovereign bond volatility denotes increased turbulence in the credit channel for sovereigns with direct pass-through to financial and non-financial corporations' credit conditions.

The liquidity conditions (LIQ_t) are proxied 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.

The geopolitical risk (GPR_t) factor is the daily global Geopolitical Risk index (log-level) of Caldara & Iacoviello (2022) downloaded from Iacoviello's website [6].

The economic activity (EC_t) is proxied by the first difference of the German Yield Curve slope (or term spread), as computed by the difference of the ten-year minus the three-month German Treasury bond yields ($YCsl_t$). It is considered among the unique daily economic activity indicators since it is established as a powerful activity predictor (Estrella & Mishkin 1997).

The 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 its first difference of log-levels.

[6] https://www.matteoiacoviello.com/gpr.htm

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 retrieved from Refinitiv Eikon Datastream, as well, 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, due to data availability on Iacoviello's website. Therefore, we first 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 run 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 levels (BAA_t, $YCsl_t$) or first difference of log-levels ($VSTOXX_t$, $REIT_t$) as indicated above in order to ensure, first and foremost, that there is no multicollinearity or unit root in the regressors and, secondly, to select the form with the most significant effect on equicorrelations. Table 2.3 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.

Table 2.3: Table 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^{***}

Notes:

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.

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 the gradual return to markets' 'calm'.

ESDC: 9/5/2010 - 31/7/2015. The ESDC starts with the Greek state default and bailout in 2010. For the major part of Euro-zone the ESDC finishes at the end of 2012 (ESDC_A, first ESDC subperiod), while for Greece the sovereign debt turbulence persisted until July 2015 (ESDC_B, second ESDC subperiod). Therefore, we distinguish between two ESDC subperiods: 1st subperiod (ESDC_A): 09/05/2010 - 31/12/2012 and 2nd subperiod (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 while the pandemic is still running until the sample's end.

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 2.4 reports the time variation of the series mean value for each macro variable used across the crisis subsamples.

Table 2.4: 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

Notes:

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

The EPU index log-level is higher on average during all crises, apart from the second ESDC period, showing a sharp jump in the recent pandemic. Financial uncertainty growth is mostly elevated in the GFC period and with a sharp jump in the recent Covid times, as well. Credit conditions tightening is mostly observed during the global financial turmoil of 2008 with higher corporate lending cost growth and treasury volatility on average. The German TED spread is significantly increased during GFC, the first ESDC period, and COVID, signifying lower liquidity in financial markets. Economic and real estate activity growth decrease in crises, while geopolitical risk is mostly elevated in the recent pandemic. We will further provide evidence that cross-country tourism correlations are higher during crises and the macro drivers' effect becomes more intense partly driven by the uncertainty channel.

2.4 Estimation Results

2.4.1 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 eleven European tourism industries through the GJR-MGARCH$(1,1)$-DECO$(1,1)$ model. Overall, we estimate all bivariate combinations of the daily index returns and the multivariate specification with all eleven indices included. Moreover, we regress the correlations (average per country / country group) computed by the DECO model on daily macro factors.

Table 2.5 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, denoting 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, computed as $(\alpha_i + \beta_i + \gamma_i/2)$.

Table 2.5: 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 (0.18)	0.0676*** (2.97)	0.0379*** (3.03)	0.9175*** (46.90)	0.0488*** (3.70)	−9930.55	10.84 [0.54]
FR	0.0154 (1.00)	0.0307*** (4.93)	0.0069 (0.88)	0.9184*** (74.95)	0.1105*** (6.91)	−8133.41	13.81 [0.31]
AT	0.0476 (1.49)	0.2873*** (3.00)	0.0807*** (4.48)	0.8446*** (24.02)	0.0731*** (2.61)	−11396.6	9.96 [0.62]
BNL	0.0531*** (2.71)	0.1306*** (2.40)	0.0664*** (2.63)	0.8559*** (23.22)	0.0502*** (2.42)	−9041.21	15.49 [0.22]
UK	0.0365*** (2.81)	0.0301*** (4.31)	0.0183** (2.05)	0.8873*** (51.69)	0.1405*** (5.59)	−7240.83	17.76 [0.12]
IRE	0.0717*** (3.78)	0.0223** (2.13)	0.0163* (1.85)	0.9521*** (79.23)	0.0477*** (3.26)	−9190.12	16.11 [0.19]
IT	0.0128 (0.75)	0.0499*** (2.89)	0.0267*** (2.68)	0.9038*** (41.47)	0.0908*** (4.30)	−8572.94	10.46 [0.58]
ES	0.0178 (0.94)	0.0602*** (2.95)	0.0443*** (3.30)	0.8817*** (36.37)	0.1176*** (3.44)	−9283.28	17.42 [0.14]
GR	0.0178 (0.87)	0.0213* (1.68)	0.0404** (2.37)	0.9404*** (47.13)	0.0295*** (2.62)	−9577.19	8.60 [0.74]
SW	0.0190 (0.98)	0.0275* (1.79)	0.0205 (1.02)	0.9345*** (36.19)	0.0798*** (3.00)	−9320.45	18.29 [0.11]
SC	0.0315 (1.40)	0.1007*** (2.40)	0.0320*** (2.35)	0.9036*** (31.36)	0.0660*** (3.65)	−9709.74	11.43 [0.49]

Panel B. Equicorrelation equation with all eleven index returns.

a	0.0296*** (6.32)
b	0.9596*** (148.2)
$logL$	−96622.8

Notes:

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.

The correlation equation, estimated with all eleven T&L indices included, gives an average overall conditional equicorrelation close to 30% (see the last graph - 'all 11 indices' - in Figure 2.1 and the last line - 'ALL' - in Table 2.6) for the whole sample and high persistence $(a + b)$ in its time-varying pattern.

Figure 2.1: Cross-border T&L sectoral dynamic conditional equicorrelations graphs

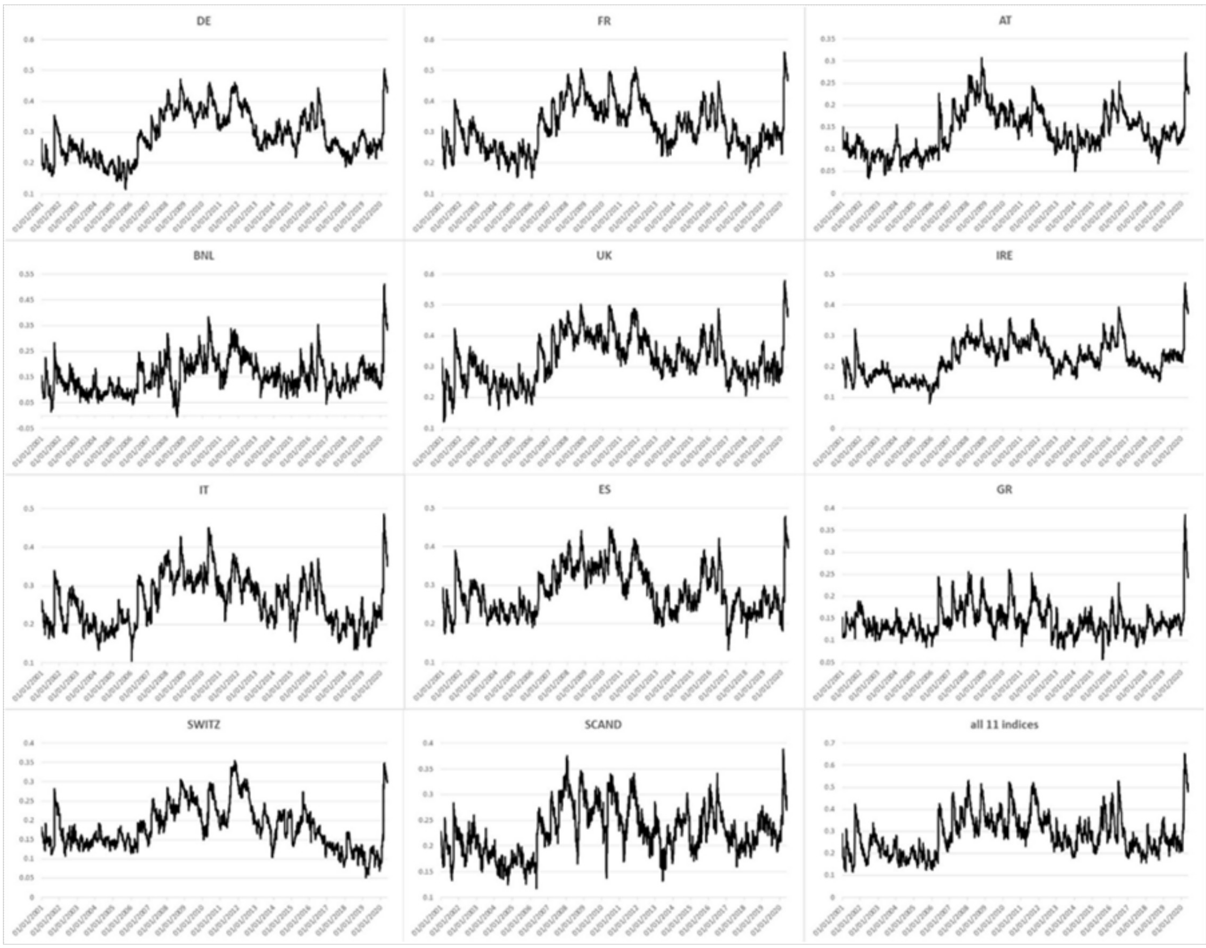
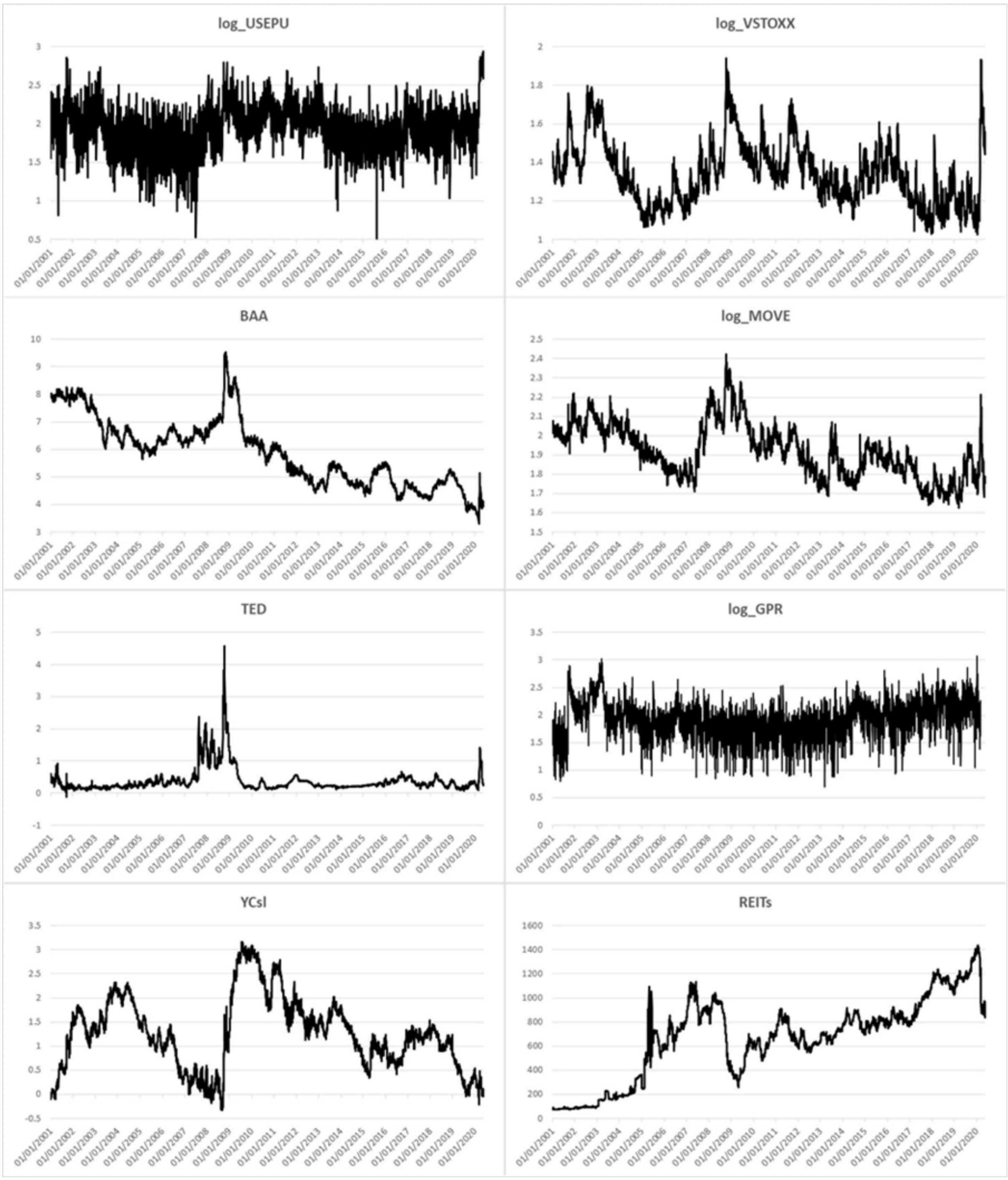


Figure 2.1 shows all pairwise cross-country sectoral correlation patterns (averaged per country from the bivariate DECO specifications) and the overall correlation dynamics with the eleven European tourism industries included altogether in the multivariate DECO model (bivariate correlations of each country with the others [not averaged] are available upon request). They increase significantly during the GFC and the first ESDC period, suggesting 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, confirming the accelerated 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 2.2).

Figure 2.2: Macro-financial variables graphs



2.4.2 Equicorrelations Regressions

We further regress the dynamic equicorrelation time series computed by 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 B.1 (in the Appendix) shows the summary statistics of the time-varying correlations. The highest mean value is observed again in the UK correlation with the other ten countries / country groups, and 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 2.6: 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

Notes:

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.

Table 2.6 summarizes the mean values of each correlation series across the crisis subsamples in contrast with the full period's mean values. We hereby confirm the conclusions drawn from the correlations' graphic analysis (Figure 2.1). We observe significantly elevated interdependence during the global turmoil of 2008 and the first subperiod of the European debt crisis, while the second ESDC subsample's means are mostlylower than the total sample's ones. During the pandemic era, most sectoral co-movements peaked at higher levels than in the GFC period, with correlation values reaching twice the whole sample's average values. This shows a significantly higher degree of financial integration among tourism stock markets in the most recent years of the last two decades under investigation.

Table 2.7: Tourism equicorrelations regressions on daily macro factors (Eq. (2.10)

↓ Macro effects	↓ Macro variables	DE	FR	AT	BNL	UK	IRE
	c_0	0.2976*** (10.72)	0.2487*** (10.07)	0.1189*** (8.45)	0.0786*** (3.26)	0.2946*** (11.16)	0.1517*** (7.79)
	$Corr_{t-1}$	0.9968*** (858.0)	0.9950*** (743.0)	0.9932*** (579.4)	0.9854*** (394.5)	0.9919*** (520.6)	0.9950*** (613.5)
EPU_{t-1}	EPU_{t-1}	0.0006* (1.74)	0.0010** (2.15)	0.0001 (0.51)	0.0012** (2.12)	0.0013** (2.02)	0.0007* (2.50)
FU_{t-1}	$VSTOXX_{t-1}$	0.0036** (2.31)	0.0027* (1.70)	0.0015* (1.66)	0.0064** (2.10)	0.0060** (2.21)	0.0229*** (2.85)
CCR_{t-1}	BAA_{t-1}	0.0051* (1.74)	0.0046** (2.27)	0.0033* (1.73)	0.0061* (1.84)	0.0065* (1.73)	0.0074** (2.39)
SCR_{t-1}	$MOVE_{t-1}$	0.0289*** (4.30)	0.0478*** (4.60)	0.0030** (2.16)	0.0358*** (2.48)	0.0059** (1.99)	0.0028* (1.65)
LIQ_{t-1}	TED_{t-1}	0.0107*** (3.14)	0.0159*** (3.91)	0.0113*** (3.16)	0.0187*** (3.10)	0.0207*** (3.23)	0.0097*** (2.51)
$GPR^{\oplus}_{t-1}$	GPR_{t-1}	0.0006*** (1.81)	0.0003* (1.69)	0.0002 (0.64)	0.0008* (1.71)	0.0003 (0.70)	0.0001 (0.10)
EC_{t-1}	$YCsl_{t-1}$	−0.0075*** (−2.69)	−0.0140*** (−3.79)	−0.0077*** (−2.68)	−0.0160*** (−3.25)	−0.0189*** (−3.26)	−0.0074** (−2.21)
RE_{t-1}	$REIT_{t-1}$	−0.0241*** (−2.81)	−0.0223*** (−2.43)	−0.0024* (−1.69)	−0.0097 (−0.59)	−0.0038 (−1.08)	−0.0049 (−0.55)
AIC		−7.2907	−6.8855	−7.7659	−6.3352	−6.2353	−7.3453
BIC		−7.2777	−6.8725	−7.7529	−6.3222	−6.2223	−7.3322
DW		1.9219	1.9496	2.0588	2.0284	1.9790	1.9431
$\overline{R}^2$		0.9928	0.9894	0.9867	0.9675	0.9832	0.9876

Notes:

The table reports the estimation results of the dynamic equicorrelations regressions on daily macro factors (eq. (2.10)). 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. $\overline{R}^2$ is the adjusted R^2. $\oplus$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table 2.7 presents the estimation results of the correlation regressions on the macro-financial variables revealing the common global macro effects on correlation dynamics. The global macro factors are chosen according to their significance and our model selection statistical criteria (AIC, BIC, $\overline{R^2}$). Therefore, we preferred for EPU the US index, 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.

Table 2.8: Tourism equicorrelations regressions on daily macro factors (Eq. (2.10)(continued))

↓ Macro effects	↓ Macro variables	IT	ES	GR	SWITZ	SCAND	ALL
	c_0	0.1112^{***} (4.53)	0.2310^{***} (12.34)	0.1118^{***} (9.02)	0.0807^{***} (3.81)	0.1402^{***} (8.14)	0.1341^{***} (8.67)
	$Corr_{t-1}$	0.9925^{***} (570.4)	0.9907^{***} (478.9)	0.9826^{***} (279.7)	0.9959^{***} (730.1)	0.9880^{***} (444.3)	0.9955^{***} (648.0)
EPU_{t-1}	EPU_{t-1}	0.0008^{*} (1.85)	0.0011^{**} (2.16)	0.0007^{**} (2.01)	0.0005^{*} (1.77)	0.0002^{***} (2.55)	0.0007^{***} (2.59)
FU_{t-1}	$VSTOXX_{t-1}$	0.0295^{***} (3.25)	0.0053^{***} (2.88)	0.0032^{*} (1.86)	0.0191^{***} (4.29)	0.0230^{***} (4.08)	0.0065^{***} (4.11)
CCR_{t-1}	BAA_{t-1}	0.0051^{**} (2.11)	0.0083^{***} (2.80)	0.0042^{**} (1.97)	0.0076^{***} (2.64)	0.0033^{*} (1.69)	0.0032^{***} (2.46)
SCR_{t-1}	$MOVE_{t-1}$	0.0377^{***} (4.11)	0.0043^{**} (1.94)	0.0043^{***} (2.64)	0.0135^{***} (2.54)	0.0140^{**} (2.11)	0.0332^{***} (4.63)
LIQ_{t-1}	TED_{t-1}	0.0114^{***} (2.45)	0.0190^{***} (3.71)	0.0110^{***} (3.01)	0.0064^{**} (2.19)	0.0077^{**} (1.98)	0.0048^{**} (1.95)
$GPR^{\oplus}_{t-1}$	GPR_{t-1}	0.0003 (0.76)	0.0005 (1.24)	0.0002 (0.83)	0.0004^{*} (1.87)	0.0004 (1.28)	0.0003^{*} (1.80)
EC_{t-1}	$YCsl_{t-1}$	-0.0100^{***} (−2.53)	-0.0167^{***} (−3.59)	-0.0096^{***} (−2.93)	-0.0068^{***} (−2.69)	-0.0081^{**} (−2.32)	-0.0066^{***} (−3.37)
RE_{t-1}	$REIT_{t-1}$	-0.0140^{*} (−1.66)	-0.0293^{***} (−2.53)	-0.0049^{**} (−2.32)	−0.0008 (−0.69)	-0.0151^{*} (−1.85)	-0.0024^{*} (−1.79)
AIC		−6.8518	−6.7191	−7.4541	−7.8279	−7.1856	−7.9556
BIC		−6.8388	−6.7060	−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

Notes:

The table reports the estimation results of the dynamic equicorrelations regressions on daily macro factors (eq. (2.10)). 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. $\overline{R}^2$ is the adjusted R^2. $\oplus$ denotes that the GPR coefficient is estimated separately with a shorter sample.

For robustness test purposes, we also ran the equicorrelation regressions replacing the US EPU index with the UK EPU, the Euro Stoxx 50 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 coefficients are estimated with the same signs but insignificant in more cases than their alternatives selected in Table 2.8.

The uncertainty effect on correlations is always positive. The economic policy uncertainty variable is estimated 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 elevated cross-country tourism correlations. Moreover, both credit proxies (corporate and sovereign credit variables coefficients positive and significant) drive correlations upwards, denoting that tighter credit conditions, mostly observed in weak economic stance, boost tourism sectoral interdependence. Similarly, liquidity tightening exerts a positive impact, as well, with the TED spread's coefficient always positive and highly significant. Geopolitics' positive effect is significant in five out of twelve cases while the activity variables are always estimated with negative coefficients. 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 correlation series growth ($\Delta Corr_t = \frac{Corr_t}{Corr_{t-1}} - 1$) on the same macro factors, all in their growth form (Table B.2 in the Appendix). Our conclusions are similar to the empirical analysis of the correlation levels. Uncertainty, credit, and liquidity growth proxies exacerbate sectoral interconnectedness while an increase in activity drives correlations trajectory lower. More interestingly, the GPR growth effect on correlations growth is positive and significant in most cases, contrary to the weak GPR level effect on correlations level.

All in all, we provide sound evidence on the common macro drivers of the cross-country tourism integration. Elevated tourism correlations are associated with higher uncertainty and tighter credit and liquidity conditions, while lower correlations are related to higher economic and real estate activity growth. Hence, our main finding confirms our first theoretical hypothesis (*H1*) and highlights the counter-cyclicality of tourism correlations, that is economic variables, associated with weak economic conditions, exacerbate correlations, while activity growth indicators mostly reduce cross-border tourism interdependence. Accordingly, the inflating EPU and crisis effect on the macro factors, investigated in the following parts of our empirical analysis (Section 2.5), is economically plausible since increased uncertainty and crisis are linked to economic downturns. Our results also contribute to the contagion literature. Forbes & Rigobon (2002) define contagion vs. interdependence. Contagion is 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. Given that higher correlations are mainly explained, here, by poor economic fundamentals, we can infer cross-country contagion effects.

2.5 Sensitivity Analysis

Following our investigation on the economic forces driving the tourism industry integration among major European countries, we continue with the sensitivity exercise for the drivers' effect across the business cycle timeline. We first explore the uncertainty channel for the transmission of the macro effects given that higher uncertainty is associated with economic downturns. Second, we focus on crisis periods, which lead to recessions, to measure the macro effects during economic turmoils. Lastly, we consider the uncertainty channel in crisis periods, separately, to estimate the inflating EPU impact on the macro drivers during crises.

2.5.1 EPU Effect on Tourism Correlations

The important role of EPU on correlation dynamics is further explored, focusing on the indirect impact on cross-country tourism sectoral interdependence through the macro factors that drive this interdependence. Hence, the question we raise is whether EPU exerts considerable influence not only directly on correlations' evolution but, more precisely, on the economic forces that determine the time-varying behavior of conditional equicorrelations. Our empirical results have important implications for macro-informed investors in the tourism industry and policymakers' stability concerns and systemic risk oversight. Admittedly, cross-country sectoral integration dynamics merit the attention of both investors in asset allocation, portfolio optimization, and risk management (diversification and hedging) and regulators in their market intervention activities (stabilization and proactive macro-prudential policies). Based on our review of the research on the tourism-uncertainty link, we diagnose that the literature has not yet delved into the EPU effect on tourism sectoral correlations and, particularly, the EPU amplifying role on the impact of financial uncertainty, credit and liquidity channel, geopolitics and activity, which is proved here through the DECO framework.

In this vein, we have already highlighted the direct positive impact of EPU on correlations. In this Section, we investigate the EPU effect on the macro drivers of dynamic equicorrelations. Table 2.8 and 2.9 reports the coefficients of the interaction terms estimated in equation (2.11). We present the uncertainty effect on each macro determinant as estimated through alternative restricted forms of equation (2.11), including each EPU effect separately (each coefficient with the superscript ^{EPU} is estimated separately). All significant interaction terms are estimated with the same sign of the respective macro effect (similar results estimated with $\Delta Corr_t$ regressions on the macro factors' growth, see Table B.4 and B.5 in the Appendix). Intriguingly, we prove that higher policy uncertainty means a stronger effect of financial uncertainty, credit and liquidity conditions, geopolitical risk, economic and real estate activity on cross-border tourism integration. Since there is widespread evidence that higher uncertainty is associated with economic worsening, we further deduce the link of credit and liquidity conditions during business cycle downturns with higher correlations heavily affected by the uncertainty channel. In other words, EPU partly drives or explains the macro determinants of equicorrelations by amplifying their effect, confirming our second hypothesis (*H2*).

Table 2.9: The EPU effect on the macro drivers of tourism equicorrelations (eq. (2.11)).

↓ Macro effects	↓ Macro variables	DE	FR	AT	BNL	UK	IRE
FU_{t-1}	$EPU_{t-1}VSTOXX_{t-1}$	0.0020^{***} (2.84)	0.0016^{*} (1.89)	0.0007^{**} (2.03)	0.0117^{***} (3.44)	0.0025^{**} (2.32)	0.0014^{***} (3.24)
CCR_{t-1}	$EPU_{t-1}BAA_{t-1}$	0.0002^{***} (2.80)	0.0025^{***} (2.38)	0.0001 (0.57)	0.0001 (0.10)	0.0009^{*} (1.65)	0.0002^{**} (2.33)
SCR_{t-1}	$EPU_{t-1}MOVE_{t-1}$	0.0023^{***} (2.88)	0.0016^{***} (3.43)	0.0010^{*} (1.70)	0.0078^{**} (2.34)	0.0026^{**} (2.10)	0.0010^{*} (1.69)
LIQ_{t-1}	$EPU_{t-1}TED_{t-1}$	0.0047^{***} (4.10)	0.0028^{***} (2.43)	0.0019^{***} (2.41)	0.0040^{***} (2.51)	0.0050^{***} (3.28)	0.0023^{***} (3.11)
$GPR^{\oplus}_{t-1}$	$EPU_{t-1}GPR_{t-1}$	0.0004^{***} (3.16)	0.0003^{*} (1.66)	0.0001 (0.67)	0.0001^{*} (1.66)	0.0004 (1.28)	0.0001 (1.14)
EC_{t-1}	$EPU_{t-1}YCsl_{t-1}$	-0.0004^{*} (−1.82)		−0.0002 (−1.08)	−0.0013 (−1.28)	-0.0021^{**} (−2.00)	-0.0003^{*} (−1.70)
RE_{t-1}	$EPU_{t-1}REIT_{t-1}$	-0.0127^{***} (−2.63)	-0.0127^{**} (−2.17)	-0.0012^{*} (−1.66)	−0.0092 (−1.31)	-0.0026^{*} (−1.70)	−0.0047 (−1.07)

Notes:

The table reports the EPU effect on the macro factors' impact on dynamic equicorrelations (eq. (2.11)).

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. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table 2.10: The EPU effect on the macro drivers of tourism equicorrelations (eq. (2.11)). (continued)

↓ Macro effects	↓ Macro variables	IT	ES	GR	SWITZ	SCAND	ALL
FU_{t-1}	$EPU_{t-1}VSTOXX_{t-1}$	0.0115*** (4.37)	0.0024*** (3.05)	0.0006* (1.89)	0.0008*** (3.11)	0.0020*** (3.79)	0.0026*** (4.03)
CCR_{t-1}	$EPU_{t-1}BAA_{t-1}$	0.0010** (2.15)	0.0016** (2.02)	0.0009* (1.67)	0.0001* (1.75)	0.0001 (1.12)	0.0012** (2.27)
SCR_{t-1}	$EPU_{t-1}MOVE_{t-1}$	0.0108*** (4.52)	0.0017** (1.92)	0.0011* (1.67)	0.0003* (1.89)	0.0005* (1.69)	0.0007*** (3.27)
LIQ_{t-1}	$EPU_{t-1}TED_{t-1}$	0.0034*** (3.00)	0.0046*** (3.59)	0.0023*** (2.84)	0.0011* (1.85)	0.0026*** (2.85)	0.0014* (1.70)
$GPR^{\oplus}_{t-1}$	$EPU_{t-1}GPR_{t-1}$	0.0001 (0.39)	0.0001 (0.88)	0.0001 (0.60)	0.0002*** (2.49)	0.0002 (1.35)	0.0001* (1.65)
EC_{t-1}	$EPU_{t-1}YCsl_{t-1}$	−0.0009 (−1.23)	−0.0023*** (−2.63)	−0.0001 (−0.65)	−0.0002* (−1.69)	−0.0001** (−0.36)	
RE_{t-1}	$EPU_{t-1}REIT_{t-1}$	−0.0071* (−1.74)	−0.0150*** (−2.50)	−0.0021** (−2.25)	−0.0008 (−1.25)	−0.0071* (−1.72)	−0.0013* (−1.76)

Notes:

The table reports the EPU effect on the macro factors' impact on dynamic equicorrelations (eq. (2.11)).

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. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

In particular, in Tables 2.9, 2.10 and Appendix section 2.7.2 , we observe that 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, partly explained by EPU. The EPU impact on the geopolitical risk factor is positive and significant in five out of twelve cases for the equicorrelation levels. Moreover, lower activity, proxied by the term spread and REITs associated with higher policy uncertainty, raise all correlations. All macro determinants receive a substantial policy uncertainty effect. Overall, we demonstrate that the cross-country correlations are consistently intensified by EPU, which amplifies the influence of the other macro drivers as well. Our leading-edge results should urge policymakers to consider and closely investigate both direct and side effects of an EPU shock on the co-movement and integration of different countries' tourism industries. To sum up, our contribution to the tourism-uncertainty literature consists of the novel empirical evidence we provide on the positive direct and indirect link between daily EPU and cross-border sectoral integration dynamics. Within the DECO framework, we, firstly, prove the EPU destabilizing impact that drives correlations higher (direct link). Secondly, we show that the macro effects on correlations evolution are state-dependent, not only based on crisis periods (see Section 2.5.2), but they are also considerably magnified under higher prevailing uncertainty conditions (indirect link). In particular, from an economic perspective, tighter credit and liquidity conditions and a worse economic stance exacerbate correlations to a degree intensified by elevated EPU.

2.5.2 Crisis Effect on Tourism Correlation

Following the regression analysis with the macro determinants of the cross-country tourism correlations' evolution, in this Section, we investigate the crisis impact on the macro regressors. In particular, we focus here on the GFC, ESDC, and COVID crisis repercussions. The time-varying behavior of the explanatory variables' parameters can be significant around a crisis period, indicative of the crisis effects on the correlation pattern. We incorporate crisis slope dummies in the DECO-X regression Eq.(2.10) and estimate equation Eq.(2.12) for each crisis period / subperiod. The crisis impact on the time-varying macro effects is captured by the slope dummies' coefficients with the ^{CRISIS} superscript. In Table 2.11 and 2.12, we sum up the crisis effect on each macro regressor as estimated through alternative restricted forms of equation Eq. (2.12) by including each slope dummy separately (similar results from the $\Delta Corr_t$ regressions with the crisis impact are not reported due to space considerations - available upon request). We choose to report the GFC, the first ESDC period, and the COVID 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 2.11 and 2.12 ,Panel A), economic and financial uncertainty, credit and liquidity conditions impacts become more positive with the slope dummies coefficients significant for most correlation series.

Table 2.11: The crisis effect on the macro drivers of tourism equicorrelations (eq. (2.12)).

↓ 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*** (2.45)	0.0041** (2.32)	0.0015 (0.99)	0.0009 (0.27)	0.0037* (1.83)	0.0018* (1.71)
FU_{t-1}	$d_{GFC,t-1}VSTOXX_{t-1}$	0.0030 (0.89)	0.0036 (0.89)	0.0028 (1.13)	0.0025 (0.35)	0.0066* (1.63)	0.0004 (0.31)
CCR_{t-1}	$d_{GFC,t-1}BAA_{t-1}$	0.0013** (2.10)	0.0068* (1.64)	0.0033 (1.18)	0.0002 (0.10)	0.0011*** (2.79)	0.0002 (1.24)
SCR_{t-1}	$d_{GFC,t-1}MOVE_{t-1}$	0.0047*** (2.51)	0.0048* (1.76)	0.0050 (0.98)	0.0011 (0.21)	0.0043 (0.40)	0.0091* (1.70)
LIQ_{t-1}	$d_{GFC,t-1}TED_{t-1}$	0.0127*** (3.45)	0.0068* (1.73)	0.0049* (1.71)	0.0147*** (2.78)	0.0146*** (3.38)	0.0050** (2.13)
GPR_{t-1}	$d_{GFC,t-1}GPR_{t-1}$	0.0014 (0.75)	0.0016 (0.68)	0.0020 (1.21)	0.0043 (0.53)	0.0013 (1.00)	0.0004 (0.51)
EC_{t-1}	$d_{GFC,t-1}YCsl_{t-1}$	−0.0045* (−1.72)	−0.0045* (−1.66)	−0.0013 (−0.87)	−0.0035 (−1.06)	−0.0016 (−0.61)	−0.0008 (−0.58)
RE_{t-1}	$d_{GFC,t-1}REIT_{t-1}$	−0.0146 (−1.10)	−0.0066 (−0.41)	−0.0040 (−0.38)	−0.0129 (−0.59)	−0.0024 (−0.12)	−0.0121 (−1.05)
Panel B. The first ESDC period effect.							
EPU_{t-1}	$d_{ESDC\_A,t-1}EPU_{t-1}$	0.0026* (1.87)	0.0049** (2.15)	0.0019*** (2.90)	0.0057* (1.63)	0.0042** (2.05)	0.0020* (1.71)
FU_{t-1}	$d_{ESDC\_A,t-1}VSTOXX_{t-1}$	0.0033 (0.99)	0.0015 (0.36)	0.0088** (2.09)	0.0243** (2.06)	0.0050 (1.12)	0.0065* (1.70)
CCR_{t-1}	$d_{ESDC\_A,t-1}BAA_{t-1}$	0.0025** (2.20)	0.0040 (0.91)	0.0018** (2.09)	0.0067** (2.26)	0.0036** (2.29)	0.0019** (1.95)
SCR_{t-1}	$d_{ESDC\_A,t-1}MOVE_{t-1}$	0.0077** (2.15)	0.0126** (2.00)	0.0097** (2.44)	0.0190** (2.01)	0.0068 (0.73)	0.0032 (0.73)
LIQ_{t-1}	$d_{ESDC\_A,t-1}TED_{t-1}$	0.0280 (1.28)	0.0635* (1.83)	0.0045 (0.81)	0.0164 (1.31)	0.0554* (1.85)	0.0189 (1.01)
GPR_{t-1}	$d_{ESDC\_A,t-1}GPR_{t-1}$	0.0001 (0.17)	0.0001 (0.05)	0.0002 (0.68)	0.0017 (1.00)	0.0007 (1.06)	0.0005 (1.15)
EC_{t-1}	$d_{ESDC\_A,t-1}YCsl_{t-1}$	−0.0040** (−1.90)	−0.0062* (−1.67)	−0.0025 (−1.23)	−0.0108* (−1.65)	−0.0051* (−1.69)	−0.0032* (−1.91)
RE_{t-1}	$d_{ESDC\_A,t-1}REIT_{t-1}$	−0.0018 (−0.10)	−0.0003 (−0.16)	−0.0016 (−0.13)	−0.0459* (−1.69)	−0.0202 (−0.87)	−0.0031 (−0.17)
Panel C. The COVID effect.							
EPU_{t-1}	$d_{COVID,t-1}EPU_{t-1}$	0.0055*** (2.58)	0.0010** (2.18)	0.0045** (2.17)	0.0022** (2.35)	0.0056* (1.81)	0.0089* (1.85)
FU_{t-1}	$d_{COVID,t-1}VSTOXX_{t-1}$	0.0251* (1.75)	0.0280* (1.66)	0.0152*** (2.68)	0.0504 (0.99)	0.0404* (1.65)	0.0297 (0.94)
CCR_{t-1}	$d_{COVID,t-1}BAA_{t-1}$	0.0005 (0.35)	0.0321*** (2.45)	0.0021** (2.26)	0.0027 (0.79)	0.0003 (0.13)	0.0010** (0.66)
SCR_{t-1}	$d_{COVID,t-1}MOVE_{t-1}$	0.0045 (0.71)	0.0236** (2.15)	0.0183** (2.36)	0.0126 (0.87)	0.0427* (1.86)	0.0213* (1.68)
LIQ_{t-1}	$d_{COVID,t-1}TED_{t-1}$	0.0055 (0.68)	0.0335 (0.94)	0.0222 (1.00)	0.0715 (0.97)	0.0038 (0.28)	0.0078 (0.80)
GPR_{t-1}	$d_{COVID,t-1}GPR_{t-1}$	0.0011* (1.70)	0.0088* (1.67)	0.0013* (1.64)	0.0021* (1.73)	0.0023** (2.08)	0.0009 (0.72)
EC_{t-1}	$d_{COVID,t-1}YCsl_{t-1}$	−0.0037 (−0.25)	−0.0154 (−0.47)	−0.0053 (−0.48)	−0.0050 (−0.17)	−0.0083 (−0.31)	−0.0034 (−0.20)
RE_{t-1}	$d_{COVID,t-1}REIT_{t-1}$	−0.0773** (−1.98)	−0.0779 (−1.16)	−0.0298 (−1.07)	−0.1350* (−1.63)	−0.1349* (−1.67)	−0.0799* (−1.67)

Notes:

The table reports the crisis effect on the macro factors' impact on dynamic equicorrelations (eq. (2.12)).

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. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table 2.12: The crisis effect on the macro drivers of tourism equicorrelations (eq. (2.12)). (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 (0.60)	0.0020 (1.12)	0.0023^{**} (1.92)	0.0035^{*} (1.84)	0.0019^{*} (1.72)	0.0021^{*} (1.76)
FU_{t-1}	$d_{GFC,t-1}VSTOXX_{t-1}$	0.0007 (0.11)	0.0060^{*} (1.67)	0.0084^{***} (4.23)	0.0082^{*} (1.65)	0.0040^{*} (1.68)	0.0116^{***} (2.45)
CCR_{t-1}	$d_{GFC,t-1}BAA_{t-1}$	0.0005 (0.39)	0.0001 (0.27)	0.0018^{***} (4.09)	0.0018^{*} (1.77)	0.0008^{*} (1.80)	0.0025 (0.88)
SCR_{t-1}	$d_{GFC,t-1}MOVE_{t-1}$	0.0018 (0.46)	0.0025 (0.31)	0.0048 (0.89)	0.0071^{*} (1.67)	0.0031^{*} (1.70)	0.0028^{***} (5.03)
LIQ_{t-1}	$d_{GFC,t-1}TED_{t-1}$	0.0065^{*} (1.67)	0.0076^{*} (1.82)	0.0060^{**} (2.35)	0.0042 (1.28)	0.0040^{*} (1.81)	0.0048^{**} (1.90)
GPR_{t-1}	$d_{GFC,t-1}GPR_{t-1}$	0.0009 (0.86)	0.0004 (0.69)	0.0009 (1.03)	0.0017 (0.66)	0.0019 (1.09)	0.0009 (1.11)
EC_{t-1}	$d_{GFC,t-1}YCsl_{t-1}$	−0.0009 (−0.32)	-0.0039^{*} (−1.71)	−0.0017 (−0.88)	−0.0004 (−0.33)	−0.0015 (−0.95)	−0.0017 (−0.99)
RE_{t-1}	$d_{GFC,t-1}REIT_{t-1}$	-0.0236^{*} (−1.64)	−0.0148 (−0.92)	−0.0055 (−0.48)	−0.0062 (−0.65)	−0.0136 (−0.93)	−0.0033 (−0.34)
Panel B. The first ESDC period effect.							
EPU_{t-1}	$d_{ESDC\_A,t-1}EPU_{t-1}$	0.0049^{**} (2.14)	0.0039^{**} (2.23)	0.0034^{**} (2.04)	0.0026^{***} (2.96)	0.0039^{**} (2.13)	0.0020^{**} (2.16)
FU_{t-1}	$d_{ESDC\_A,t-1}VSTOXX_{t-1}$	0.0152^{**} (1.95)	0.0009 (0.21)	0.0115^{**} (2.00)	0.0079^{**} (2.21)	0.0148^{**} (2.42)	0.0046^{*} (1.62)
CCR_{t-1}	$d_{ESDC\_A,t-1}BAA_{t-1}$	0.0042^{**} (2.06)	0.0031^{**} (2.14)	0.0029^{**} (1.93)	0.0015^{*} (1.86)	0.0031^{**} (1.94)	0.0015 (0.59)
SCR_{t-1}	$d_{ESDC\_A,t-1}MOVE_{t-1}$	0.0119^{*} (1.84)	0.0048 (0.68)	0.0020 (0.37)	0.0047^{*} (1.83)	0.0097^{**} (1.96)	0.0076^{**} (1.93)
LIQ_{t-1}	$d_{ESDC\_A,t-1}TED_{t-1}$	0.0198^{**} (2.22)	0.0161^{**} (2.29)	0.0095^{*} (1.66)	0.0195 (1.18)	0.0112^{*} (1.73)	0.0293 (1.28)
GPR_{t-1}	$d_{ESDC\_A,t-1}GPR_{t-1}$	0.0005 (1.17)	0.0005 (1.03)	0.0004 (1.01)	0.0009 (0.82)	0.0008 (0.78)	0.0001 (0.16)
EC_{t-1}	$d_{ESDC\_A,t-1}YCsl_{t-1}$	-0.0077^{*} (−1.83)	−0.0042 (−1.15)	−0.0045 (−1.24)	−0.0020 (−1.12)	−0.0046 (−1.16)	−0.0034 (−1.37)
RE_{t-1}	$d_{ESDC\_A,t-1}REIT_{t-1}$	−0.0244 (−1.05)	−0.0048 (−0.19)	−0.0037 (−0.27)	−0.0104 (−0.85)	−0.0028 (−0.13)	−0.0098 (−0.82)
Panel C. The COVID effect.							
EPU_{t-1}	$d_{COVID,t-1}EPU_{t-1}$	0.0043^{*} (1.71)	0.0010^{**} (2.20)	0.0109^{**} (2.14)	0.0094^{**} (2.26)	0.0025^{***} (2.91)	0.0007^{***} (2.87)
FU_{t-1}	$d_{COVID,t-1}VSTOXX_{t-1}$	0.0281 (0.83)	0.0322^{*} (1.75)	0.0328 (1.08)	0.0205 (0.92)	0.0156 (0.96)	0.0277^{**} (2.02)
CCR_{t-1}	$d_{COVID,t-1}BAA_{t-1}$	0.0005 (0.34)	0.0015 (0.52)	0.0018 (1.32)	0.0001 (0.05)	0.0020 (0.80)	0.0146^{*} (1.66)
SCR_{t-1}	$d_{COVID,t-1}MOVE_{t-1}$	0.0065 (0.73)	0.0264^{*} (1.64)	0.0223^{*} (1.84)	0.0033 (0.63)	0.0046 (0.88)	0.0035 (0.56)
LIQ_{t-1}	$d_{COVID,t-1}TED_{t-1}$	0.0415 (0.99)	0.0588 (0.95)	0.0460^{*} (1.81)	0.0028 (0.40)	0.0417 (0.83)	0.0026 (0.29)
GPR_{t-1}	$d_{COVID,t-1}GPR_{t-1}$	0.0014^{*} (1.75)	0.0023^{*} (1.77)	0.0030^{*} (1.64)	0.0012 (0.84)	0.0005 (0.48)	0.0002^{**} (2.17)
EC_{t-1}	$d_{COVID,t-1}YCsl_{t-1}$	−0.0249 (−1.12)	−0.0052 (−0.22)	−0.0010 (−0.06)	−0.0064 (−0.58)	−0.0005 (−0.27)	−0.0009 (−0.10)
RE_{t-1}	$d_{COVID,t-1}REIT_{t-1}$	−0.0597 (−1.30)	-0.1124^{*} (−1.66)	-0.0725^{**} (−1.98)	-0.0694^{**} (−2.30)	−0.0461 (−0.74)	-0.0755^{*} (−1.65)

Notes:

The table reports the crisis effect on the macro factors' impact on dynamic equicorrelations (eq. (2.12)). 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. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

The economic activity effect is more negative but insignificant in most cases. Turning to the first ESDC period (Table 2.11 and 2.12 , Panel B), we draw similar conclusions. Higher uncertainty, tighter credit and liquidity conditions further exacerbate 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. Geopolitics' incremental effect is not estimated significant in both GFC and ESDC periods. Regarding the recent pandemic outbreak (Table 2.11 and 2.12, Panel C), uncertainty, credit, and geopolitics effect is intensified while the liquidity slope dummies are insignificant. The real estate activity's negative impact becomes stronger in contrast with the economic activity proxy whose effect during the pandemic is not reflected on the yield curve data so far (see also Table 2.15, Panel A, for a sum-up of significant crisis effects - number of significant cases over 12 total cases).

Overall, crises add an increment in absolute terms across most macro parameters. Considering the GFC, ESDC, and COVID turbulence, we provide sound evidence that crises intensify the macro effects, driving correlations either lower or higher, consistently with the EPU incremental effect on financial uncertainty, credit, liquidity, GPR, and activity (see Section 2.5.1). Higher uncertainty and GPR (during the COVID crisis only), tighter credit and liquidity conditions proxies receive a substantial boost from crises in increasing correlations, while lower activity exacerbates correlations during crises (mostly in ESDC and COVID periods). Our crisis and EPU analyses give clear evidence that there is significant contagion between the different tourism industries. The crisis slope dummies estimated coefficients show that the macro impact on correlations' rise is partly attributed to the turmoil following the crisis advent. Thus, apart from the effect on correlations from common global factors at all times, we observe the distinct contagion effect of the same factors during crises (*H3*) or higher EPU levels (*H2*) connected to turmoil periods (EPU analysis in Section 2.5.1), in line with empirical results for VIX as a contagion driver in Akay et al. (2013), among others. Moreover, we do not observe significant differences in the macro drivers of the various countries' correlation pairs. Most macro, EPU, and crisis effects on tourism interlinkages are similar (in magnitude and significance) across the different countries' combinations.

Table 2.13: The EPU effect on the macro drivers of tourism equicorrelations during crises (eq. (2.13)).

Macro variables Macro effect	DE	FR	AT	BNL	UK	IRE
Panel A. The GFC effect.						
$d_{GFC,t-1}EPU_{t-1}VSTOXX_{t-1}$ FU_{t-1}	0.0012** (1.99)	0.0014* (1.87)	0.0012 (1.32)	0.0007 (0.33)	0.0026* (1.81)	0.0013* (1.70)
$d_{GFC,t-1}EPU_{t-1}BAA_{t-1}$ CCR_{t-1}	0.0007*** (2.62)	0.0030* (1.67)	0.0001 (0.44)	0.0001 (0.12)	0.0005** (1.94)	0.0003* (1.83)
$d_{GFC,t-1}EPU_{t-1}MOVE_{t-1}$ SCR_{t-1}	0.0023*** (2.65)	0.0022*** (2.50)	0.0018 (0.98)	0.0003 (0.19)	0.0012 (0.31)	0.0033* (1.65)
$d_{GFC,t-1}EPU_{t-1}TED_{t-1}$ LIQ_{t-1}	0.0044*** (3.26)	0.0029** (2.33)	0.0014* (1.73)	0.0033* (1.83)	0.0040*** (2.55)	0.0020** (2.40)
$d_{GFC,t-1}EPU_{t-1}GPR_{t-1}$ GPR_{t-1}	0.0009*** (2.85)	0.0009** (2.35)	0.0004* (1.65)	0.0002* (1.69)	0.0008* (1.71)	0.0002 (0.70)
$d_{GFC,t-1}EPU_{t-1}YCsl_{t-1}$ EC_{t-1}	−0.0021*** (−2.52)	−0.0015* (−1.73)	−0.0005 (−0.98)	−0.0012 (−0.96)	−0.0010 (−1.12)	−0.0004 (−0.79)
$d_{GFC,t-1}EPU_{t-1}REIT_{t-1}$ RE_{t-1}	−0.0047 (−0.91)	−0.0017 (−0.26)	−0.0014 (−0.35)	−0.0040 (−0.47)	−0.0009 (−0.12)	−0.0053 (−1.21)
Panel B. The first ESDC period effect.						
$d_{ESDC\_A,t-1}EPU_{t-1}VSTOXX_{t-1}$ FU_{t-1}	0.0013 (1.00)	0.0006 (0.37)	0.0018** (2.11)	0.0044* (1.69)	0.0020 (1.13)	0.0018** (2.20)
$d_{ESDC\_A,t-1}EPU_{t-1}BAA_{t-1}$ CCR_{t-1}	0.0005** (2.23)	0.0014 (0.82)	0.0004* (1.76)	0.0011* (1.71)	0.0007* (1.69)	0.0004** (2.27)
$d_{ESDC\_A,t-1}EPU_{t-1}MOVE_{t-1}$ SCR_{t-1}	0.0017** (2.43)	0.0025** (2.16)	0.0038** (2.39)	0.0030* (1.69)	0.0028 (0.78)	0.0014 (0.82)
$d_{ESDC\_A,t-1}EPU_{t-1}TED_{t-1}$ LIQ_{t-1}	0.0075* (1.78)	0.0131** (1.93)	0.0015 (1.06)	0.0045* (1.66)	0.0095* (1.81)	0.0052* (1.68)
$d_{ESDC\_A,t-1}EPU_{t-1}GPR_{t-1}$ GPR_{t-1}	0.0001 (0.22)	0.0001 (0.27)	0.0001* (1.69)	0.0006 (0.97)	0.0003** (2.12)	0.0002** (2.23)
$d_{ESDC\_A,t-1}EPU_{t-1}YCsl_{t-1}$ EC_{t-1}	−0.0011** (−2.20)	−0.0017** (−2.05)	−0.0007* (−1.64)	−0.0023 (−1.30)	−0.0012* (−1.76)	−0.0009*** (−2.46)
$d_{ESDC\_A,t-1}EPU_{t-1}REIT_{t-1}$ RE_{t-1}	−0.0008 (−0.11)	−0.0002 (−0.10)	−0.0010 (−0.20)	−0.0178* (−1.72)	−0.0075 (−0.84)	−0.0012 (−0.16)
Panel C. The COVID effect.						
$d_{COVID,t-1}EPU_{t-1}VSTOXX_{t-1}$ FU_{t-1}	0.0087** (1.90)	0.0090* (1.71)	0.0059*** (2.89)	0.0135* (1.71)	0.0135* (1.73)	0.0075* (1.68)
$d_{COVID,t-1}EPU_{t-1}BAA_{t-1}$ CCR_{t-1}	0.0001 (0.94)	0.0114*** (2.53)	0.0009* (1.71)	0.0003 (0.15)	0.0006 (0.30)	0.0001 (0.10)
$d_{COVID,t-1}EPU_{t-1}MOVE_{t-1}$ SCR_{t-1}	0.0008 (0.40)	0.0091* (1.71)	0.0070*** (2.47)	0.0024 (0.73)	0.0143** (1.99)	0.0069* (1.68)
$d_{COVID,t-1}EPU_{t-1}TED_{t-1}$ LIQ_{t-1}	0.0022 (0.46)	0.0090 (0.86)	0.0082 (0.96)	0.0225 (0.86)	0.0013 (0.27)	0.0021 (0.59)
$d_{COVID,t-1}EPU_{t-1}GPR_{t-1}$ GPR_{t-1}	0.0001** (2.21)	0.0041* (1.63)	0.0005** (2.03)	0.0010*** (2.50)	0.0008* (1.70)	0.0002* (1.65)
$d_{COVID,t-1}EPU_{t-1}YCsl_{t-1}$ EC_{t-1}	−0.0012 (−0.23)	−0.0006 (−0.06)	−0.0018 (−0.38)	−0.0016 (−0.14)	−0.0020 (−0.23)	−0.0010 (−0.18)
$d_{COVID,t-1}EPU_{t-1}REIT_{t-1}$ RE_{t-1}	−0.0232* (−1.78)	−0.0212 (−0.97)	−0.0087 (−0.88)	−0.0397* (−1.68)	−0.0379* (−1.66)	−0.0234* (−1.67)

Notes:

The table reports the EPU effect during crises on the macro factors' impact on dynamic equicorrelations (eq. (2.13)). 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 2.14: The EPU effect on the macro drivers of tourism equicorrelations during crises (eq. (2.13) (continued)).

Macro variables Macro effect	IT	ES	GR	SWITZ	SCAND	ALL
Panel A. The GFC effect.						
$d_{GFC,t-1}EPU_{t-1}VSTOXX_{t-1}$ FU_{t-1}	0.0013 (0.76)	0.0023^{*} (1.73)	0.0020^{***} (2.54)	0.0022^{*} (1.71)	0.0012^{*} (1.76)	0.0042^{**} (2.30)
$d_{GFC,t-1}EPU_{t-1}BAA_{t-1}$ CCR_{t-1}	0.0002 (0.63)	0.0002 (0.87)	0.0004^{***} (2.82)	0.0005^{*} (1.81)	0.0003^{*} (1.77)	0.0011 (1.00)
$d_{GFC,t-1}EPU_{t-1}MOVE_{t-1}$ SCR_{t-1}	0.0008 (0.64)	0.0005 (0.19)	0.0019 (0.93)	0.0017^{*} (1.82)	0.0008 (1.26)	0.0010^{**} (1.91)
$d_{GFC,t-1}EPU_{t-1}TED_{t-1}$ LIQ_{t-1}	0.0024^{*} (1.86)	0.0022^{*} (1.71)	0.0020^{***} (2.51)	0.0015^{*} (1.68)	0.0012^{*} (1.74)	0.0016^{*} (1.64)
$d_{GFC,t-1}EPU_{t-1}GPR_{t-1}$ GPR_{t-1}	0.0002 (0.42)	0.0002^{*} (1.77)	0.0004 (1.11)	0.0008^{**} (1.95)	0.0007^{**} (2.20)	0.0006^{***} (2.56)
$d_{GFC,t-1}EPU_{t-1}YCsl_{t-1}$ EC_{t-1}	-0.0002 (-0.20)	-0.0015^{*} (-1.78)	-0.0010^{**} (-1.98)	-0.0001 (-0.09)	-0.0001 (-0.12)	-0.0006 (-0.97)
$d_{GFC,t-1}EPU_{t-1}REIT_{t-1}$ RE_{t-1}	-0.0084^{*} (-1.70)	-0.0049 (-0.77)	-0.0018 (-0.40)	-0.0024 (-0.53)	-0.0043 (-0.75)	-0.0014 (-0.37)
Panel B. The first ESDC period effect.						
$d_{ESDC\_A,t-1}EPU_{t-1}VSTOXX_{t-1}$ FU_{t-1}	0.0037^{**} (2.35)	0.0004 (0.25)	0.0029^{***} (2.49)	0.0024^{***} (3.57)	0.0032^{***} (2.66)	0.0018^{*} (1.62)
$d_{ESDC\_A,t-1}EPU_{t-1}BAA_{t-1}$ CCR_{t-1}	0.0009^{**} (2.27)	0.0007^{**} (2.11)	0.0007^{**} (2.21)	0.0005^{***} (3.25)	0.0006^{*} (1.89)	0.0005 (0.53)
$d_{ESDC\_A,t-1}EPU_{t-1}MOVE_{t-1}$ SCR_{t-1}	0.0026^{**} (2.15)	0.0018 (0.65)	0.0005 (0.25)	0.0014^{***} (3.18)	0.0020^{**} (2.07)	0.0015^{**} (2.13)
$d_{ESDC\_A,t-1}EPU_{t-1}TED_{t-1}$ LIQ_{t-1}	0.0050^{**} (2.11)	0.0042^{**} (2.22)	0.0030^{*} (1.82)	0.0074^{***} (2.64)	0.0038^{**} (2.15)	0.0068^{*} (1.66)
$d_{ESDC\_A,t-1}EPU_{t-1}GPR_{t-1}$ GPR_{t-1}	0.0002^{**} (2.26)	0.0002^{**} (2.01)	0.0002^{**} (2.04)	0.0005^{**} (2.18)	0.0004 (1.01)	0.0001 (0.41)
$d_{ESDC\_A,t-1}EPU_{t-1}YCsl_{t-1}$ EC_{t-1}	-0.0022^{**} (-2.14)	-0.0013^{*} (-1.68)	-0.0013^{*} (-1.76)	-0.0009^{***} (-2.98)	-0.0013^{*} (-1.80)	-0.0010^{*} (-1.84)
$d_{ESDC\_A,t-1}EPU_{t-1}REIT_{t-1}$ RE_{t-1}	-0.0091 (-1.00)	-0.0014 (-0.15)	-0.0017 (-0.31)	-0.0042 (-0.87)	-0.0010 (-0.12)	-0.0038 (-0.79)
Panel C. The COVID effect.						
$d_{COVID,t-1}EPU_{t-1}VSTOXX_{t-1}$ FU_{t-1}	0.0054 (1.04)	0.0109^{*} (1.82)	0.0086^{*} (1.70)	0.0069 (1.33)	0.0071 (1.33)	0.0093^{**} (2.01)
$d_{COVID,t-1}EPU_{t-1}BAA_{t-1}$ CCR_{t-1}	0.0007 (0.45)	0.0005 (0.32)	0.0001 (0.05)	0.0001 (0.14)	0.0014 (1.06)	0.0052^{*} (1.71)
$d_{COVID,t-1}EPU_{t-1}MOVE_{t-1}$ SCR_{t-1}	0.0001 (0.62)	0.0090^{*} (1.69)	0.0074^{**} (2.03)	0.0014 (0.70)	0.0029 (1.16)	0.0008 (0.38)
$d_{COVID,t-1}EPU_{t-1}TED_{t-1}$ LIQ_{t-1}	0.0116 (0.85)	0.0209 (0.95)	0.0138^{*} (1.76)	0.0008 (0.34)	0.0182 (0.99)	0.0009 (0.27)
$d_{COVID,t-1}EPU_{t-1}GPR_{t-1}$ GPR_{t-1}	0.0003^{*} (1.69)	0.0010^{*} (1.69)	0.0007^{**} (2.33)	0.0004 (0.81)	0.0001 (0.31)	0.0003 (0.89)
$d_{COVID,t-1}EPU_{t-1}YCsl_{t-1}$ EC_{t-1}	-0.0106 (-1.21)	-0.0012 (-0.13)	-0.0011 (-0.15)	-0.0013 (-0.35)	-0.0001 (-0.19)	-0.0017 (-0.32)
$d_{COVID,t-1}EPU_{t-1}REIT_{t-1}$ RE_{t-1}	-0.0157 (-1.06)	-0.0327 (-1.33)	-0.0230^{**} (-1.94)	-0.0226^{**} (-2.16)	-0.0119 (-0.58)	-0.0238^{*} (-1.71)

Notes:

The table reports the EPU effect during crises on the macro factors' impact on dynamic equicorrelations (eq. (2.13)). 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 2.15: 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 up of Tables 2.13 & 2.14)

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**

Notes:

The table reports the number of significant coefficients for the crisis and EPU under crisis effect on each DECO macro factor displayed in Tables 2.13 & 2.14.

The final part of our sensitivity analysis investigates the EPU impact on the correlation drivers' effect during crises. We estimate equation (2.13) for each crisis period. The crisis impact on the EPU interaction term is captured by the coefficients with the $^{EPU\_CR}$ superscript. Table 2.13 and 2.14 reports the interaction terms as estimated through alternative restricted forms of equation (2.13) by including each term separately (similar results from the $\Delta Corr_t$ regressions with the crisis impact are not reported due to space considerations - available upon request)[7].

We focus again on the GFC, the first ESDC period, and the COVID effects given that the second ESDC period effect is weak or insignificant in most cases. Similar to our crisis analysis on the macro effects (Table 2.11 and 2.12), we observe that all EPU interaction terms are inflated during crises (Table 2.13 and 2.14, Panel A for the GFC impact, Panel B for the ESDC_A impact, and Panel C, for the COVID impact), with estimated coefficients

[7]The estimation results of the whole equations (2.11), (2.12), and (2.13), when each EPU, crisis, and EPU under crisis effect, is incorporated separately, are not reported for space considerations. They are available upon request by the authors.

for financial uncertainty, credit, liquidity, and geopolitics more positive, and activity more negative in most cases (see also Table 2.15, Panel B, for a sum-up of significant indirect EPU effects during crisis - number of significant cases over 12 total cases).

2.6 Conclusion

Our study addresses a highly topical issue in the empirical macro-finance literature, that is the drivers of markets' financial integration. We focus on the tourism sector, one of the most vulnerable industries in the recent pandemic-induced crisis, and identify the common macro determinants of the time-varying correlations among eleven European Travel & Leisure sectoral stock indices. Our novel evidence shows that cross-border tourism interlinkages are attributed to economic policy and financial uncertainty, credit and liquidity conditions, geopolitical risk, economic and real estate activity.

Our results are in line with the contagion literature and confirm the counter-cyclical dynamics of tourism sectoral correlations given that contractive economic forces (uncertainty, tight credit, shallow liquidity, and geopolitical turbulence) increase the cross-country connectedness while strong fundamentals (economic and real estate activity) move correlations down. Furthermore, the sensitivity analysis on the economic transmission mechanism of the correlations' evolution indicates the destabilizing impact of the policy uncertainty channel and crisis events' repercussions on tourism integration.

The conclusions on the driving forces of the tourism sectors' nexus across major European countries are useful for policymakers and market practitioners in policy interventions, regulation enforcement, investment analysis, and portfolio management. Elevated correlations in economic slowdowns increase the contagion risk with catalytic effects for the whole economy's systemic risk and financial stability. Increased interconnectedness driven by poor fundamentals should be considered by regulatory authorities as an alarming signal to act proactively and alleviate sectoral systemic stress during economic downturns. Tourism managers and investors are urged to assess the cross-border contagion risks in crisis periods when international diversification benefits fade away due to increased sectoral correlations.

Lastly, future research could further delve into 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 integration drivers framework can be also applied to further economic sectors and multiple financial markets.

2.7 Appendix

2.7.1 Summary Statistics

Table B.1: 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^{***}

Notes:

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.

2.7.2 Dynamic equicorrelations growth regressions

Table B.2: 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^{**} (−2.12)	-0.0071^{**} (−1.95)	-0.0137 (−1.26)	0.0033^{**} (2,21)	-0.0091^{*} (−1.65)	-0.0096^{**} (−2.34)
	$\Delta Corr_{t-1}$	0.0446^{**} (2.41)	0.0260^{*} (1.61)	-0.0530^{***} (−2.68)	-0.0535 (−0.51)	0.0204 (1.06)	0.0324^{*} (1.75)
EPU_{t-1}	EPU_{t-1}	0.0023^{*} (1.79)	0.0025^{**} (2.01)	0.0004 (1.00)	0.0021 (0.86)	0.0017^{*} (1.76)	0.0028^{**} (1.92)
FU_{t-1}	$VSTOXX_{t-1}$	0.0333^{***} (2.89)	0.0254^{*} (1.85)	0.0558^{***} (2.98)	0.0477^{*} (1.73)	0.0494^{***} (3.84)	0.0267^{**} (2.11)
CCR_{t-1}	BAA_{t-1}	0.0442^{***} (3.76)	0.0156^{*} (1.87)	0.0152 (1.16)	0.0308 (0.83)	0.0358^{***} (2.87)	0.0261^{**} (2.14)
SCR_{t-1}	$MOVE_{t-1}$	0.0377^{***} (3.51)	0.0494^{***} (3.30)	0.0072^{*} (1.67)	0.0355 (0.94)	0.0473^{***} (3.41)	0.0403^{***} (3.01)
LIQ_{t-1}	TED_{t-1}	0.0334^{***} (2.85)	0.0272^{***} (2.79)	0.0266^{**} (2.08)	0.1653^{**} (2.36)	0.0257^{***} (2.49)	0.0266^{***} (2.57)
$GPR^{\oplus}_{t-1}$	GPR_{t-1}	0.0013^{*} (1.76)	0.0009^{*} (1.70)	0.0016 (0.74)	0.0002 (0.05)	0.0029^{*} (1.69)	0.0018^{*} (1.66)
EC_{t-1}	$YCsl_{t-1}$	-0.0437^{***} (−3.68)	-0.0450^{***} (−4.00)	-0.0008 (−1.17)	-0.0798^{**} (−2.00)	-0.0392^{***} (−3.48)	-0.0327^{***} (−2.92)
RE_{t-1}	$REIT_{t-1}$	-0.1782^{***} (−3.47)	-0.0263^{*} (−1.73)	-0.0504^{*} (−1.70)	-0.7337^{***} (−3.32)	-0.0240^{*} (−1.78)	-0.1661^{***} (−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

Notes:

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. $\overline{R}^2$ is the adjusted R^2. $\oplus$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table B.3: Tourism equicorrelations growth ($\Delta Corr_t$) regressions on daily macro factors (continued)

↓ 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^{*}
		(1.69)	(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

Notes:

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. $\overline{R}^2$ is the adjusted R^2. $^{\oplus}$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table B.4: The EPU effect on the macro drivers of tourism equicorrelations growth ($\Delta Corr_t$).

$\downarrow$ Macro effects	$\downarrow$ Macro variables	DE	FR	AT	BNL	UK	IRE
FU_{t-1}	$EPU_{t-1}VSTOXX_{t-1}$	0.0128*** (2.92)	0.0203*** (4.65)	0.0237*** (3.13)	0.0174* (1.66)	0.0196*** (4.13)	0.0099** (2.15)
CCR_{t-1}	$EPU_{t-1}BAA_{t-1}$	0.0150*** (3.46)	0.0158*** (3.80)	0.0073* (1.68)	0.0121 (0.81)	0.01348*** (3.00)	0.0107** (2.30)
SCR_{t-1}	$EPU_{t-1}MOVE_{t-1}$	0.0143*** (3.53)	0.0168*** (3.29)	0.0005 (0.45)	0.0140 (0.93)	0.0173*** (3.38)	0.0142*** (2.79)
LIQ_{t-1}	$EPU_{t-1}TED_{t-1}$	0.0105** (2.32)	0.0063* (1.86)	0.0094** (1.96)	0.0622** (2.33)	0.0074** (1.96)	0.0076** (1.93)
$GPR^{\oplus}_{t-1}$	$EPU_{t-1}GPR_{t-1}$	0.0003* (1.67)	0.0010* (1.80)	0.0002 (0.30)	0.0009 (0.64)	0.0012* (1.66)	0.0009 (1.14)
EC_{t-1}	$EPU_{t-1}YCsl_{t-1}$	−0.0167*** (−3.48)	−0.0154*** (−3.74)	−0.0004 (−1.29)	−0.0296* (−1.83)	−0.0159*** (−3.56)	−0.0132*** (−2.90)
RE_{t-1}	$EPU_{t-1}REIT_{t-1}$	−0.0660*** (−3.32)	−0.0114** (−1.98)	−0.0262* (−1.72)	−0.2705*** (−3.16)	−0.0119** (−1.99)	−0.0691*** (−2.85)

Notes:

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. $\oplus$ denotes that the GPR coefficient is estimated separately with a shorter sample.

Table B.5: The EPU effect on the macro drivers of tourism equicorrelations growth ($\Delta Corr_t$). (continued)

$\downarrow$ Macro effects	$\downarrow$ Macro variables	IT	ES	GR	SWITZ	SCAND	ALL
FU_{t-1}	$EPU_{t-1}VSTOXX_{t-1}$	0.0186*** (3.66)	0.0206*** (4.52)	0.0279*** (2.92)	0.0166*** (3.31)	0.0197*** (4.41)	0.0191*** (4.35)
CCR_{t-1}	$EPU_{t-1}BAA_{t-1}$	0.0102** (2.31)	0.0121*** (2.42)	0.0199** (2.02)	0.0136*** (3.37)	0.0094** (2.09)	0.0133*** (2.90)
SCR_{t-1}	$EPU_{t-1}MOVE_{t-1}$	0.0217*** (4.00)	0.0172*** (3.33)	0.0399*** (5.22)	0.0104* (1.91)	0.0116** (2.22)	0.0185*** (4.16)
LIQ_{t-1}	$EPU_{t-1}TED_{t-1}$	0.0061* (1.65)	0.0014 (0.33)	0.0031 (0.31)	0.0110* (1.89)	0.0118* (1.79)	0.0065* (1.66)
$GPR^{\oplus}_{t-1}$	$EPU_{t-1}GPR_{t-1}$	0.0010* (1.68)	0.0008 (1.24)	0.0009* (1.68)	0.0004* (1.87)	0.0009* (1.65)	0.0009** (1.92)
EC_{t-1}	$EPU_{t-1}YCsl_{t-1}$	−0.0117*** (−2.66)	−0.0106** (−2.21)	−0.0227** (−2.03)	−0.0138*** (−2.40)	−0.0146** (−2.22)	−0.0147*** (−3.30)
RE_{t-1}	$EPU_{t-1}REIT_{t-1}$	−0.0136*** (−2.44)	−0.0101* (−1.83)	−0.0347*** (−3.02)	−0.0629*** (−2.88)	−0.0130* (−1.87)	−0.0158*** (−3.10)

Notes:

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. $\oplus$ denotes that the GPR coefficient is estimated separately with a shorter sample.

3 Short- and Long-run cross countries interdependences

3.1 Introduction

Sustainable development and green transition have become primary objectives in modern societies globally. Policymakers, concerned about climate change risks and environmental degradation, urge corporations for responsible corporate strategies to safeguard the environment (Aloui et al. 2023, Huang et al. 2017, Nechi et al. 2020, Tsai et al. 2022). Green finance and transformation, climate change physical and transition risks are at the epicenter of corporate governance priorities (Behl et al. 2022, Garefalakis & Dimitras 2020, Giannarakis et al. 2020, Kalaitzoglou et al. 2021). Similarly, investors have started targeting at corporate securities with high ESG (environmental, social, governance) standards to fulfill strong sustainability mandates (Benedetti et al. 2021, Jawadi et al. 2019, Liagkouras et al. 2020, Semmler et al. 2022).

Against this backdrop, we investigate the cross-border co-movement of major sustainability benchmarks through a time-varying (dynamic) correlations econometric framework. The interconnectedness of sustainable equity markets, measured by their volatilities and correlations, is crucial for both market practitioners and policymakers. On the one hand, ESG investment and risk managers try to hedge their ESG positions and maximise their diversification benefits by investing in sustainable equities of multiple countries and use correlation analytics, a critical input for their risk assessments (Chai et al. 2022, Liagkouras et al. 2020, Naeem et al. 2021, Rizvi et al. 2021, Yadav et al. 2022) . On the other hand, policymakers proactively act to curb the risk of financial contagion when cross-market correlations explode in response to a crisis shock since this directly jeopardises financial stability through systemic stress episodes (Benkraiem et al. 2022, Cerqueti et al. 2021, Lin et al. 2018, Miled et al. 2022, Zhu et al. 2018).

In this vein, we delve into cross-country sustainable equities interdependence. Our objective is to study the interlinkages among national sustainability benchmarks through the DCC-GARCH-MIDAS or DCC-MIDAS model (Dynamic Conditional Correlations - Generalised Autoregressive Conditional Heteroskedasticity - Mixed Data Sampling). The DCC-MIDAS specification of Colacito et al. (2011) quantifies the stock index dependence dynamics by computing their short- and long-run dynamic conditional correlations in contrast with the simpler DCC of Engle (2002), which allows for short-run dynamics only. We use the Dow Jones Sustainability indices (DJSI) for Europe, Australia, Brazil, Japan, US, and Canada and estimate five bivariate correlation models combining the European DJSI with each of the other five national indices. Short-run (daily) and long-run (monthly) correlations measure the interconnectedness of Europe's sustainable corporations' stock performance with the other countries' sustainable firms.

Our empirical analysis of the cross-border interlinkages first focuses on the correlation time series behaviour across three crisis periods, the 2008 Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC), and the Covid-19 pandemic-induced crisis (COV). The correlations' analysis and crisis response define the interdependence types among the sustainability indices and their hedging characteristics. We diagnose contagion or flight-to-quality phenomena (interdependence types) and hedge, diversifier, or safe haven properties (hedging features) of sustainable financial markets by distinguishing between short- and long-run horizons. Secondly, we reveal the high- and low-frequency driving forces of the DJSI daily and monthly correlations. Global macro-financial fundamentals (uncertainty-related fundamentals, credit conditions, economic activity, inflation), climate change risks, news sentiment, and policy considerations are among the determinants of cross-country sustainability co-movements.

Our findings demonstrate stronger connectivity between European and North American indices and a weaker link of Europe with Japan, Australia, and Brazil. Financial contagion is the interdependence type identified for most sustainability pairs and crisis episodes. Most correlations increase after the crisis shock. Flight-to-quality phenomena and safe haven properties are not observed given the in-crisis average values of the DCC time series, while we measure lower interdependence during ESDC for the pairs of Europe with Japan and Brazil in the short run and with Japan only in the long run. All indices act as diversifiers rather than hedges, given the correlation properties in the whole sample under investigation. Moreover, the daily (high-frequency) and monthly (low-frequency) drivers of the cross-border sustainability co-movement are found in the macro environment. Global proxies of economic policy and financial uncertainties, disease and climate change risk, credit conditions, news, confidence, economic activity, prices, and freights are significant determinants of the dynamic correlation pattern in the short and long run. Economic policy uncertainty (EPU) and crisis shocks are further found to magnify the impact of the macro drivers on all cross-border correlations with various degrees of macro- and crisis-sensitivity across countries.

Overall, the present paper's contribution to the sustainable finance literature is manifold. There are only a few recent studies on ESG ratings and sustainable investments dependences that measure the connectivity between ESG benchmarks and further asset classes (see, for example, Chen & Lin (2022), Zhang et al. (2022) , and the literature therein). Hence, adding to this burgeoning strand of economics and finance bibliography, our study is the first to distinguish between short- and long-run correlation dynamics among cross-border sustainability indices. We further fill the literature gap by unveiling the common high- and low-frequency determinants of these time-varying correlations, and by scrutinising the correlations' sensitivity to macro fundamentals and crisis shocks. Our results on the interdependence types, the hedging features, and the macro- and crisis-relevance of sustainability investing have important implications for market practitioners and policymakers. Lower interdependences and macro- or crisis-vulnerability can ensure higher diversification benefits for investors and a milder threat for financial stability and systemic risk build-ups for policymakers. Contagion and strong macro effects decrease the hedging potential and effectiveness of cross-country sustainability investment strategies and alarm regulatory authorities to devise stabilising policies that mitigate contagion turbulence.

The remainder of the study is structured as follows. Section 3.2 presents the theoretical framework of our paper, reviews the related literature, and develops the hypotheses to test our research questions. In Section 3.3, we describe the methodological approach and the data used. Section 3.4 analyses and discusses the estimations of the sustainability interdependences, the correlation determinants, and the macro/crisis-sensitivity of our findings. Finally, the last Section concludes our empirical analysis.

3.2 Theoretical Framework

The recent growing literature on sustainable investments is mainly related to sustainable economic development and finance, green transition, and environmental responsibility research, given the urgent concerns about climate change and environmental degradation (Benedetti et al. 2021, Boroumand et al. 2022, Kumar et al. 2022). Existing studies mostly investigate the portfolio performance and valuations of investment strategies based on high ESG standards or sustainability indices in stock and bond markets (Aouadi & Marsat 2018, El Ghoul & Karoui 2017, Joliet & Titova 2018, Oikonomou et al. 2018, Rossi et al. 2019). They compare such 'green' investments with the more conventional 'brown' ones and explore, among others, ESG effects on corporate/accounting numbers, firm valuations, or fund exposures.

Stemming from the financial connectedness and integration bibliography (Baur 2012, Forbes & Rigobon 2002), there are a few recent studies that explore interdependences among ESG leaders' performance benchmarks (stock or bond indices) and other asset classes (other aggregate or sectoral equities and bonds, commodities, emissions etc.). For instance, Zhang et al. (2022) investigate the volatility spillovers among ESG stock indices, renewable energy sectoral equities, green bonds, sustainability indices, and emissions futures, while Chen & Lin (2022) focus on spillovers among global ESG leaders. Such ESG interdependence studies (see also, Jin et al. (2020), Le et al. (2021), Reboredo (2018)) use short-run metrics for the quantification of spillovers, causality, or interconnectedness without answering the question about the driving forces of these dependences.

Therefore, we fill a notable literature gap in three ways: first, by focusing on the cross-border interdependences of sustainable equities without considering further asset classes; second, by analysing and comparing short- versus long-run interconnectedness dynamics with time-varying MIDAS conditional correlations; and third, by identifying the high- and low-frequency correlation determinants and their macro- and crisis-sensitivity.

Moreover, taking into consideration existing research on financial markets co-movements (see, for example, Christodoulakis & Satchell (2002), Engle & Figlewski (2015), Karanasos et al. (2016), Naeem et al. (2021)), on asset hedging properties (Baur & Lucey 2009, 2010), and the recent studies on the drivers of financial interdependences Karanasos & Yfanti (2021), Yfanti et al. (2023), we hereby develop the theoretical hypotheses we will test in our empirical analysis. On the one hand, based on the dynamic sustainability correlation time series computed by the DCC-MIDAS model, we can conclude on the interdependence types among DJSIs and their hedging characteristics, as well. On the other hand, our macro-sensitivity regression analysis will reveal the correlation macro determinants and their impact on countercyclical or procyclical DJSI interlinkages.

Against this backdrop, the first two hypotheses are as follows:

Hypothesis 1 (*H1*): Contagion is characterised by a significant increase and positive level of correlations in crisis periods.
Hypothesis 2 (*H2*): Flight-to-quality is characterised by a significant decrease and negative level of correlations in crisis periods.
According to Baur & Lucey (2009), Forbes & Rigobon (2002), contagion is a significant rise in correlations with a positive (on average) in-crisis level in response to a crisis shock. Flight-to-quality episodes occur when correlations significantly drop during crises with a negative (on average) in-crisis level. By testing the statistical properties of short- and long-run correlations across the crisis subsamples, we will accept or reject *H1* and/or *H2* and identify contagion or flight-to-quality phenomena. When the correlation change is not significant, or the in-crisis correlation level does not follow the level rule of *H1* and *H2*, we can conclude on higher or lower interdependence phenomena (see Table 3.1, Panel A, for all possible scenarios given correlation changes and levels during crises). Turning to the hedging features, we will follow Baur & Lucey (2010). Regarding the first two hedging properties, we will define diversifiers and hedges based on the whole sample average of the correlation time series. Diversifiers are the (not perfectly) positively correlated assets, while hedges are negatively correlated or uncorrelated. Finally, for safe havens, we will focus on crisis subsamples to find pairs that are negatively correlated or uncorrelated during crises. The safe havens are mostly associated with flight-to-quality periods (*H2*). Moving to the correlation drivers and macro-sensitivity, we develop the last two hypotheses as follows:
Hypothesis 3 (*H3*): Economic worsening increases correlations (contagion or higher interdependence in crisis).
Hypothesis 4 (*H4*): Economic worsening decreases correlations (flight-to-quality or lower interdependence in crisis).
According to hypotheses 3 and 4, we will test the correlation determinants across the business cycle dynamics (see Table 3.2, Panel B). When the macro-financial proxies portray an economic slowdown, the correlations will either increase or decrease during crisis periods. In the first case of increasing correlations, that is contagion or higher interdependence, the cross-border sustainability correlation pattern is countercyclical (*H3*). In the second case of decreasing correlations, that is flight-to-quality or lower interdependence, the dynamic correlation pattern is procyclical (*H4*).

Table 3.1: Theoretical framework of sustainability interdependences

Panel A. Hypotheses on the types of sustainability interdependence		
H1	Contagion	Correlations increase and positive in-crisis
H2	Flight-to-quality	Correlations decrease and negative in-crisis

in-crisis correlations change ↓ / level ⟶	positive average level	negative average level
significant increase	Contagion (H1)	Higher interdependence
insignificant increase	Higher interdependence	Higher interdependence
significant decrease	Lower interdependence	Flight-to-quality (H2)
insignificant decrease	Lower interdependence	Lower interdependence

Notes:

The table presents the theoretical underpinnings of the sustainability interdependences. Panel A summarises our hypotheses on the interdependence types (H1 & H2).

Motivated by recent studies on correlation macro determinants (Karanasos & Yfanti 2021, Yfanti et al. 2023), we will include global proxies that capture the various aspects of the macro environment where financial markets operate (see also the next Section 3.3 for the data description of the macro variables). Economic policy (EPU) and financial uncertainty (FU), news sentiment (NW), and confidence (CONF) are among the most striking features of the economic stance. Agents' feelings like uncertainty, confidence, optimism, or pessimism define the expectations and perceptions about the economy and play a decisive role in nowcasting the economic performance (Baker et al. 2016, Bekaert et al. 2013, Berger et al. 2020). News and sentiment reflected by news dissemination are equally catalytic for the economy Buckman et al. (2020), Shapiro et al. (2022). Furthermore, disease (DIS) and climate change (CC) risks are important in the macro environment, given that such exogenous forces threaten economic activity and financial markets (Baker et al. 2020, Gavriilidis 2021). The credit channel (CR) is a further major aspect of the economy that contributes significantly to economic fluctuations (Gilchrist & Zakrajšek 2012). The last macro proxies used are economic activity (EA), freights (FT), and price dynamics (PR), which complete the macro environment canvas we use to identify correlations' determinants (Conrad et al. 2014, Engle et al. 2013, Mobarek et al. 2016).

Table 3.2: Theoretical framework of sustainability interdependences

Panel B. Hypotheses on the macro-sensitivity of sustainability interdependence		
H3	Contagion or Higher Interdependence	Economic worsening increases correlations
H4	Flight-to-quality or Lower Interdependence	Economic worsening decreases correlations

	Macro impact sign	
Macro determinant	H3	H4
Economic uncertainty (EPU)	+	−
Financial uncertainty (FU)	+	−
Disease risk (DIS)	+	−
Credit conditions (CR)	+	−
Climate change risk (CC)	+	−
News sentiment (NW)	−	+
Confidence (CONF)	−	+
Economic activity (EA)	−	+
Freights (FT)	−	+
Prices (PR)	−	+

Notes:

The table presents the theoretical underpinnings of the sustainability interdependences. Panel B recaps our hypotheses on the macro-sensitivity of sustainability interdependences (H3 & H4).

In Table 3.2, Panel B, we present the expected signs of the macro coefficient estimates under each hypothesis. For countercyclical correlations (*H3*), the variables increasing in economic worsening will be estimated with a positive sign (EPU, FU, DIS, CR, CC), and the ones decreasing are expected with a negative sign (NW, CONF, EA, FT, PR). The opposite signs hold for procyclical pairs (*H4*). Finally, under the umbrella of *H3* and *H4*, we will further test the EPU moderating role and the crisis effect on the macro impact of the correlation determinants. We expect that uncertainty and crisis shocks magnify the influence of the macro fundamentals on the time-varying interdependences, in line with Pástor & Veronesi (2013) and Karanasos & Yfanti (2021), among others.

3.3 Data Description and Methodological Approach

In this Section, we present the DJSI and macro dataset we use and the methodological framework of our empirical study. We first describe our dataset, the DJSI returns applied as the DCC-MIDAS input, and the macro fundamentals identified as the correlation drivers. Second, we detail the DCC-MIDAS model to be estimated for the computation of the time-varying cross-border sustainability correlations. We will analyse the statistical properties of the short- (daily) and long-run (monthly) correlation time series of Europe's DJSI with the other countries' indices in order to diagnose the interdependence types and hedging features of the sustainability benchmarks. The correlation time series are used as dependent variables in the macro-sensitivity regressions. We intend to identify the determinants of DJSI co-movements and their crisis-vulnerability. Hence, we finally describe the regression analysis of the DCC-MIDAS output on global daily and monthly macro proxies, the moderating role of the uncertainty channel, and the crisis impact.

3.3.1 Data Description

Firstly, our daily dataset of sustainability indices covers the period from 01/03/2005 until 01/02/2022, that is 4,416 observations. Dow Jones Sustainability indices at the country level are used as sustainability benchmarks for companies with high ESG ratings in each country. We use the DJSI data (retrieved from Refinitiv Eikon Datastream) for Europe (EU), Australia (AUS), Brazil (BRA), Japan (JP), United States of America (US), and Canada (CA) and calculate the returns to be included as input in the bivariate DCC-MIDAS model as follows: $r_{it} = [\ln(X_{it}) - \ln(X_{i,t-1})] \times 100$, with X_{it} the daily closing price on day t (Table 3.3, Panel A). The summary statistics (descriptive statistics and unit root tests) of the return series are reported in Table C.1 of the Appendix. Since we will focus on the dynamic correlations of the EU with the other five countries, we also compute the static correlation coefficient of EU returns with the other series (EU Corr column in Table C.1). We first observe positive correlations across all pairs. However, EU sustainability benchmarks are more correlated with US and CA and less correlated with JP and AUS. The statistics further result in a rejection of the unit root hypothesis (Augmented Dickey-Fuller - ADF test statistic highly significant), indicating that the returns are in the appropriate form to be included in the DCC-MIDAS system of equations.

Table 3.3: Data description for Dow Jones Sustainability Indices and macro fundamentals

Panel A. Dow Jones Sustainability Indices (DJSI)		
EU: Europe, AUS: Australia, BRA: Brazil, JP: Japan, US: United States of America, CA: Canada		
Panel B. Macro fundamentals		
Variable	Description	Macro impact
$EPU_{t/\tau}$	US Economic policy uncertainty index (d/m)	EPU: Economic uncertainty
IV_t	S&P 500 Implied volatility (VIX) index (d)	FU: Financial uncertainty
ID_t	Infectious disease equity market volatility tracker (d)	DIS: Disease risk
$CISS_t$	US Composite indicator of systemic stress (d)	CR: Credit conditions
$KCFSI_\tau$	US Financial stress index of the Kansas City Fed (m)	CR: Credit conditions
CPU_τ	Climate policy uncertainty index (m)	CC: Climate change risk
NSI_t	News sentiment index (d)	NW: News sentiment
BCI_τ	US Business confidence index growth (m)	CONF: Confidence
ADS_t	Aruoba-Diebold-Scotti (ADS) US business conditions index (d)	EA: Economic activity
$CFNAI_\tau$	US Chicago Fed national activity index (m)	EA: Economic activity
BDI_t	Baltic dry index (d)	FT: Freights
CFI_τ	Cass freight index (m)	FT: Freights
INF_τ	US Producer price index (PPI) growth (m)	PR: Prices

Notes:

The table reports the description of the variables used: the daily Dow Jones Sustainability Indices (DJSI) in Panel A and the daily (d) and monthly (m) macro fundamentals in Panel B. The DJSI series are retrieved from Refinitiv Eikon Datastream. The macro variable sources are the following: EPU, ID, CPU from www.policyuncertainty.com, IV, BDI from Refinitiv Eikon Datastream, CISS from the ECB Data Warehouse, KCFSI, CFNAI from FRED, NSI from the San Francisco Fed, BCI, INF from the OECD database, ADS from the Philadelphia Fed, CFI from Cass Information Systems Inc.

Next, we detail the macro variables used as correlation determinants in the macro-sensitivity analysis (Table 3.3, Panel B). We use both daily and monthly proxies (independent variables) for explaining the short- and long-run correlations (dependent variables), respectively, which are extracted from the DCC-MIDAS estimation. The daily series cover the same period as the index returns, while the monthly data span from March 2002 until February 2022 (204 observations). The high- and low-frequency macro determinants cover all major aspects of the economic environment around financial markets. The regressors which explain the correlation pattern are global factors acting as common drivers of cross-border financial spillovers. Therefore, we mostly choose US-related indices for each macro effect due to their wider impact for the world economy and data availability reasons. We also test various European or international indices for robustness purposes and get similar results for the macro-sensitivity, but the US proxies are preferred in most cases. The choice of the macro impacts we include is aligned with previous studies on high- and low-frequency correlation drivers (Conrad et al. 2014, Engle 2002, Karanasos & Yfanti 2021, Mobarek et al. 2016, Yfanti et al. 2023). Hence, the variables used for each economic driver are as follows (see also Table 3.3 notes for the sources of the regressor data, and Table C.2 in the Appendix for the regressors' summary statistics):

Variables increasing in economic worsening

Economic uncertainty (EPU): The economic uncertainty proxies are the daily and monthly (d/m) US economic policy uncertainty indices ($EPU_{t/\tau}$, t for daily frequency, τ for monthly frequency) of Baker et al. (2016), who quantify uncertainty based on news analytics and incorporate policy considerations. The EPU indices are shown to exert a strong influence on financial markets as a key economic force (see Karanasos & Yfanti (2021), for a literature review on EPU indices, their interaction with macro-financial fundamentals, and their relative merits compared to other uncertainty measures). The log-transformed $EPU_{t/\tau}$ variable is included in both short- and long-run correlations regressions and increases in weak economic periods.

Financial uncertainty (FU): For uncertainty in financial markets, we use the daily log-transformed S&P 500 implied volatility (VIX) index (IV_t) as a short-run correlation determinant. VIX is well-documented as a global fear and risk aversion proxy (Bekaert et al. 2013, Bloom 2014) and soars in turbulent times.

Disease risk (DIS): The disease risk is proxied by the daily infectious disease equity market volatility tracker (ID_t) of Baker et al. (2020). ID_t quantifies the disease news impact on financial market uncertainty and can significantly affect financial correlations, especially during health crises such as the recent Covid-19 pandemic. The disease risk is included as a high-frequency driver of sustainability spillovers.

Credit conditions (CR): The credit channel is proxied by the daily US composite indicator of systemic stress ($CISS_t$) in the short run and the monthly US financial stress index of the Kansas City Fed ($KCFSI_\tau$) in the long run. The credit channel is a major part of the macro environment. It plays a catalytic role in economic growth and recessionary phases of the business cycle dynamics Gilchrist & Zakrajšek (2012). Both proxies measure the financial stress in the economy and increase as credit conditions become tighter in economic slowdowns.

Climate change risk (CC): The log-transformed monthly climate policy uncertainty index (CPU_τ) proxies climate change risk in long-run correlation regressions (Gavriilidis 2021). Climate change physical and transition risks are highly connected to corporations' performance and economic resilience. Higher CC, if not assessed and proactively mitigated, can damage the whole economic outlook.

Variables decreasing in economic worsening

News sentiment (NW): The sentiment reflected in economic news is measured by the daily US news sentiment index (NSI_t) of the San Francisco Fed Buckman et al. (2020), Shapiro et al. (2022) and is used as a high-frequency regressor of short-run correlations. Good news can lead to economic optimism (higher NSI_t), while bad news prompts pessimism (lower NSI_t) apparent in recessionary periods.

Confidence ($CONF$): The log-transformed monthly US business confidence index (BCI_τ) is the economic confidence proxy in long-run interdependences. We expect the opposite signed effect compared to uncertainty. Higher confidence is associated with economic growth, while low confidence occurs at the same time as high uncertainty in recessions.

Economic activity (EA): The economic activity effect is included in daily and monthly macro-sensitivity regressions. The daily Aruoba-Diebold-Scotti (Aruoba et al. 2009) US business conditions index (ADS_t) and the monthly US Chicago Fed national activity index ($CFNAI_\tau$) are our US activity proxies decreasing in weak economic periods.

Freights (FT): The freight level is important in business cycle fluctuations and is included as a high- and low-frequency regressor. We use the log-transformed daily Baltic dry index (BDI_t) and the monthly Cass freight index (CFI_τ). BDI_t is a global freights metric and CFI_τ is a North American index for the freights market.

Prices (PR): The price impact is our last component of the macro environment used as a long-run correlation determinant. The monthly US producer price index (PPI) growth (INF_τ) is our global PR proxy.

The ten economic forces detailed above are included in the correlations macro-sensitivity regression analysis as independent variables explaining the daily and monthly correlation pattern extracted from the DCC-MIDAS model. The daily macro-financial variables are short-run determinants of the cross-border sustainability interconnectedness, and the monthly ones are the long-run determinants. Due to data availability, not all driving forces can be tested in both short- and long-run dynamics. However, the wide variety of our high- and low-frequency proxies captures the entire macro environment. EPU, FU, DIS, CR, and CC are expected with a positive sign in contagion cases (*H3*) since higher uncertainty, tighter credit conditions, elevated disease and climate change risks are connected with economic, health, or climate crises, and increase countercyclical correlations. NW, CONF, EA, FT, and PR will negatively affect correlations in contagion periods, given that lower news sentiment, confidence, activity, freights, and inflation will increase correlations during recessions. The opposite signs are expected in the procyclical cases (*H4*).

Finally, we list the three crisis periods investigated in the identification of interdependence types, safe-haven properties, and the correlations' crisis-vulnerability. We consider the crisis timelines of the Bank for International Settlements for the GFC, the European Central Bank for the ESDC, and the World Health Organisation for the COV. The crisis subsamples are as follows:

GFC: 09/08/2007 - 31/03/2009.

ESDC: 09/05/2010 - 31/12/2012.

COV: 11/03/2020 - 30/09/2020.

The GFC starts with the BNP Paribas fund suspension and the ESDC with the Greek sovereign debt default. The COV subsample covers the first pandemic waves from March until September 2020. During the first two financial crises and the third health crisis, most fundamentals used as correlation drivers give a worse economic outlook than the pre-crisis times. Therefore, in the crisis subsamples, countercyclical dynamic correlations should increase, and procyclical ones are expected to decrease.

3.3.2 Methodological Approach

This subsection is separated into two parts to introduce this chapter's methodology, we calculate the estimated correlation via bivariate DCC-MIDAS progress; then we use the correlation to examine the impact of macroeconomic variables to the correlations. Firstly, we explain bivariate DCC-MIDAS. Secondly, we detail the regressions' analysis for macro variables.

3.3.3 Dynamic Conditional Correlations Specification

This subsection is going to present the detail of DCC-MIDAS model, but due to specification of DCC-MIDAS model, its estimation method is two-step method; hence, we need to introduce the conditional means, and to classify two type of errors at first, then we can process to compute conditional variance (GARCH-MIDAS). Once we have the conditional variance, we can progress to calculate the conditional correlation (DCC-MIDAS).

3.3.3.1 Conditional Mean

Firstly, we need to consider each daily index return, so we define t as daily time scale (or we can call it is the high frequency time scale). Therefore, we define the daily index return at time t as $r_{i,t}, i = 1, 2$; because we consider this is bivariate DCC-MIDAS progress. Then, we can assumed the conditional distribution of $r_{i,t}$ present as $r_{it}\,|\Omega_{t-1} \sim i.i.d.$ $N(\mu_i, h_{it})$, this assumption shows $r_{i,t}$ follows the normal distribution with independent and identically distributed (i,i,d); and it is based on given information at the previous time Ω_{t-1}. We denote $\mathbb{E}$ as the expectation operator, so the conditional mean can present as $\mu_i = \mathbb{E}(r_{i,t}|\Omega_{t-1})$. Meanwhile, the conditional variance is $h_{it} \overset{def}{=} h_{ii,t} = \mathbb{V}ar(r_{it}\,|\Omega_{t-1}\,)$,

$i = 1, 2$. We can write down the $r_{i,t}$ as:

$$r_{it} = \mu_i + \varepsilon_{it}, \tag{3.1}$$

with the error term of ε_{it}. The next section is going to define the error term in the conditional return and DCC-GARCH-MIDAS model.

3.3.3.2 The Errors

We can consider the DCC-GARCH-MIDAS model as the double TV-MGARCH (Time-Varying Multivariate GARCH) type of model; and, Colacito et al. (2011) describe DCC-GARCH-MIDAS model is mixture of MIDAS and DCC model, DCC-GARCH-MIDAS model can provide the short- and long-run correlations. Based on double TV-MGARCH, we will consider two sets of errors: one error ε_{it} is from Eq. (3.1), the other one error e_{it} is for Eq. (3.11).

The ε_{it}

As Eq. (3.1) state, the assumption of ε_{it} is defined by following the normal distribution with mean 0 and conditional variance $h_{i,t}$. Meanwhile, the conditional covariance is $h_{ij,t} = \mathbb{E}(\varepsilon_{it}\varepsilon_{jt}|\Omega_{t-1})$, $i, j = 1, 2; \forall i \neq j$. In addition, the conditional variance $h_{i,t}$ is based on GARCH-MIDAS model (see the below subsection 3.3.3.3). Hence, we define conditional correlation $\rho_{ij,t}$ is given by:

$$\rho_{ij,t} = h_{ij,t}/\sqrt{h_{it}}\sqrt{h_{jt}}, i, j = 1, 2, 3 \tag{3.2}$$

with $|\rho_{ij,t}| \leq 1$. From Eq. (3.2), we can present that $\varepsilon_{it} = \sqrt{h_{it}}\xi_{it}$, so we can rewrite $\xi_{it} = \varepsilon_{it}/\sqrt{h_{it}}$, and called ξ_{it} as *devolatilised* error; it also indicate the conditional correlation of ξ_{it} is $\rho_{ij,t}$.

The e_{it}

For e_{it}'s assumption, it is followed normal distribution with 0 mean and its conditional covariance which can present as $q_{ij,t} = \mathbb{E}(e_{it}e_{jt}|\Omega_{t-1}), i, j = 1, 2$; it can equal to $e_{it} = \sqrt{q_{ii,t}}\xi_{it}$. If we relate these two assumptions together, we can see the conditional correlation of e_{it} is $\rho_{ij,t}$ which state as followed:

$$\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}. \tag{3.3}$$

As previous stated, DCC-MIDAS needs to use two-steps estimation, so we can assume $q_{ij,t}$ follows DCC-MIDAS model in the second step estimation. Then we can restructure from the formula (3.2) and (3.3), so the equation is as followed:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} = \frac{h_{ij,t}}{\sqrt{h_{it}}\sqrt{h_{jt}}}. \tag{3.4}$$

In the short conclusion, the estimation method of DCC-GARCH-MIDAS model is two-step; firstly, we estimate the first errors ε_{it} and the conditional variances h_{it} via the GARCH-MIDAS model, both of them are vectors (Conrad & Loch 2015, Engle et al. 2013). Secondly, we can calculate the vector of the *devolatilised* errors ξ_{it} after we estimated first errors and conditional variance from GARCH-MIDAS. Once we have conditional variance, we can calculate the matrix of conditional covariances' errors e_{it} and q_{it} by using DCC-GARCH-MIDAS process. Therefore, the order of estimation is estimated h_{ij} and $q_{ij,t}$ at first, and then we can calculate $\rho_{ij,t}$. The last two need to pay attention, it is the conditional correlations of error (e_{it}, ξ_{it}, or ε_{it}) which obtain from the Eq.(3.4); and the second one is the estimated conditional covariances $h_{ij,t}$, which also can be calculated by second term in the Eq. (3.4) [8].

3.3.3.3 The Conditional Variances

As previous mentioned, the estimation of DCC-MIDAS is two step methods and also it involved two-components (short- and long-run) specification. Therefore, this section is going to introduce the GARCH-MIDAS model to calculate the conditional variances. Firstly, we identify short- and long-run time scales; the first time scale is high-frequency (which is the daily data in this chapter), and it describe in section 3.3.3.1 which is t. The second time scale is the low-frequency (i.e. monthly, quarterly, or biannual) which we denote by τ, and this chapter is using monthly data as long-run component. Additionally, σ_i and m_i denote as the components of short- and long-run variances for each asset i. The long-run component (MIDAS part) remains constant across the days of the month, quarter or half-year; so m_i is held fixed (i.e. month, quarter, or biannual) for the number of days, we denote this number of days as $K_v^{(i)}$. The superscript i means

[8] Comte & Lieberman (2003), Ling & McAleer (2003), McAleer et al. (2008) discuss the two-step estimator's asymptotic properties, but all of them only focused on fixed-parameter DCC models. Additionally, Wang & Ghysels (2015) discuss the maximum likelihood estimation for GARCH-MIDAS. However, the problem of DCC-MIDAS's two-step estimation method is still an open question Colacito et al. (2011).

the specific asset, and subscript v is for variances; it also differentiates the similar scheme from the conditional correlation.

Now, we present GARCH-MIDAS process to estimate the conditional variance $h_{i,t}$, and the composition of $h_{i,t}$ will be two parts (short- and long-run), it shows as below[9]:

$$h_{it} = m_{i\tau}\sigma_{it}, \text{for all } t = (\tau-1)K_v^{(i)} + 1, \ldots, \tau K_v^{(i)}, \tag{3.5}$$

here, we introduce separately these two components, σ_{it} is short-run component, so it follows a GARCH (1,1) process:

$$\sigma_{i,t} = (1-\alpha_i-\beta_i) + \alpha_i \xi_{i,t-1}^2 \sigma_{i,t-1} + \beta_i \sigma_{i,t-1} \tag{3.6}$$

Based on the conditional mean from Eq. (3.1), we can rewrite $\varepsilon_{it} = r_{it} - \mu_i$, and then we can have $\varepsilon_{it}^2 = m_{i\tau}\sigma_{it}\xi_{it}^2$. Hence, we will have $\xi_{i,t-1}^2\sigma_{i,t-1} = (r_{it}-\mu_i)^2/m_{i\tau}$.

The long-run component is called MIDAS model, it presents as below:

$$m_{i,\tau} = m_i + \theta_i \sum_{l=1}^{M_v^{(i)}} \varphi_l(\omega_v^{(i)}) RV_{i,\tau-l} \tag{3.7}$$

from this Eq. (3.7), we notice that $m_{i,\tau}$ is a constant and also a weighted sum of $M_v^{(i)}$ of realised variances (RV) over a long horizon. Additionally, it is clearly notice that m_i is the constant in the MIDAS part, and $\varphi_l(\omega_v^{(i)})$ is so call beta weight. In this chapter, we only consider one ω[10], so our beta weight is defined as:

$$\varphi_l(\omega_v^{(i)}) = \frac{\left(1-\frac{l}{M_v^{(i)}}\right)^{\omega_v^{(i)}-1}}{\sum_{j=1}^{M_v^{(i)}}\left(1-\frac{j}{M_v^{(i)}}\right)^{\omega_v^{(j)}-1}}, \tag{3.8}$$

Additionally, the realised variances are equal to the sum $K_v^{(i)}$ squared returns:

$$RV_{i,\tau} = \sum_{t=(\tau-1)K_v^{(i)}+1}^{\tau K_v^{(i)}} r_{it}^2. \tag{3.9}$$

Overall, GARCH-MIDAS progress has three parts to be paid attention to. Firstly, its progress is that m_i can be pre-determined,

$$\mathbb{E}_{t-1}[(r_{i,t}-\mu_i)^2] = m_{i,\tau}\mathbb{E}_{t-1}(\sigma_{i,t}) = m_{i,\tau} \tag{3.10}$$

[9]Notice that GARCH-MIDAS is two-components model, so we should use the notation $h_{it,\tau}$, but we drop the subscript τ for notational simplicity.

[10]According to Engle et al. (2013), they present two type of weighting schemes. We use the beta weight.

so, it points out the short-term (GARCH) can be $\mathbb{E}_{t-1}(\sigma_{i,t}) = 1$ in the starting point. Secondly, in Eq. (3.8), $\omega_v^{(i)}$'s size can determine the rate of decay in the beta weight, if $\omega_v^{(i)}$ is large value which will generate a rapidly decaying pattern; if it is small value, it will be opposite. The last part of GARCH-MIDAS process needs to define the parameters $M_v^{(i)}$ and $K_v^{(i)}$, both of them are the same across different assets, which can represent as $M_v^{(i)} = M_v$ and $K_v^{(i)} = K_v$ for $i = 1, 2$. For K_v , if we want to compute the monthly realised volatility we can set $K_v = 22$; if we want to have the quarterly case, which it can be $K_v = 66$. Therefore, this chapter is using $K_v = 22$ to indicate our data is monthly data. As τ varies, the time span that $m_{i\tau}$ is fixed (that is M_v) also changes. Hence, the selection of K_v related to M_v. In our empirical analysis, we choose $m_{i,\tau}$ changes from one to four years; it means that if we select the monthly component for MIDAS part, $M_v = 12, 24, 36, 48, 60$. If our analysis is based on quarterly realised volatility which will be $M_v = 4, 8, 12, 16$. In this chapter, we use $K_v = 22$ to show monthly data, and the monthly realised volatility will be $M_v = 12$.

In the short conclusion for conditional variance part (GARCH-MIDAS model), the short-run component is using daily (squared) returns of each assets via a GARCH(1,1), and then the long-run component is based on monthly (quarterly or biannual) realised volatilities to compute (see Eq. (3.8 - 3.9))[11].

Summarised for the number of parameters, we will have a parameter space as $\Theta = \{\mu_i, \alpha_i, \beta_i, m_i, \theta_i, \omega_v^{(i)}\}, i = 1, 2$. Meanwhile, our parameters are fixed, so we can use different time span to compute the GARCH-MIDAS, then we compare the estimated parameters from different GARCH-MIDAS. Additionally, we follow the concept of Colacito et al. (2011), Engle et al. (2013) about GARCH-MIDAS, we use the log-likelihood function to estimate the conditional variance for short- and long-run. The next subsection will be the description of DCC-MIDAS.

[11] Base on Engle et al. (2013), they notice $m_{i,\tau}$ can be constant in the fixed period or be constant during the rolling window period, but the estimation results between both of them are very closed. Additionally, Colacito et al. (2011) stated the case of correlation can consider neither fixed span or rolling window. However, we consider the fixed span can offer much general results, we remain the fixed span in our formulas' setting instead of including rolling window notation.

3.3.3.4 The Conditional Correlation

Before we are going to introduce DCC-MIDAS model, we need to make one definition for K_c and $c_{ij,\tau}$.

Definition 3.1 *Let* $K_c = \max_{ij} K_c^{(ij)}$ *and* $c_{ij,\tau} = \frac{\sum_{t=(\tau-1)K_c+1}^{K_c} \xi_{it}\xi_{jt}}{\sqrt{\sum_{t=(\tau-1)K_c+1}^{K_c} \xi_{it}^2}\sqrt{\sum_{t=(\tau-1)K_c+1}^{K_c} \xi_{jt}^2}}$.

Based on GARCH-MIDAS estimation, we can get the two components (short- and long-run); this also means that we can estimate two components' correlation. In particular, we can call DCC-MIDAS as the MIDAS version of DCC. Once, we calculate the vector of *devolatilised* residuals, we can obtain the $q_{ij,t}$ which shows as below:

$$q_{ij,t} = \rho_{ij,\tau}(1-a-b) + a\xi_{i,t-1}\xi_{j,t-1} + bq_{ij,t-1}, \tag{3.11}$$

where the long-run competent (MIDAS with correlation) presents as below:

$$\rho_{ij,\tau} = \sum_{l=1}^{M_c^{(ij)}} \varphi_l(\omega_r^{(ij)})c_{ij,\tau-l}. \tag{3.12}$$

In addition, $q_{ij,t}$ is the covariance (off-diagonal elements) in the correlation's matrix, so we can write the main diagonal elements of $q_{ii,t}$ is given by:

$$q_{ii,t} = (1-a-b) + a\xi_{i,t-1}^2 + bq_{ii,t-1}. \tag{3.13}$$

In the Eq. (3.12), we need to set up the weights $\omega_c^{(ij)}$, lag lengths $M_c^{(ij)}$ and historical correlation's span lengths $K_c^{(ij)}$; based on these settings, we can differ across any pair of series. We use a single setting apply to all pairs of assets' combination, and our selection of these three elements are similar choice of MIDAS in the univariate models (in this chapter, the univariate model is GARCH-MIDAS). As previous stated, ω_c is the common decay parameter which it is independent selection for the pair of assets. From Eq. (3.11), we can notice the covariance matrices are positive definite; it means the matrix $\mathbf{Q}_t = [q_{ij,t}]$ is a weighted average of three matrices. Additionally, the matrix $\mathbf{R}_t = [\rho_{ij,t}]$ needs to remain semi-positive based on the assumption; another element needs to be positive semi-definite is the matrix $\boldsymbol{\xi}_t\boldsymbol{\xi}_t^{'}$ where the $\boldsymbol{\xi}_t = [\xi_{it}]$. Hence, the initial value $\mathbf{Q}_0$ defines to be a semi-positive matrix, then the $\mathbf{Q}_t$ must be the same as $\mathbf{Q}_0$ which is the semi-positive matrix at each time t (see Colacito et al. (2011) for the implication of a single parameter selection verse the multiple parameter for DCC-MIDAS).

In Eq. (3.4,) we can notice the estimated long-run correlation can based on short-run correlation between asset i and j. Hence, we can relocate the formula 3.11 which shows as below:

$$q_{ij,t} - \rho_{ij,\tau} = a(\xi_{i,t-1}\xi_{j,t-1} - \rho_{ij,\tau}) + b(q_{ij,t-1} - \rho_{ij,\tau}) \tag{3.14}$$

we can notice from this equation, short-run (daily) correlation and covariance are base on DCC scheme, and includes the slowly moving long-run correlation.

3.3.3.5 Correlations Macro-sensitivity Specification

Next, we extract the short- and long-run conditional correlation time series ($\rho_{ij,t}$ and $\rho_{ij,\tau}$ for each returns pair ij) from the bivariate DCC-MIDAS models estimated. We first analyse the statistical properties of daily and monthly correlations of each sustainability pair of the EU with the other five countries. The whole sample statistics show an overview of the interdependence level for the cross-country pairs. Our crisis analysis further investigates the correlations' time series behaviour across the crisis subsamples and identifies the types of interdependence (*H1* and *H2*). We apply mean difference tests to compare the pre-crisis with the in-crisis mean values. The Satterthwaite-Welch t-test and the Welch F-test statistics indicate the significance of the change in the average level of correlations due to the crisis shock.

After the statistical analysis, we continue with the regression analysis to unveil the determinants of the sustainability co-movements. We first compute the Fisher Z transformation of short- and long-run correlations to remove the $[-1, 1]$ bounds so that they can be used as dependent variables in the OLS macro regressions. The Fisher transformed daily and monthly series, $\rho^*_{ij,t}$ and $\rho^*_{ij,\tau}$, are explained by the macro-financial proxies detailed in the data Section 3.3.1. According to *H3* and *H4* (see Section 3.2), we expect weak fundamentals to increase countercyclical correlations or decrease the procyclical ones. The short-run correlations, $\rho^*_{ij,t}$, are explained by the first lag of daily variables proxying economic policy and financial uncertainty, disease risk, credit conditions, news sentiment, economic activity, and freights as follows:

$$\rho^*_{ij,t} = \delta_0 + \delta_1\rho^*_{ij,t-1} + \delta_2 EPU_{t-1} + \delta_3 FU_{t-1} + \delta_4 DIS_{t-1} + \delta_5 CR_{t-1} + \delta_6 NW_{t-1} + \delta_7 EA_{t-1} + \delta_8 FT_{t-1} + u_t, \tag{3.15}$$

The long-run correlations, $\rho^*_{ij,\tau}$, are regressed on the monthly proxies of economic policy uncertainty, credit conditions, climate change risk, confidence, economic activity, freights, and prices as follows:

$$\rho^*_{ij,\tau} = \zeta_0+\zeta_1\rho^*_{ij,\tau-1}+\zeta_2 EPU_{\tau-1}+\zeta_3 CR_{\tau-1}+\zeta_4 CC_{\tau-1}+\zeta_5 CONF_{\tau-1}+\zeta_6 EA_{\tau-1}+\zeta_7 FT_{\tau-1}+\zeta_8 PR_{\tau-1}+u_\tau. \tag{3.16}$$

δ_0, ζ_0 are the constants and u_t, u_τ are the error terms.

Next, we proceed our macro-sensitivity analysis of the short-run correlations (similar results for the monthly correlations available upon request) with a focus on the uncertainty channel. Given the potent devastating effects of uncertainty on the economy (Bloom 2009, 2014), we investigate the moderating role of EPU on the correlation drivers. EPU is expected to intensify the macro impact of the correlation determinants. Uncertainty will add an increment (in absolute terms) on both positive and negative effects on sustainability correlations (see also Pástor & Veronesi (2013)). The uncertainty increment is captured by the EPU interaction terms in the following regression:

$$\begin{aligned}\rho^*_{ij,t} &= \delta_0 + \delta_1\rho^*_{ij,t-1} + \delta_2 EPU_{t-1} + (\delta_3 + \delta_3^{EPU} EPU_{t-1}) FU_{t-1} \\ &\quad +(\delta_4 + \delta_4^{EPU} EPU_{t-1}) DIS_{t-1} + (\delta_5 + \delta_5^{EPU} EPU_{t-1}) CR_{t-1} \\ &\quad +(\delta_6 + \delta_6^{EPU} EPU_{t-1}) NW_{t-1} + (\delta_7 + \delta_7^{EPU} EPU_{t-1}) EA_{t-1} \\ &\quad +(\delta_8 + \delta_8^{EPU} EPU_{t-1}) FT_{t-1} + u_t,\end{aligned} \tag{3.17}$$

where we quantify the indirect EPU effect with the interaction terms computed by multiplying EPU with each regressor (EPU interaction term parameters denoted with the superscript ^{EPU}).

After the uncertainty channel, we focus on the crisis impact on correlations and their macro regressors' effects. We add intercept and slope crisis dummies in eq. (3.15) to capture the crisis-vulnerability of sustainability interdependences. Intercept dummies measure the crisis influence on correlation levels, and slope dummies the crisis impact on the macro determinants' effects on correlations. The three crisis intercept dummies, $DUM_{C,t}$, are constructed based on the crisis timelines (see Section 3.3.1). $DUM_{C,t} = 1$ if t is in crisis and $DUM_{C,t} = 0$ if t is out of crisis, with C denoting the crises under investigation ($C = GFC, ESDC, COV$). The slope dummies are calculated with the multiplication of intercept dummies with the macro regressors. To sum up, the macro regression with the crisis impact is the following:

$$\begin{aligned}\rho^*_{ij,t} &= \delta_0 + \delta_0^C DUM_{C,t} + \delta_1 \rho^*_{ij,t-1} + (\delta_2 + \delta_2^C DUM_{C,t-1})EPU_{t-1} + (\delta_3 + \delta_3^C DUM_{C,t-1})FU_{t-1} \\ &+(\delta_4 + \delta_4^C DUM_{C,t-1})DIS_{t-1} + (\delta_5 + \delta_5^C DUM_{C,t-1})CR_{t-1} + (\delta_6 + \delta_6^C DUM_{C,t-1})NW_{t-1} \\ &+(\delta_7 + \delta_7^C DUM_{C,t-1})EA_{t-1} + (\delta_8 + \delta_8^C DUM_{C,t-1})FT_{t-1} + u_t, \end{aligned} \tag{3.18}$$

where the superscript ^{C} denotes the crisis dummies coefficients.

Finally, we close the macro- and crisis-sensitivity analysis by combining the EPU moderating effect with the crisis impact as follows:

$$\begin{aligned}\rho^*_{ij,t} &= \delta_0 + \delta_1 \rho^*_{ij,t-1} + \delta_2 EPU_{t-1} + (\delta_3 + \delta_3^{EPU\_C} DUM_{C,t-1}EPU_{t-1})FU_{t-1} \\ &+(\delta_4 + \delta_4^{EPU\_C} DUM_{C,t-1}EPU_{t-1})DIS_{t-1} + (\delta_5 + \delta_5^{EPU\_C} DUM_{C,t-1}EPU_{t-1})CR_{t-1} \\ &+(\delta_6 + \delta_6^{EPU\_C} DUM_{C,t-1}EPU_{t-1})NW_{t-1} + (\delta_7 + \delta_7^{EPU\_C} DUM_{C,t-1}EPU_{t-1})EA_{t-1} \\ &+(\delta_8 + \delta_8^{EPU\_C} DUM_{C,t-1}EPU_{t-1})FT_{t-1} + u_t. \end{aligned} \tag{3.19}$$

The EPU interaction terms are multiplied with the crisis slope dummies to capture the indirect EPU effect under crisis (parameters denoted by the superscript $^{EPU\_C}$).

3.4 Empirical Analysis

After detailing our methodological approach, we discuss our empirical results. We first present the DCC-MIDAS estimation and analyse the dynamic sustainability correlations extracted from the five bivariate models of EU with AUS, BRA, JP, US, and CA. Lastly, we proceed with the macro-sensitivity regressions to identify the interdependence determinants, the uncertainty channel, and the crisis impact on the correlation pattern.

3.4.1 Dynamic Correlations Estimation Results

The DCC-MIDAS specification uses the DJSI returns as input, estimates the short- and long-run conditional variance of each series in the bivariate system, and then computes the pairwise short- and long-run correlations for each sustainability combination. Table 3.4 reports the variance (Panel A) and the correlation (Panel B) equation results given the following lag lengths: $M_v = 24$ and $M_c = 36$.

The EU variance equation is the same for all bivariate systems where the EU returns are included. For Variance equation Panel A, we notice all the DJSI returns' conditional mean are positive from 0.0409 (CA) up to 0.0621 (JP). The arch (α_i) and garch (β_i) coefficients are significant and with a sum lower than the unity so that the short-run variance component is mean-reverting to the long-run one. Meanwhile, the smallest arch (α_i) coefficient is from CA (0.0937) and the highest one is EU (0.1428) on our sample period. Also, EU has the lowest β_i is 0.7956, it presents the EU is more stable than other return in the short-run. In the MIDAS variance part (long-run), the intercepts (m_i), the monthly RV coefficients (θ_i), and the weights (ω_v^i) are always significant. For the first two parameters (m_i, θ_i), the values are similar across the six sustainability indices, while the smoothing weights (ω_v^i) vary considerably (between 1.77 and 6.14).

For the correlation equation, all the parameters of short-run correlation are significant exclude the pair of EU-US, and $a + b$ are always lower than unity to make sure the short-run correlation component is mean-reverting to the long-run. Only in the EU-US pair, we estimate a much smaller (compared with the other pairs) and insignificant b. The ω_r^{ij} are significant in this table, and it is from 1.001 up to 6.5572. Meanwhile, The pairs of EU-BRA, EU-JP and EU-CA are higher than 0.9, it also means these pairs' short-run have more impact on the correlation. The next part is the correlation analysis.

Table 3.4: DCC-MIDAS estimation results for DJSI return

Panel A. Variance equation

	EU	AUS	BRA	JP	US	CA
μ_i	0.0564*** (0.0118)	0.0482*** (0.0166)	0.0550** (0.0236)	0.0621*** (0.0164)	0.0596*** (0.0107)	0.0409*** (0.0114)
α_i	0.1428*** (0.0096)	0.1202*** (0.0083)	0.0767*** (0.0060)	0.1187*** (0.0077)	0.1360*** (0.0090)	0.0937*** (0.0053)
β_i	0.7956*** (0.0152)	0.8212*** (0.0162)	0.8861*** (0.0128)	0.8210*** (0.0145)	0.8188*** (0.0115)	0.8856*** (0.0079)
m_i	0.6487*** (0.0449)	0.6189*** (0.0487)	1.5957*** (0.1113)	0.8432*** (0.0619)	0.7705*** (0.0422)	0.8343*** (0.0557)
θ_i	0.1642*** (0.0097)	0.1568*** (0.0112)	0.0935*** (0.0229)	0.1639*** (0.0095)	0.1172*** (0.0093)	0.0979*** (0.0160)
ω_v^i	6.0923*** (1.2999)	6.1359*** (1.6914)	4.6169*** (1.4225)	6.0276*** (1.4234)	4.6122*** (1.1341)	1.7688*** (0.6515)
$logL$	−6284.7	−6059.7	−9182.3	−7677.5	−5924.0	−5953.9
AIC	12581.4	12131.4	18376.6	15364.3	11859.9	11919.8
BIC	12620.8	12170.8	18415.9	15403.7	11899.3	11959.2

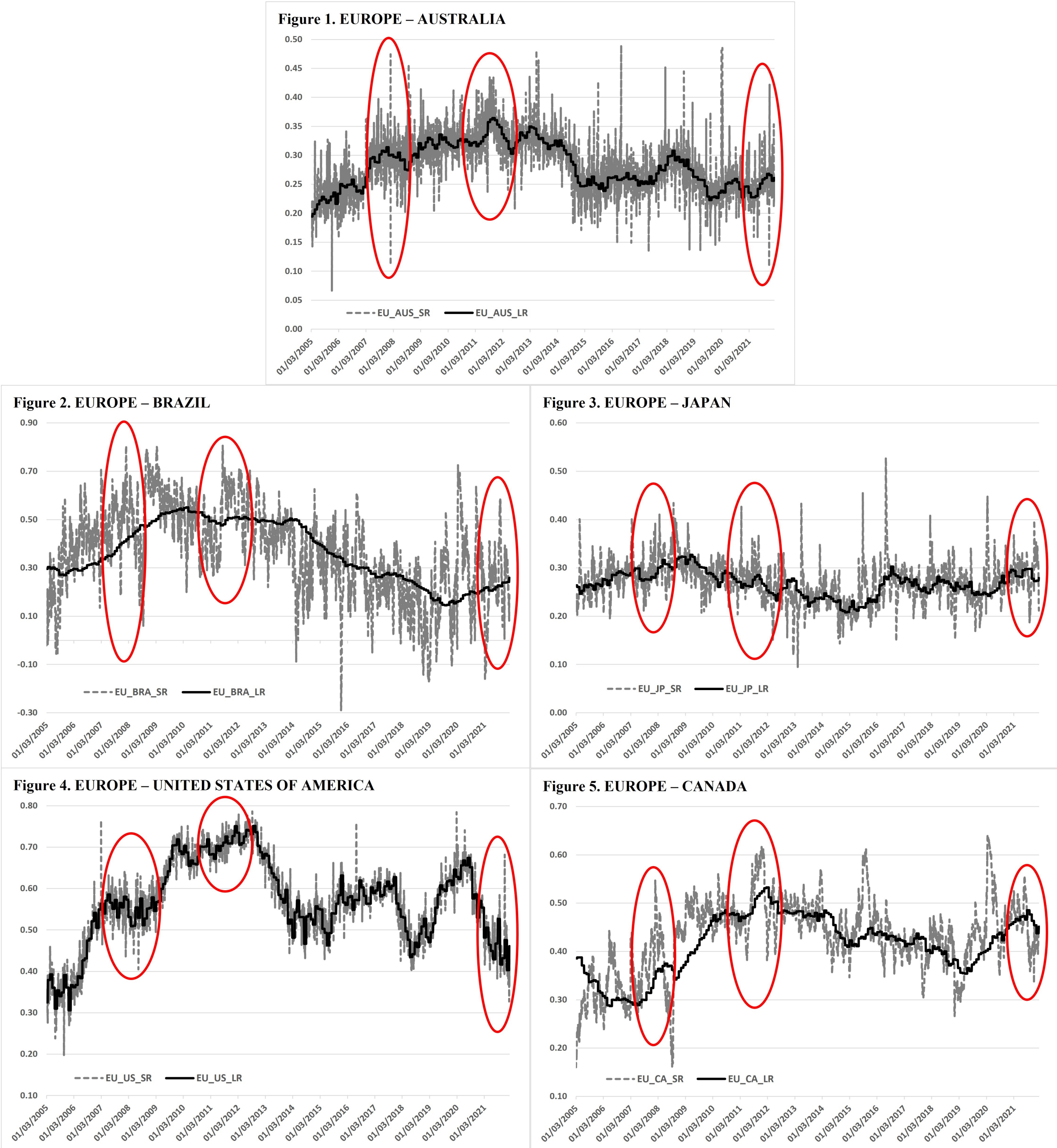
Panel B. Correlation equation

	a	b	ω_r^{ij}	$logL$	AIC	BIC
EU-AUS	0.0171** (0.0067)	0.9614*** (0.0293)	4.4143* (2.4662)	−12347.5	24701.1	24720.7
EU-BRA	0.0148*** (0.0030)	0.9803*** (0.0046)	1.0010*** (0.2907)	−12169.7	24345.4	24365.1
EU-JP	0.0159** (0.0064)	0.8816*** (0.0833)	1.0010*** (0.0908)	−12387.9	24781.8	24801.5
EU-US	0.0269*** (0.0077)	0.2614 (0.3015)	6.5572*** (1.3875)	−11621.4	23248.9	23268.5
EU-CA	0.0136*** (0.0035)	0.9676*** (0.0106)	1.1156** (0.5189)	−12073.7	24153.4	24173.1

Notes:

The table reports the DCC-MIDAS variance and correlation estimation results for the five bivariate combinations. The variance estimation of the EU index is the same for all bivariate models (Panel A). The correlation equation is estimated for five bivariate combinations of the EU sustainability index with the other five countries' indices (Panel B). Numbers in parentheses (square brackets) are standard errors (p-values). ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. $logL$ denotes the log likelihood. AIC and BIC are the Akaike and the Schwartz Information Criteria, respectively.

Figure 3.1: Dynamic Cross-country Sustainability Correlations



Note:

Grey dotted series: short-run correlation, solid black series: long-run correlation, red circle: crisis sub-sample.

The short- (daily) and long-run (monthly) correlation time series are the output of the DCC-MIDAS variance-covariance matrix estimated. Figures 3.1 show the time-varying interdependence of the European sustainability benchmark with Australia, Brazil, Japan, United States, and Canada. In most cases, the cyclical pattern follows the business

Table 3.5: Descriptive statistics of dynamic sustainability correlations

	Short-run sustainability correlations					Long-run sustainability correlations				
	Mean	Median	Max	Min	Std.Dev.	Mean	Median	Max	Min	Std.Dev.
EU-AUS	0.2820	0.2787	0.4901	0.0667	0.0450	0.2813	0.2762	0.3632	0.1966	0.0383
EU-BRA	0.3683	0.3805	0.8062	−0.2905	0.1849	0.3622	0.3453	0.5498	0.1461	0.1239
EU-JP	0.2713	0.2720	0.5281	0.0949	0.0416	0.2676	0.2683	0.3262	0.2082	0.0253
EU-US	0.5684	0.5703	0.7861	0.1979	0.1013	0.5677	0.5683	0.7448	0.3289	0.0994
EU-CA	0.4301	0.4380	0.6424	0.1604	0.0773	0.4157	0.4263	0.5318	0.2879	0.0607

Notes:

The table reports the descriptive statistics of the short- (daily) and long-run (monthly) dynamic sustainability correlations extracted from the bivariate DCC-MIDAS estimations: Mean, Median,Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.). The DJSI variables notation is as follows: Europe (EU), Australia (AUS), Brazil (BRA), Japan (JP), United States of America (US), and Canada (CA).

cycle dynamics since correlations increase in most crisis intervals (red circles). Daily and monthly correlations are mainly countercyclical with the exception of Japan and Brazil for the ESDC subsample. The graphs demonstrate differences between the short- and the long-term response of correlations to the crisis shock, which will be evident in the crisis analysis of the time series statistical properties (mean difference tests).

The whole sample's descriptive statistics (Table 3.5) show that all correlation mean values in the short and long term are positive but significantly lower than the unity. This means that DJSI assets act as diversifiers rather than hedges since they are not perfectly positively correlated, nor negatively or uncorrelated (Baur & Lucey 2010). The mean values demonstrate a tighter daily and monthly interlinkage of EU with CA and US (highest mean values between 0.42 and 0.57), while the weakest interlinkages are observed in the cases of JP and AUS (lowest means between 0.27 and 0.37), confirming the static correlations coefficients computed in the summary statistics of returns in Table C.1 (column: EU Corr). As expected, short-run correlations are more volatile than long-run ones. The lowest volatility is measured in the EU-JP pair and the highest in the EU-BRA pair for both short- and long-term horizons (Table 3.5, columns:Std.Dev.). Overall, the whole period statistics do not show any striking difference between short- and long-run patterns (similar mean, median, maximum, and minimum values) with the exception of daily EU-BRA correlations' minimum. We compute negative correlations only in the case of Brazil in the short-term (minimum short-run correlations: -0.29).

Next, we continue with the statistical analysis of the correlation time series extracted from the DCC-MIDAS across the crisis subsamples in order to diagnose the types of interdependence in the cross-border sustainability pairs. We focus on the mean changes in the correlation level before and during the crisis periods and test the first two hypotheses (*H1* and *H2*). We implement the Satterthwaite-Welch t-test and the Welch F-test, which show whether the correlation mean change from the pre-crisis to the in-crisis subsample is significant. The pre-crisis subsamples cover an equally long period with the crisis interval before the crisis start. We further test alternative pre-crisis subsample lengths for robustness purposes and result in similar conclusions for the interdependence types.

Table 3.6 (Panels A and B) reports the correlation means before and during the crisis, the sign of the change (increase [+] or decrease [−]), and the t- and F-test statistics that define the significance of the mean difference. Our results demonstrate a significant increase of correlations with a positive in-crisis level for most short- and long-run correlations and crisis periods, in line with existing studies on green, sustainable, or ESG cross-asset interdependences (Chen & Lin 2022, Zhang et al. 2022). Contagion (*H1*) is the main interdependence type for cross-border sustainability interconnectedness. We further estimate three correlation decreases during the ESDC only. Although the few decreases are significant, we should reject the flight-to-quality hypothesis (*H2*) because the in-crisis correlation level is positive. Therefore, we conclude on lower interdependences for EU-BRA and EU-JP in the short-term. In the long-term, only for EU-JP we diagnose lower interdependence, while the EU-BRA pair is characterised by contagion. This is a case where the short-run pattern does not follow the long-run one.

Finally, we have one case where the increase during COV is not significant, and we diagnose higher interdependence rather than contagion. This is the case of the long-run EU-JP correlation. However, the increase is significant for this pair in the short term, meaning short-run contagion of EU-JP in the health crisis. Table 3.6, Panel C reports our diagnosis of the interdependence type for both daily and monthly correlation series. Regarding the safe-haven properties, no sustainability pair acts as a safe haven since we don't have cases of uncorrelated or negatively correlated pairs during the three crises under investigation. Overall, from the investment and policymaking perspective, it is bad news that most cross-border sustainability spillovers are contagious because this means lower diversification benefits for traders and higher systemic risks for regulators. However, investors can still find better hedging opportunities in the few cases of lower interdependences or in the DJSI pairs whose short-run correlations reach negative values (EU-BRA) or values close to zero ($\rho_{ij,t} < 0.10$) at least for some daily observations.

Table 3.6: Dynamic sustainability correlations: Crisis mean difference t- and F-tests

Panel A. Short-run (daily) sustainability correlations

	GFC				ESDC				COV			
	before crisis	during crisis	mean change	t-test F-test	before crisis	during crisis	mean change	t-test F-test	before crisis	during crisis	mean change	t-test F-test
EU-AUS	0.2555	0.2999	$+^{***}$	−20.90 436.68	0.3085	0.3305	$+^{***}$	−14.58 212.55	0.2344	0.2529	$+^{***}$	−4.87 23.76
EU-BRA	0.4238	0.5369	$+^{***}$	−12.73 162.09	0.5373	0.5117	$-^{***}$	3.74 13.95	0.2164	0.3755	$+^{***}$	−7.89 62.24
EU-JP	0.2867	0.3102	$+^{***}$	−10.24 104.93	0.3019	0.2714	$-^{***}$	16.35 267.37	0.2432	0.2796	$+^{***}$	−7.77 60.34
EU-US	0.4723	0.5495	$+^{***}$	−17.19 295.55	0.5962	0.7059	$+^{***}$	−38.63 1492.4	0.6183	0.6482	$+^{***}$	−9.07 82.26
EU-CA	0.3299	0.3937	$+^{***}$	−14.98 224.46	0.4295	0.4931	$+^{***}$	−18.48 341.43	0.4443	0.5086	$+^{***}$	−8.46 71.55

Panel B. Long-run (monthly) sustainability correlations

	GFC				ESDC				COV			
	before crisis	during crisis	mean change	t-test F-test	before crisis	during crisis	mean change	t-test F-test	before crisis	during crisis	mean change	t-test F-test
EU-AUS	0.2524	0.2985	$+^{***}$	−8.46 71.55	0.3085	0.3298	$+^{***}$	−5.54 30.65	0.2304	0.2502	$+^{***}$	−5.62 31.64
EU-BRA	0.3129	0.4416	$+^{***}$	−11.84 140.27	0.4816	0.5063	$+^{**}$	−2.50 6.26	0.1528	0.1827	$+^{***}$	−4.90 24.06
EU-JP	0.2825	0.2993	$+^{***}$	−3.72 13.85	0.3009	0.2669	$-^{***}$	9.03 81.47	0.2485	0.2539	$+$	−1.19 1.41
EU-US	0.4672	0.5488	$+^{***}$	−4.04 16.34	0.5943	0.7055	$+^{***}$	−8.89 79.00	0.6143	0.6488	$+^{***}$	−3.91 15.29
EU-CA	0.3002	0.3497	$+^{***}$	−8.22 67.62	0.3835	0.4892	$+^{***}$	−12.10 146.54	0.3860	0.4237	$+^{***}$	−5.46 29.86

Panel C. Short- and long-run sustainability interdependence types

	Short-run sustainability correlations			Long-run sustainability correlations		
	GFC	ESDC	COV	GFC	ESDC	COV
EU-AUS	Contagion	Contagion	Contagion	Contagion	Contagion	Contagion
EU-BRA	Contagion	Lower interdependence	Contagion	Contagion	Contagion	Contagion
EU-JP	Contagion	Lower interdependence	Contagion	Contagion	Lower interdependence	Higher interdependence
EU-US	Contagion	Contagion	Contagion	Contagion	Contagion	Contagion
EU-CA	Contagion	Contagion	Contagion	Contagion	Contagion	Contagion

Notes:

The table reports the mean difference (change) t- and F-tests of the sustainability short- (Panel A) and long-run (Panel B) correlations for the three crises (GFC, ESDC, COV). 'before crisis' and 'during crisis' columns report the correlation means for the pre-crisis and the in-crisis subsamples, respectively. The 'mean change' column reports the increase (+) and decrease (−) of the dynamic correlations during crises. ***, **, * denote significance of the mean difference test at the 0.01, 0.05, 0.10 level, respectively. 't-test' and 'F-test' denote the two mean difference test statistics: the Satterthwaite-Welch t-test and the Welch F-test statistics, respectively. Panel C summarises the interdependence types based on the correlations pattern during crisis periods. The types of interdependence identified here are the following: Contagion, Higher, and Lower interdependence.

3.4.2 Correlations Macro-sensitivity Results

Our initial crisis analysis shows the countercyclical pattern in most crises for the cross-border sustainability short- and long-run correlations. Next, we attempt to answer a critical question: what drives the time-varying behaviour of these interdependences? Under the third and fourth hypotheses (*H3* and *H4*), the macro environment partly determines the correlation pattern. In countercyclical patterns, correlations increase in economic worsening. In the case of procyclical correlations, we expect higher correlations in good times and lower correlations in turbulent times. The correlation determinants are detected in all major aspects of the economy. Sentiment, disease, credit, climate change, news, activity, freights, and prices proxies portray the whole macro canvas that drives cross-border DJSI connectedness. Our first macro-sensitivity analysis identifies the correlation drivers. This way, we also test hypotheses 3 and 4 on the sign of each macro impact. We distinguish between higher or lower interdependences across the business cycle fluctuations, that is, countercyclicality or procyclicality.

Table 3.7 and 3.8 report the baseline daily and monthly correlation macro regressions, where we identify the correlation drivers for the whole sample period. We use the Fisher-transformed correlation series as dependent variables. In Panel A, short-run correlations are explained by high-frequency macro fundamentals (eq. (3.15)). In all cases, we observe a countercyclical correlation pattern, confirming *H3*. Uncertainties, disease risk, and credit conditions positively affect interdependences, while news sentiment, activity, and freights have a negative impact, in line with Karanasos & Yfanti (2021), and contrary to *H4*. Higher daily correlations are associated with higher uncertainties and disease risk, tighter credit, bad news sentiment, lower activity and freights (see also Yfanti et al. (2023)).

Similarly, the long-run correlations explained by low-frequency macros (eq.(3.16)) are countercyclical in the whole sample (*H3*). Elevated uncertainties, financial stress, and climate change risk, low confidence, activity, freights, and inflation drive interdependences higher, in line with Conrad et al. (2014). Considering the estimated significance of the global macro coefficients, we observe only two insignificant cases in the short-run regressions, for activity in EU-CA and for freights in EU-BRA. The vast majority of high-frequency determinants are significant. In the long-run regressions, more low-frequency factors are insignificant in the EU-JP pair, which is among the procyclical pairs in the

ESDC. More insignificant macros in the long-run than in the short-run regressions can be indicative of a slightly lower macro-sensitivity in the long run or a more sluggish response to the macro input. The difference in the macro-sensitivity of short- and long-run correlations can be important for the investment strategies and risk assessment practices of macro-informed traders. Overall, although we observe procyclical patterns for EU-JP and EU-BRA during ESDC in the crisis statistical analysis (Section 3.4.1), the countercyclical pattern prevails in the whole sample macro-sensitivity.

Table 3.7: Dynamic sustainability correlations short-run macro regressions

	EU-AUS	EU-BRA	EU-JP	EU-US	EU-CA
Panel A. Short-run sustainability correlations (eq. (3.15))					
δ_0	0.1293***	−0.1730	0.1965***	0.1546*	0.2710***
	(0.0375)	(0.1237)	(0.0395)	(0.0915)	(0.0366)
$\rho^*_{ij,t-1}$	0.8974***	0.9499***	0.9197***	0.9648***	0.9877***
	(0.0205)	(0.0049)	(0.0072)	(0.0044)	(0.0026)
EPU_{t-1}	0.0073***	0.0071**	0.0084***	0.0038*	0.0012***
	(0.0026)	(0.0036)	(0.0011)	(0.0022)	(0.0004)
FU_{t-1}	0.0262***	0.0159***	0.0422**	0.0228***	0.0835***
	(0.0085)	(0.0048)	(0.0175)	(0.0041)	(0.0119)
DIS_{t-1}	0.0134***	0.0041**	0.0016*	0.0033*	0.0008*
	(0.0023)	(0.0020)	(0.0009)	(0.0020)	(0.0005)
CR_{t-1}	0.0953***	0.0562***	0.0720***	0.0415***	0.0187***
	(0.0169)	(0.0109)	(0.0294)	(0.0074)	(0.0033)
NW_{t-1}	−0.0674***	−0.0115**	−0.0316**	−0.0231***	−0.0229*
	(0.0103)	(0.0051)	(0.0136)	(0.0076)	(0.0121)
EA_{t-1}	−0.0110**	−0.0089***	−0.0034**	−0.0013**	−0.0013
	(0.0047)	(0.0016)	(0.0016)	(0.0006)	(0.0015)
FT_{t-1}	−0.0002*	−0.0005	−0.0006*	−0.0011***	−0.0003**
	(0.0001)	(0.0005)	(0.0004)	(0.0003)	(0.0001)
AIC	−3.9444	−2.9326	−5.3559	−3.8366	−5.6920
BIC	−3.9212	−2.9095	−5.3327	−3.8134	−5.6688
DW	2.0393	2.0403	2.0096	2.0670	2.0523
$\overline{R^2}$	0.9330	0.9330	0.9658	0.9751	0.9781

Notes:

The table reports the correlations macro regression analysis for each bivariate combination. Each short- and long-run correlation is regressed on a constant (δ_0, ζ_0), the first autoregressive term ($\rho^*_{ij,t-1/\tau-1}$), and the daily (Eq. (3.15).) The numbers in parentheses are standard errors. ***, **, * 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. $\overline{R}^2$ is the adjusted R^2.

Table 3.8: Dynamic sustainability correlations long-run macro regressions

	EU-AUS	EU-BRA	EU-JP	EU-US	EU-CA
Panel A. Long-run sustainability correlations (eq. (3.16))					
ζ_0	0.8429 (1.4777)	0.2710 (1.3201)	0.3201*** (0.0557)	0.8636*** (0.2448)	0.5112*** (0.1002)
$\rho^*_{ij,\tau-1}$	0.9762*** (0.0132)	0.9694*** (0.0139)	0.9631*** (0.0200)	0.9605*** (0.0160)	0.9801*** (0.0088)
$EPU_{\tau-1}$	0.0021** (0.0010)	0.0046*** (0.0011)	0.0108** (0.0047)	0.0278*** (0.0053)	0.0132*** (0.0049)
$CR_{\tau-1}$	0.0009*** (0.0002)	0.0025*** (0.0010)	0.0015 (0.0015)	0.0054*** (0.0016)	0.0010* (0.0006)
$CC_{\tau-1}$	0.0053* (0.0029)	0.0015*** (0.0004)	0.0023*** (0.0006)	0.0060*** (0.0017)	0.0034** (0.0015)
$CONF_{\tau-1}$	−0.1649** (0.0694)	−0.0020 (0.0047)	−0.0023 (0.0049)	−0.0178*** (0.0018)	−0.0076* (0.0040)
$EA_{\tau-1}$	−0.0002 (0.0006)	−0.0004* (0.0003)	−0.0004 (0.0005)	−0.0011* (0.0006)	−0.0004** (0.0002)
$FT_{\tau-1}$	−0.0046*** (0.0014)	−0.0198** (0.0100)	−0.0029 (0.0131)	−0.0241*** (0.0062)	−0.0089* (0.0046)
$PR_{\tau-1}$	−0.0004 (0.0006)	−0.0003 (0.0004)	−0.0003*** (0.0001)	−0.0024*** (0.0010)	−0.0015*** (0.0005)
AIC / BIC	−6.7680 / −6.5521	−6.6714 / −6.4563	−6.9415 / −6.7256	−3.8374 / −3.6215	−6.5582 / −6.3408
DW / $\overline{R}^2$	2.0140 / 0.9834	2.0725 / 0.9867	2.0757 / 0.9742	2.0966 / 0.9451	2.0313 / 0.9853

Notes:

The table reports the correlations macro regression analysis for each bivariate combination. Each short- and long-run correlation is regressed on a constant (δ_0, ζ_0), the first autoregressive term ($\rho^*_{ij,t-1/\tau-1}$), and the monthly macro regressors (eqs. (3.16)). The numbers in parentheses are standard errors. ***, **, * 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. $\overline{R}^2$ is the adjusted R^2.

Our macro-sensitivity analysis continues with the uncertainty channel (eq. (3.17)). Uncertainty is a major contributor to the business cycle dynamics with a potent devastating impact on the real economy and the financial markets (Jones & Olson 2013, Kelly et al. 2016). Increased EPU levels exert a positive influence on correlations. After estimating the direct EPU impact, which is highly significant in all cases of short- and long-run correlations (Table 3.7 and Table 3.8), we focus on the indirect EPU effect on the macro drivers of sustainability co-movements. Table 3.9 reports the coefficients of the EPU interaction terms in the daily correlations regression analysis.

We run eq. (3.17) by including each interaction term separately to make the OLS estimation more efficient and report the parameters of the indirect EPU effect for space considerations. Our results show that the positive macro impacts become more positive and the negative ones more negative. The EPU moderating effect has the same sign as the macro regressor and is significant in most cases. In other words, EPU adds a significant increment in the economic influence of correlation determinants. This means that the uncertainty channel partly drives the macro forces behind sustainability correlations. Their economic influence is magnified by or partially attributed to higher uncertainty levels. This confirms previous studies on the powerful indirect effect of the uncertainty channel on correlations (Karanasos & Yfanti 2021, Pástor & Veronesi 2013, Yfanti et al. 2023) and alarms macro-informed traders and policymakers in investing and regulating the financial system by promoting sustainable investments and green transition.

Table 3.9: The economic uncertainty impact on the macro determinants of short-run sustainability correlations, eq. (3.17)

$EPU_{t-1}\times$	EU-AUS	EU-BRA	EU-JP	EU-US	EU-CA
FU_{t-1}	0.0057^{***} (0.0012)	0.0045^{***} (0.0016)	0.0123^{**} (0.0023)	0.0076^{***} (0.0023)	0.0302^{***} (0.0041)
DIS_{t-1}	0.0051^{***} (0.0008)	0.0017^{*} (0.0010)	0.0006^{*} (0.0003)	0.0011^{*} (0.0006)	0.0003^{**} (0.0002)
CR_{t-1}	0.0277^{***} (0.0064)	0.0098^{***} (0.0023)	0.0108^{*} (0.0056)	0.0079^{***} (0.0013)	0.0031^{***} (0.0006)
NW_{t-1}	-0.0210^{***} (0.0041)	-0.0096^{***} (0.0024)	-0.0068^{*} (0.0038)	-0.0084^{***} (0.0029)	-0.0023^{***} (0.0006)
EA_{t-1}	-0.0034^{***} (0.0009)	-0.0023^{*} (0.0013)	-0.0011^{**} (0.0005)	-0.0007^{***} (0.0002)	-0.0005 (0.0005)
FT_{t-1}	-0.0001 (0.0001)	-0.0001 (0.0002)	-0.0002^{*} (0.0001)	-0.0004^{***} (0.0001)	-0.0001^{***} (0.0000)

Notes:

The table reports the economic uncertainty (EPU) impact on the macro effect on short-run sustainability correlations. We present the parameters of each EPU interaction term, estimated separately. The EPU interaction terms are computed with the multiplication of EPU ($EPU_{t-1}\times$) with each macro determinant. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Our macro-sensitivity regression analysis proceeds with the crisis impact on the macro determinants of daily correlations. The crisis effect on correlation levels is captured by the intercept dummies of eq. (3.18). The estimated parameters of the crisis intercept dummies are reported in Table C.3 of the Appendix. They are significant and positive in all but two cases, that is, the two procyclical pairs (EU-BRA and EU-JP) in the ESDC, identified in the crisis statistical analysis with the mean difference tests (Table 3.6 , Panel A).

Next, we run eq. (3.18) to estimate the crisis slope dummies, reported in Table 3.10. Most slope dummies are significant except for the freight effect during the first two financial crises. In the first crisis period (Panel A), the GFC shock amplifies the macro impacts in line with our contagion or countercyclicality diagnosis for the GFC period. It adds a positive incremental effect for macros with a positive impact and a negative incremental effect for macros with a negative impact. The ESDC shock (Panel B) on the correlation drivers' impact is estimated with the same sign as the macros in the whole sample for the three countercyclical pairs (EU-AUS, EU-US, EU-CA). For EU-BRA and EU-JP, the two procyclical pairs in the European crisis, the crisis slope dummies have the opposite sign than the sign for the whole period, as expected. Lastly, the COV slope dummies (Panel C) are estimated with the same sign as the effect in the whole sample since all pairs are countercyclical during the pandemic. Our analysis provides strong evidence of how the whole economic environment drives sustainability correlations during crises which should be at the core of investors' and regulators' considerations. These results confirm previous studies on cross-asset or cross-country correlation determinants which are found to be highly crisis-sensitive (Karanasos & Yfanti 2021, Yfanti et al. 2023).

In the final part of our macro-sensitivity analysis, we investigate the crisis impact on the indirect EPU effect captured by the slope dummies on the EPU moderators of eq. (3.19). In Table 3.11, we report the coefficients of the slope dummies on the EPU interaction terms. The signs of the dummies' parameters are the same for each macro driver as in the crisis analysis of Table 3.10. The EPU moderation makes more slope dummies significant for the freights proxy compared with the crisis impact (Table 3.10). Overall, the uncertainty channel's magnifying impact on the macro determinants is aggravated by the crisis shocks in all cases, confirming the increased macro-sensitivity during turbulent times.

Table 3.10: The crisis impact on the macro determinants of short-run sustainability correlations, eq. (3.18)

Panel A. GFC impact							
$DUM_{GFC,t-1}\times$	EPU_{t-1}	FU_{t-1}	DIS_{t-1}	CR_{t-1}	NW_{t-1}	EA_{t-1}	FT_{t-1}
EU-AUS	0.0059^{*} (0.0033)	0.0121^{**} (0.0060)	0.0065^{***} (0.0020)	0.0751^{***} (0.0166)	-0.1092^{***} (0.0413)	-0.0376^{***} (0.0083)	-0.0016 (0.0012)
EU-BRA	0.0027^{***} (0.0010)	0.0171^{***} (0.0022)	0.0110 (0.0146)	0.0895^{***} (0.0097)	-0.1860^{***} (0.0138)	-0.0294^{***} (0.0059)	-0.0023 (0.0022)
EU-JP	0.0009^{***} (0.0003)	0.0151^{**} (0.0071)	0.0054^{*} (0.0030)	0.0081^{***} (0.0016)	-0.0403^{***} (0.0137)	-0.0467^{**} (0.0210)	-0.0007 (0.0005)
EU-US	0.0057^{***} (0.0017)	0.0229^{***} (0.0085)	0.0012^{**} (0.0005)	0.0199^{***} (0.0039)	-0.0313^{***} (0.0081)	-0.0061^{***} (0.0010)	-0.0019 (0.0014)
EU-CA	0.0051^{***} (0.0022)	0.0216^{***} (0.0038)	0.0016^{***} (0.0006)	0.0230^{***} (0.0092)	-0.0847^{**} (0.0374)	-0.0295^{***} (0.0036)	-0.0012^{**} (0.0005)
Panel B. ESDC impact							
$DUM_{ESDC,t-1}\times$	EPU_{t-1}	FU_{t-1}	DIS_{t-1}	CR_{t-1}	NW_{t-1}	EA_{t-1}	FT_{t-1}
EU-AUS	0.0171^{***} (0.0013)	0.0334^{***} (0.0028)	0.0558^{***} (0.0205)	0.1096^{***} (0.0091)	-0.1667^{***} (0.0230)	-0.0236^{***} (0.0068)	-0.0004 (0.0009)
EU-BRA	-0.0199^{*} (0.0104)	-0.0635^{**} (0.0285)	-0.0486^{*} (0.0254)	-0.0493^{***} (0.0075)	0.0269^{**} (0.0116)	0.0203^{***} (0.0065)	0.0015 (0.0015)
EU-JP	-0.0042^{**} (0.0019)	-0.0089^{*} (0.0051)	-0.0005 (0.0084)	-0.0215^{***} (0.0022)	0.0569^{**} (0.0282)	0.0061^{**} (0.0029)	0.0002 (0.0004)
EU-US	0.0212^{***} (0.0072)	0.0772^{***} (0.0256)	0.0194 (0.0214)	0.0433^{***} (0.0056)	-0.0732^{***} (0.0168)	-0.0051^{***} (0.0011)	-0.0012^{**} (0.0006)
EU-CA	0.0061^{***} (0.0021)	0.0261^{**} (0.0117)	0.0221^{**} (0.0095)	0.1158^{***} (0.0303)	-0.0470^{*} (0.0281)	-0.0343^{***} (0.0038)	-0.0027^{**} (0.0014)
Panel C. COV impact							
$DUM_{COV,t-1}\times$	EPU_{t-1}	FU_{t-1}	DIS_{t-1}	CR_{t-1}	NW_{t-1}	EA_{t-1}	FT_{t-1}
EU-AUS	0.0220^{***} (0.0030)	0.0387^{***} (0.0060)	0.0175^{***} (0.0022)	0.0145^{***} (0.0029)	-0.0718^{***} (0.0170)	-0.0007^{*} (0.0004)	-0.0005 (0.0008)
EU-BRA	0.0266^{***} (0.0039)	0.0408^{***} (0.0032)	0.0025^{***} (0.0006)	0.0258^{***} (0.0083)	-0.0372^{***} (0.0029)	-0.0033^{***} (0.0007)	-0.0012^{**} (0.0005)
EU-JP	0.0056^{**} (0.0025)	0.0058^{***} (0.0005)	0.0018^{***} (0.0006)	0.0234^{***} (0.0041)	-0.0483^{**} (0.0220)	-0.0035^{**} (0.0017)	-0.0008^{***} (0.0003)
EU-US	0.0156^{***} (0.0033)	0.0089^{***} (0.0014)	0.0186^{***} (0.0045)	0.0586^{***} (0.0146)	-0.1887^{**} (0.0784)	-0.0080^{*} (0.0044)	-0.0008 (0.0008)
EU-CA	0.0133^{***} (0.0030)	0.0098^{***} (0.0027)	0.0126^{***} (0.0011)	0.0099^{***} (0.0033)	-0.1363^{**} (0.0571)	-0.0029^{*} (0.0017)	-0.0004^{*} (0.0002)

Notes:

The table reports the crisis impact on the macro effect on short-run sustainability correlations. We present the parameters of each crisis slope dummy, estimated separately. The slope dummies are computed with the multiplication of the crisis dummy for each crisis period (GFC: $DUM_{GFC,t-1}\times$, ESDC: $DUM_{ESDC,t-1}\times$, COV: $DUM_{COV,t-1}\times$) with each macro factor. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table 3.11: The economic uncertainty impact on the macro determinants of short-run sustainability correlations in crisis periods, eq. (3.19)

Panel A. The indirect EPU impact in the GFC period						
$DUM_{GFC,t-1}EPU_{t-1}\times$	FU_{t-1}	DIS_{t-1}	CR_{t-1}	NW_{t-1}	EA_{t-1}	FT_{t-1}
EU-AUS	0.0048* (0.0028)	0.0025*** (0.0010)	0.0268*** (0.0064)	−0.0455*** (0.0163)	−0.0164*** (0.0034)	−0.0007* (0.0004)
EU-BRA	0.0033*** (0.0012)	0.0044 (0.0056)	0.0158*** (0.0022)	−0.0372*** (0.0046)	−0.0097*** (0.0034)	−0.0010*** (0.0004)
EU-JP	0.0067*** (0.0023)	0.0020 (0.0013)	0.0078** (0.0036)	−0.0259* (0.0146)	−0.0187* (0.0101)	−0.0003 (0.0002)
EU-US	0.0014*** (0.0004)	0.0006 (0.0017)	0.0135*** (0.0022)	−0.0114*** (0.0027)	−0.0019*** (0.0005)	−0.0008** (0.0004)
EU-CA	0.0015*** (0.0002)	0.0006** (0.0003)	0.0037*** (0.0016)	−0.0138*** (0.0054)	−0.0107*** (0.0040)	−0.0004** (0.0002)
Panel B. The indirect EPU effect in the ESDC period						
$DUM_{ESDC,t-1}EPU_{t-1}\times$	FU_{t-1}	DIS_{t-1}	CR_{t-1}	NW_{t-1}	EA_{t-1}	FT_{t-1}
EU-AUS	0.0124*** (0.0011)	0.0220*** (0.0080)	0.0394*** (0.0036)	−0.0595*** (0.0093)	−0.0095*** (0.0027)	−0.0001 (0.0003)
EU-BRA	−0.0134* (0.0080)	−0.0201** (0.0100)	−0.0108*** (0.0024)	0.0138*** (0.0030)	0.0010** (0.0005)	0.0004 (0.0006)
EU-JP	−0.0021* (0.0012)	−0.0002 (0.0012)	−0.0059*** (0.0018)	0.0135** (0.0068)	0.0003 (0.0012)	0.0001 (0.0002)
EU-US	0.0175*** (0.0048)	0.0083* (0.0044)	0.0165*** (0.0053)	−0.0262*** (0.0032)	−0.0032** (0.0017)	−0.0005* (0.0003)
EU-CA	0.0048* (0.0026)	0.0088** (0.0038)	0.0209** (0.0096)	−0.0049*** (0.0015)	−0.0147*** (0.0015)	−0.0008*** (0.0001)
Panel C. The indirect EPU effect in the COV period						
$DUM_{COV,t-1}EPU_{t-1}\times$	FU_{t-1}	DIS_{t-1}	CR_{t-1}	NW_{t-1}	EA_{t-1}	FT_{t-1}
EU-AUS	0.0141*** (0.0021)	0.0061*** (0.0007)	0.0055*** (0.0009)	−0.0251*** (0.0061)	−0.0003 (0.0004)	−0.0002 (0.0003)
EU-BRA	0.0161*** (0.0021)	0.0008*** (0.0001)	0.0102*** (0.0035)	−0.0095*** (0.0028)	−0.0012*** (0.0004)	−0.0004*** (0.0001)
EU-JP	0.0038* (0.0021)	0.0011*** (0.0003)	0.0088*** (0.0029)	−0.0144* (0.0080)	−0.0012** (0.0006)	−0.0004 (0.0010)
EU-US	0.0031*** (0.0006)	0.0050*** (0.0015)	0.0183*** (0.0022)	−0.0420*** (0.0133)	−0.0027** (0.0012)	−0.0003 (0.0003)
EU-CA	0.0045* (0.0027)	0.0048*** (0.0018)	0.0042*** (0.0012)	−0.0308** (0.0134)	−0.0009* (0.0006)	−0.0002*** (0.0001)

Notes:

The table reports the economic uncertainty (EPU) impact during crises on the macro effect on short-run sustainability correlations. We present the parameters of each EPU interaction term under crisis, estimated separately. The EPU interaction terms under crisis are computed with the multiplication of the dummy for each crisis period and EPU (GFC: $DUM_{GFC,t-1} \times EPU_{t-1}\times$, ESDC: $DUM_{ESDC,t-1} \times EPU_{t-1}\times$, COV: $DUM_{COV,t-1} \times EPU_{t-1}\times$) with each macro factor. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

3.4.3 Discussion and Implications

Our empirical study on cross-border sustainability interconnectedness investigates the interdependence among EU and five international sustainability equity benchmarks. The dynamic correlations framework reveals the countercyclical pattern of time-varying sustainability interlinkages for most country pairs and crisis periods. The connectedness increases when the economy slows down in the short and long run. Among the few exceptions are the EU-JP and EU-BRA combinations, where during the European crisis, they exhibit procyclical behaviour in the short term and EU-JP in the long term. During crises, we mainly diagnose contagion phenomena except for the procyclical cases in ESDC, where we observe lower interdependence rather than flight-to-quality episodes.

All indices act as diversifiers, and we do not conclude on safe haven features in any crisis subsample. The highest dynamic correlations on average are measured for the EU with US and CA, meaning that European and North American sustainability markets are more integrated compared to EU with JP, AUS, and BRA. We further demonstrate the significant macro-relevance of correlations by revealing their macro determinants, EPU-sensitivity, and crisis-vulnerability. Proxies of sentiment (uncertainty/confidence), disease and climate change risks, credit, news, activity, freights, and inflation are among the high- and low-frequency correlation drivers. Economic uncertainty and crisis shocks magnify all macro effects on sustainability interdependences. Long-run correlations are less macro-sensitive than short-run ones. Finally, the fact that policy considerations and climate change (EPU and CPU coefficients) are highly significant driving forces, among others, provides strong evidence on the critical policy and market implications of our study.

Market practitioners and policymakers concerned about sustainable development and investments, ESG ratings, green transition, and climate change threats should utilise our novel findings on cross-border sustainability interdependences. Macro-informed trading is crucial for investors and risk managers. Since the DJSI correlations are driven by economic fundamentals, investment and risk managers should proactively take into account the short- and long-run macro developments when taking positions in sustainable markets and cross-hedging their portfolios. Higher interdependences erode the diversification benefits and decrease the hedging effectiveness (see (Yfanti et al. 2023)). They could further identify the few index combinations with lower correlations to achieve their optimal hedge ratios and immunisation in case of crisis. For regulatory authorities, it is necessary to realise the importance of policy interventions in driving sustainability spillovers. They should systematically monitor the cross-border interconnectedness dynamics and limit their crisis-vulnerability. When urging corporations for green finance and ESG strategies, it is critical to design action plans that mitigate contagion effects and financial stability threats. Climate change policies should address climate financial risks for corporations and encourage a smooth and effective transition to the greener. Lastly, ESG risk regulatory frameworks should incorporate possible risk concentrations driven by increased sustainability interdependences.

3.5 Conclusion

We have explored a novel research field in sustainable investments, that is, cross-border sustainability interdependences. Our contribution to the literature is manifold. We first differentiate between short- and long-run dynamic correlations among major sustainability benchmarks, where we find that countercyclicality and contagion prevail. We further identify a few DJSI procyclical cases during the ESDC. Then, we reveal the high- and low-frequency drivers of the correlation pattern, which is found to be macro- and crisis-sensitive. All aspects of the macro environment exert significant causal effects on correlations that are magnified by the uncertainty channel and crisis shocks. Countercyclical correlations increase with a bad economic outlook characterised by higher uncertainty, disease and climate risk, tighter credit, worse news sentiment, and lower confidence, activity, freights, and inflation. Therefore, investors and policymakers should consider our results on DJSI correlation dynamics in designing their sustainable investment strategies and sustainable development policies in the short and long term. Finally, future research can explore further cross-border sustainability interlinkages among more regions and countries. In a future course of study, we could also distinguish between country-specific and global correlation drivers that act as warning signals or alarms of imminent correlation changes.

3.6 Appendix

Table C.1: Descriptive statistics and unit root tests of the DJSI index returns

	Mean	Median	Max	Min	Std.Dev.	ADF	EU Corr
EU	0.0117	0.0517	9.2935	-11.7018	1.1697	-73.5235^{***}	
AUS	0.0102	0.0268	6.9278	-9.8994	1.1046	-76.4539^{***}	0.3822
BRA	0.0220	0.0000	15.9383	-13.8649	1.9501	-73.2259^{***}	0.4639
JP	0.0096	0.0000	13.9163	-11.4582	1.4924	-71.3991^{***}	0.3246
US	0.0265	0.0349	10.2377	-13.2723	1.1733	-82.6034^{***}	0.6031
CA	0.0239	0.0307	11.3280	-10.9250	1.1633	-28.8212^{***}	0.5196

Notes:

The table presents the descriptive statistics of the Dow Jones Sustainability Index (DJSI) returns: Mean, Median, Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.), the Augmented Dickey-Fuller (ADF) test statistic of the unit root test, and the correlation of EU returns with the other five return series (EU Corr). The DJSI variables notation is as follows: Europe (EU), Australia (AUS), Brazil (BRA), Japan (JP), United States of America (US), and Canada (CA). ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table C.2: Descriptive statistics and unit root tests of the macro variables

	Mean	Median	Max	Min	Std.Dev.	ADF
Panel A. Daily macros						
EPU_t	1.9590	1.9566	2.9072	0.5211	0.2913	-6.6985^{***}
IV_t	1.2469	1.2170	1.9175	0.9609	0.1653	-5.7387^{***}
ID_t	0.2333	0.0320	6.8370	0.0000	0.6508	-3.6858^{**}
$CISS_t$	0.1133	0.0291	0.8964	0.0002	0.1735	-3.3884^{**}
NSI_t	−0.0168	0.0036	0.4325	−0.6722	0.2013	-3.7554^{***}
ADS_t	−0.3095	−0.1303	8.9889	−26.332	2.2669	-7.7437^{***}
BDI_t	3.2232	3.1685	4.0716	2.4624	0.3305	-2.8529^{**}
Panel B. Monthly macros						
EPU_τ	2.1124	2.1036	2.7024	1.6511	0.1918	-5.2296^{***}
$KCFSI_\tau$	0.1113	−0.2834	5.7130	−0.9207	1.1868	-2.5903^{*}
CPU_τ	2.0425	2.0196	2.6141	1.4497	0.2075	-4.3006^{***}
BCI_τ	2.0001	2.0003	2.0086	1.9810	0.0049	-3.3523^{***}
$CFNAI_\tau$	−0.1504	−0.0300	6.1200	−17.960	1.5244	-11.0416^{***}
CFI_τ	1.1299	1.1345	1.3470	0.8510	0.0998	-2.9244^{**}
INF_τ	2.6878	2.4996	16.812	−9.9677	5.1719	-2.5709^{*}

Notes:

The table presents the descriptive statistics of the macro fundamentals used as correlation determinants: Mean, Median, Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.) and the Augmented Dickey-Fuller (ADF) test statistic of the unit root test. The macro variables notation is as follows: US EPU index ($EPU_{t/\tau}$), VIX index (IV_t), Infectious disease equity market volatility tracker (ID_t), US Composite indicator of systemic stress ($CISS_t$), US Financial stress index of the Kansas City Fed ($KCFSI_\tau$), CPU index (CPU_τ), NSI index (NSI_t), US Business confidence index growth (BCI_τ), ADS US business conditions index (ADS_t), US Chicago Fed national activity index ($CFNAI_\tau$), Baltic dry index (BDI_t), Cass freight index (CFI_τ), and US PPI growth (INF_τ). ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table C.3: The crisis impact on the level of daily sustainability correlations, eq. (3.18)

	$DUM_{GFC,t}$	$DUM_{ESDC,t}$	$DUM_{COV,t}$
EU-AUS	0.0320^{***} (0.0050)	0.0649^{***} (0.0032)	0.0258^{***} (0.0097)
EU-BRA	0.1218^{***} (0.0295)	-0.0228^{***} (0.0051)	0.0317^{***} (0.0028)
EU-JP	0.0331^{***} (0.0123)	-0.0072^{***} (0.0016)	0.0015^{***} (0.0005)
EU-US	0.0213^{*} (0.0121)	0.0729^{***} (0.0233)	0.0054^{*} (0.0030)
EU-CA	0.0051^{***} (0.0016)	0.0177^{**} (0.0094)	0.0090^{*} (0.0052)

Notes:

The table reports the crisis impact on daily correlations (eq. (3.18)). The crisis intercept dummies are estimated separately from the crisis slope dummies. The intercept dummies for each crisis subsample are as follows: GFC subsample: $DUM_{GFC,t}$, ESDC subsample: $DUM_{ESDC,t}$, COV subsample: $DUM_{COV,t}$. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

4 cDCC-MIDAS evidence form Short- and Long-run financial asset

4.1 Introduction

Recent economic turmoil is triggered by the Covid-19 health crisis, this crisis brings back academic researchers' and policymakers' attention to discover the problem that triggered the economic turmoil. The economic turmoil not only can be triggered by financial crises (e.g. 2008 subprime crisis and sovereign debt crisis) but also can be caused by non-economic events (such as the health crisis of Covid-19 and climate-related disasters). Meanwhile, these events' impact will spread to other countries to create a global economic crisis. For example, the starting point of the 2008 subprime crisis is from the US housing market, and then it spreads to the banking sector and to the global economy. Iwanicz-Drozdowska et al. (2021) points out that economic and non-economic events have an impact on the stock market. In addition, a financial crisis defines as an endogenous problem in the financial system, and the health crisis and climate change can be exogenous factors to the economic environment. The sovereign debt crisis is sort of the extension episode for the 2008 subprime crisis, Leschinski & Bertram (2017) states the connection between the subprime mortgage crisis and the sovereign debt crisis are strong. Allen & Gale (2000), Forbes & Rigobon (2002) classify that this shock spillover effect is defined as financial contagion. The empirical evidence for financial contagion presents a significant increase in the correction in the cross-border or cross-asset market during the crisis period. Meanwhile, economic turmoil has a high impact on the whole macro-financial stability; this is the reason why policymakers and market practitioners should pay more attention to financial co-movement.

The aim of this chapter is to the time-varying interconnectedness among the three main asset market indexes which are global equities, real estate and commodities. Inspired by Karanasos & Yfanti (2021), they state that these three assets are playing a major role in the global financial market. In particular, the real estate asset market is the starting point for the 2008 subprime crisis. In this chapter, we propose corrected Dynamic Conditional Correlations - Mixed Data Sampling (cDCC-MIDAS) model to estimate trivariate systems of asset returns. cDCC-MIDAS model is the combination of Dynamic Conditional Correlations(DCC) from Engle (2002) and MIDAS from Ghysels et al. (2005), but this form with Aielli's correction . In addition, corrected DCC-MIDAS follows a two-step estimation method which allows us to study assets' volatility in the GARCH-MIDAS (Engle et al. 2013), and provide the correlation between assets from DCC-MIDAS. In addition, we are based on the estimation of short- and long-run correlation from corrected DCC-MIDAS to classify the hedging properties of the assets; and, we also define assets are flight-to-quality or contagion based on short- and long-run correlation. Additionally, we classify the pre-crisis period and in-crisis period to notice the change in correlation. We conclude the daily and monthly macro fundamentals which have a significant impact on the short- and long-run correlation in the crisis period.

Our empirical results present that contagion appears most in these three asset markets during the three periods of turmoil. The pair of real estate and commodities satisfied the condition of flight-to-quality but it is not across all the crises. Overall, we find the correlation between commodities and global equities is stronger than the pair of commodities and real estate and the pair of global equities and real. However, the short-run and long-run results are quite different between the pair of global equities and real estate; this pair performs contagion in the short-run correlation during the Covid period, but it is higher interdependence in the long-run correlation. Additionally, our results present significant differentiation during the three crisis periods (the 2008 global financial crisis [GFC], the European sovereign debt crisis [ESDC], and the Covid-19 crisis [COV]); the short- and long-run correlation brings up different pictures in these three crisis periods. Firstly, we find a significant change in the short-run for these three assets during the GFC. Secondly, the correlations between these three pairs have hugely increased in the ESDC. However, COV has quite different results in the short-run and long-run correlation. In short conclusion for the type of independence for assets, we find all of them are contagion in the ESDC period.

This chapter is mainly to contribute to the financial contagion literature. We analyse global equities- real estate -commodities benchmarks via trivariate cDCC-MIDAS. Meanwhile, our results bring up conclusions about the combinations of financial and financialised assets (global equities - real estate, real estate - commodities), and financialised assets (real estate - commodities). In addition, this chapter is following the idea from (Karanasos & Yfanti 2021), they investigate three asset classes and analyse these three assets' correlation. Therefore, we use the cDCC-MIDAS model to verify the short- and long-run correlation of three asset classes together. Secondly, we conclude the hedging properties for three cross-assets based on the whole sample period. The third contribution classifies three pairs under different hedging properties to responding crisis periods. Fourth, we apply macroeconomic factors to the correlations, inspired by Karanasos & Yfanti (2021), to discover how the macroeconomic factor influences on the dynamic correlations. The last contribution of this chapter is to the financial econometrics literature with the modification of the DCC-GARCH-MIDAS with Aielli's correction on correlations estimation, establishing the novel estimation of the cDCC-GARCH-MIDAS specification.

The remainder of the paper is structured as follows. The next section presents the theoretical background which includes the literature review of the assets' correlations and the hypothesis for this chapter. Section 4.3 is the methodology and data description for this chapter; Firstly, we detail the corrected DCC-GARCH-MIDAS model, and it also includes the preliminaries' model (GARCH-MIDAS) and estimation method for correct DCC-MIDAS. Secondly, we introduce our macro regression for macroeconomic sensitivity analysis. The last part of this section will be the data description for this chapter. The fourth section 4.4 is the empirical analysis of the correct DCC-GARCH-MIDAS and the correlations' hedging property during the crisis periods. The following section 4.5 is the macro sensitivity and the last section is the conclusion of this chapter.

4.2 Theoretical background

This section separates into two parts, the first part is explaining the financial literature review about financial contagion; the second part is presenting our hypotheses for this chapter and how we are going to test our hypotheses in this chapter.

4.2.1 Literature review

4.2.1.1 Literature for financial co-movement

A lot of research is studying financial integration and tight interconnectedness for at last three decades, many researchers noticed that globalisation enhances the tight interconnectedness of the whole economy. Allen & Gale (2000), Forbes & Rigobon (2002) bring out the concept of financial contagion, and point out the crisis can increase financial correlations. Numerous studies have focused on different markets' financial contagions. For example, Bae et al. (2003) capture the financial contagion from the emerging market during the 1990s by using a multinomial logistic regression model. Eiling & Gerard (2015) notice the equity market's interconnection is increasing during the last two decades. Additionally, Bartram & Wang (2015) states that European equity market dependence significantly increases, especially in financials and Industrials markets. Overall, most of the financial literature found the economic connection has increased. However, Bekaert et al. (2009) has the opposite opinion about the international stock market co-movement, they did not find any evidence of the increased correlation in the international stock market. We believe that this chapter will be interesting to investigate the interconnection between three asset markets.

As previously stated, Financial market literature presents how the financial crisis influences different countries' stock markets, and the crisis enhances the co-movement. This spillover effect results in the crisis moving from one region to the next region or to the whole country, or even to the global economy. Some financial instruments, such as bonds, equities, real estate and commodities, these markets interconnections have been increasing during the crisis period. For example,Dungey et al. (2006) present the bond market as such spillover effect during Russian bond default. Baele (2005) find the spillover effect in the equities market via using the regime-switching model, and he also points out that the correlation between EU and US equities markets increased due to the EU and US shock over the 1980s and 1990s. For the real estate market, Hiang Liow (2012) and Hurn et al. (2022) have the similar finding about the spillover effect in the real state market; Hiang Liow (2012) state the market of real estate and the global stock has significant comove over their sample period from 1995 to 2009, Hurn et al. (2022) investigate Chinese and Australian housing market. For the commodities market, Alquist et al. (2020) and Flori et al. (2021) focus on intra-commodity co-movement; Alquist et al. (2020) present the commodity market's co-movement has a negative contribution to the global economy during the crisis period, and Flori et al. (2021) find the co-movement of intra-commodity due to climate change.

The time-varying interdependence among markets is quantified by the multivariate GARCH framework, which computes the conditional correlations of asset returns (see, for example, the DCC of Engle (2002), the Asymmetric DCC - ADCC of Cappiello et al. (2006), the DCC-GARCH-MIDAS of (Colacito et al. 2011), and the Dynamic Equicorrelations - DECO of Engle & Kelly (2012)). Among the few studies that go beyond the computation of correlations and explore the drivers of their evolution are mostly the ones applying the DCC-GARCH-MIDAS model, where they explain the long-term component of asset co-movements with low-frequency macro fundamentals Asgharian et al. (2016), Conrad et al. (2014), Mobarek et al. (2016). Moreover, Yang et al. (2012) and Karanasos & Yfanti (2021) use high-frequency correlation determinants with non-MIDAS dynamic correlation models. Yang et al. (2012) investigate the stocks - bonds - real estate correlations through the ADCC model and attribute their time-varying pattern to daily macro-financial factors. Karanasos & Yfanti (2021) reveal the daily and monthly cross-asset correlation determinants with a DECO specification. The DECO model computes the daily equicorrelations and the authors proceed with monthly averaging of the daily series to achieve both high and low-frequency correlation macro analyses. Motivated by Karanasos & Yfanti (2021), we choose the MIDAS framework, by improving its estimation with Aielli's correction (see Aielli (2013), for the relative merits of the DCC correction), because it is the only specification that computes both short- and long-run correlation dynamics (see also the DCC merits for contagion testing in Chiang et al. (2007)). Therefore, we further demarcate our study from existing literature with the correction of the classic DCC-GARCH-MIDAS, the analysis of the short- and the long-run dimension of the cross-asset nexus, and the macro sensitivity based on both high and low-frequency correlation determinants. Next, we develop the theoretical hypotheses to be tested in our investigation of markets' co-movements.

4.2.2 Hypotheses

This chapter's empirical analysis of three assets (global equities, real estate and commodities) has two steps. Firstly, we need to compute the correlation from the trivariate cDCC-MIDAS system; then, we can use the estimated correlation to explain which type of hedging properties(diversifier, hedge or safe haven) for these three assets are. In addition, we also need to identify the type of independence (contagion or flight-to-quality) for these assets. After we determine the type of hedging properties and independence of these three assets, we will continue to estimate the macro sensitivity exercise, this step can allow us to study how the asset's market co-movement has an impact on the global economy.

In this chapter, we use the same method as Forbes & Rigobon (2002) and Baur & Lucey (2009, 2010) to determine the asset's hedging properties and then to identify the type of independence. According to Baur & Lucey (2010), they define the three types of hedging property which a hedge, diversifies and safe havens; they use the asset's overall average correlation to classify the asset's hedging feature. They point out that if an asset's hedging property is a "diversifier", then the correlation with another asset will be positive and its correlation will not be perfectly correlated; whereas the hedges are uncorrelated or negatively correlated.

In other words, if the correlation of one pair is positive on average it means these two assets acts as "diversifier" in the portfolio, the investors should consider to reduce one of the assets in this portfolio during the crisis periods, because this pair will increase the risk of portfolio. Similar to "hedge", if the correlation of one pair is negative or uncorrelated on average it means these two assets acts "hedge" in the portfolio, the investors can reduce their lost or increase their profit during the crisis periods.

Based on this assumption, we consider another term "uncorrelated assets" which if the pair of assets have zero correlation or a positive correlation but are lower than 0.1 on average, we classify this pair as uncorrelated assets in the portfolio. Once, we define the "diversifier" and "hedge", we can consider the safe-haven property, it has more requirements than diversifiers and hedges, safe-haven property needs to verify the change of correlation during the non-crisis period and turbulent times. As previously stated, we use the overall average of correlation estimated by cDCC-MIDAS to investigate the asset's hedging properties.

We discover the hedging properties for the assets, and the next step is that we want to investigate the asset's independence. Therefore, this chapter follows a similar idea from Forbes & Rigobon (2002), which states the condition of contagion means the correlation trajectory between two assets will significantly increase during the crisis period compared to the pre-crisis period. The crisis shock increases the assets' correlation because the macroeconomic environment shifts to a worse situation. Meanwhile, the definition of contagion is to require a positive correlation during the crisis period. Baur & Lucey (2009) classify the flight-to-quality, the assets' correlation has significantly decreased compared to the pre-crisis level and their correlation is negative during the crisis period. For example, if the correlation is positive in the pre-crisis, then the correlation turns negative during the crisis period.

In short summary of our five hypotheses; the property of diversifier and hedges will base on the whole sample's average correlation to identify. However, safe havens need to confirm whether the correlations perform negatively or 0 during the crisis. We also notice there are similar requirements between safe havens and flight-to-quality; both of them require the in-crisis correlation level to be negative. Meanwhile, if we consider the contagion / flight-to-quality relate to the crisis vulnerability of the correlation, the safe-haven property also appears in this connection. Therefore, we need to detail the rest of the hypotheses about safe havens, contagion and flight-to-quality. Firstly, if the pair's correlation increases during the crisis period, but their correlation level remains negative in this period; we will not consider this case will be the contagion, this case will be the higher interdependence and also the safe-haven property. Secondly, if the correlation decrease during the crisis, but the correlation level remains positive; we classify this case will not flight-to-quality. We consider this case is lower interdependence and also diversifier. Thirdly, if the assets' correlation increases to positive, but the correlation's level is low during the crisis period (the assets are uncorrelated with average dynamic correlations between 0 and 0.1), so we define this case as the safe-haven property. Hence, we identify the interdependence case will be[12]:

i) weak contagion if the change is significant

ii) higher weak interdependence if the change is insignificant

As previously stated, safe haven requires a low correlation (or close to 0) but a positive level, and it will have a similar condition to higher interdependence or weak contagion. Therefore, this chapter's five hypotheses are shown as below:

Hypothesis 1(*H1*): Positively, but not perfectly, correlated (on average) assets act as *diversifier* (whole sample: $+, < 1$).

Hypothesis 2 (*H2*): Uncorrelated or negatively correlated (on average) assets act as *hedges* (whole sample: 0 or $-$).

[12]see also Table 4.1, we detail the in-crisis correlation change and correlation level for each interdependence type and safe-haven during the crisis period.

Hypothesis 3 (*H3*): In-crisis uncorrelated or negatively correlated assets act as *safe havens* (in-crisis: 0 or $-$).

Hypothesis 4 (*H4*): Significant positive change and level of correlations during crises mean *contagion* (in-crisis: $\uparrow, +$).

Hypothesis 5 (*H5*): Significant negative change and level of correlations during crises mean *flight-to-quality* (in-crisis: $\downarrow, -$).

After we test these five hypotheses, we turn to the macro sensitivity exercise; because we want to test the relationship between correlation patterns and economic fluctuations. We expect contagion or flight-to-quality to lead to safe havens when the economic condition is weak, which is based on rising interdependences in turbulent times(contagion) and lower negative correlation during the crisis period (flight-to-quality). On the contrary, cross-asset correlation is influenced by a strong economic environment, and the strong fundamentals can also increase diversification which will benefit investors or financial institutions. Baur & Lucey (2009) summarise flight-from-quality moments is a negative change in the assets' correlation or the correlation level is negative, so we might have the same results for safe havens. In addition, our macro sensitivity exercise involved short- and long-run which was inspired by previous studies on high and low frequency (Conrad et al. 2014, Karanasos & Yfanti 2021). Therefore, our study is going to discover how the daily and monthly macro variables influence the three asset markets (global equity, real estate and commodity), the macro variables' explanation will be the section 4.3.3.

First, we are going to test the uncertainty which is the major factor for the business cycle; Fernández-Villaverde et al. (2015) state that if the uncertainty increase, it will influence the fundamental economy. Meanwhile, Bloom et al. (2018) present similar though as Fernández-Villaverde et al. (2015), they discover the uncertainty increased during the great recession, and the uncertainty shock has a negative impact on the gross domestic product. The uncertainty shocks have a stronger impact on the macroeconomy than a financial crisis from Alessandri & Mumtaz (2019), they investigate the uncertainty shock in the USA from 1973 to 2014 by using non-linear VAR. From the previous studies, uncertainty not only involves agents' aggregate sentiment but also includes risk perceptions and expectations of the economy. Additionally, uncertainty has a direct impact on the financial markets co-movement due to market participators' behaviour. In fact, uncertainty shock infects the supply and demand side, it affects the stability of the financial market and also the global economy. Therefore, we use economic policy(EPU), financial uncertainty(FU), infectious disease news effect on financial uncertainty(ID) and investors' confidence-sentiment (SENT), these four factors to investigate uncertainty shock; if EPU, FU and ID increase, these three cases will be the situation which is contagion(the correlation is higher) or flights-to-quality and safe haven (the correlation is lower). SENT is the opposite case which expects to decrease.

Our second macro sensitivity exercise tests the high-frequency news effect; according to Albuquerque & Vega (2009), their study presents that the public news has a significant impact on the world economy, and they also state that the high-frequency news effect can predict economy. This is the reason that we consider the economic news sentiment (NS) index, if the NS is positive sentiment means the investors are confident in the economy and financial market, and positive NS can reduce the effect of contagion; but if NS is negative, this situation means the correlation increase.

Third, one of the important features of the macroeconomic environment is the credit channel, the presentation of this element is financial stress(FS). Numerous studies point out the credit channel has a significant to economic activity, and also a strong impact on monetary policy (Alessandri & Mumtaz 2019, Bernanke & Gertler 1995, Gertler & Karadi 2015, Gilchrist & Zakrajšek 2012). If the credit and liquidity conditions are tight, the financial stress indices will be of higher values than usual; this means the correlation of assets increases and leads to contagion. Otherwise, if financial stress indices are low, it will be the opposite situation.

Fourth, another key correlation determinant is activity growth proxies(EC) which EC has a negative impact on the contagion shocks. The primary crisis feature is the main economic activity is reduced, and the whole economy collapses; but if the financial asset is safe havens or flights-to-quality, it will be less influenced by the crisis. In addition, the economic condition is weak during the crisis period, the policy uncertainty will have a significant impact on the economy (Asgharian et al. 2016, Pástor & Veronesi 2013). Therefore, we include this index in the macroeconomic sensitivity test.

The last part of economic fluctuation is prices which we consider two indexes(freights indices(FR) and inflation indicator (INFL)) and foreign exchange rates(FX), three of which are calculated by the US dollar value. If the financial contagion increase, it means the inflation level and freights reduce, or the US dollar is strong compared to other currency.

In this chapter, we use soft (news and sentiment) and hard (real activity, prices or financial flows) data to estimate the impact of macroeconomic variables on the correlation, because all of them are playing a major role in the macroeconomic environment. Although soft data might not have a significant impact on the macroeconomy in the long-term compared to hard data, soft data is still a major player in the business cycle. Market participators' behaviour (spending or investment) will cause the economy to shift to a horrible situation. The massive bad news (economic, political and climate) and aggregate fear appear, and the economic expectation will shift to the bad situation; at the same time, the public did not consider if the news is real or fake. We can conclude that information contagion for the real news, and infodemics for the fake one. Therefore, our study wants to point out the significant impact of soft data on the macroeconomy, and soft data can be the exogenous variable to create a crisis for the market and global economy. Based on our macroeconomic sensitivity exercise, we are going to conclude our last two hypotheses which are going to determine the type of interdependence for the macro effect[13], so our last two hypotheses are as followed:

Hypothesis 6 (*H6*): Weak economic fundamentals increase correlations in the case of contagion.

Hypothesis 7 (*H7*): Weak economic fundamentals decrease correlations in the case of flight-to-quality.

Finally, this chapter's macro sensitivity exercise discovers the uncertainty and also the asset's correlation performance during the crisis period. In the case of flight-to-quality or contagion, we consider the higher level of uncertainty and crisis shocks will enhance the impact of news and macroeconomic effect on the cross-assets correlation based on our H6 and H7. Additionally, the core of this chapter is to investigate the impact of cross-asset correlations on financial stability and systemic risk. The most important reason that we want to discover contagious shocks, is because they can lead major financial markets to the neighbour regional financial market or the whole economy similar to domino effects; the existence of contagious shocks will erode the financial system. Meanwhile, we need

[13]Table 4.1, we detail the expected signs for macro effect

to pay more attention to contagion, because it can lead to weak economic activity and correlation performance during the crisis period. These events reduce the benefit of diversification and create a great loss to the economy. According to Dungey et al. (2006), Martínez-Jaramillo et al. (2010), they state that most market participators suffer capital shortfalls during the crisis period.

Overall, this subsection develops our seven hypotheses, which include assets' hedging properties and independence; we also explain how we decide the macro variable for our macroeconomic sensitivity exercise. Therefore, table 4.1 and table 4.2 include our hypotheses and the expected results. The next section will be Methodology which details the corrected DCC-GARCH-MIDAS model and correlation analysis.

Table 4.1: Overview of hypotheses and expected results

Panel A. Hedging properties & interdependence hypotheses			Panel B. Macro sensitivity (correlation determinants)		
	Hedging property			Expected sign	
Correlation pattern	Interdependence	Hypothesis	Macro effect on correlations	H6	H7
Positively, but not perfectly, correlated	Diversifier	H1	Economic policy uncertainty (EPU)	$+$	$-$
(whole sample average: $+, < 1$)			Financial uncertainty (FU)	$+$	$-$
Uncorrelated or negatively correlated	Hedge	H2	Infectious disease news impact (ID)	$+$	$-$
(whole sample average: 0 or $-$)			Financial Stress (FS)	$+$	$-$
In-crisis uncorrelated or negatively	Safe haven	H3	Sentiment / Confidence (SENT)	$-$	$+$
correlated (in-crisis: 0 or $-$)			News sentiment (NS)	$-$	$+$
In-crisis increase & positive level	Contagion	H4	Economic activity (EC)	$-$	$+$
(in-crisis: $\uparrow, +$)			Inflation (INFL)	$-$	$+$
In-crisis decrease & negative level	Flight-to-quality	H5	Freights (FR)	$-$	$+$
(in-crisis: $\downarrow, -$)			Foreign Exchange rates (FX)	$-$	$+$

Notes:

The Table presents an overview of the hypotheses we test in the statistical and macro sensitivity correlation analysis. Panel A illustrates the correlation pattern features, characterising each hedging property and interdependence phenomenon (H1 - H5). Panel B recaps the expected signs of each macro effect on correlation evolution under H6 and H7.

Table 4.2: Overview of hypotheses and expected results

Panel C. Interdependence types and safe haven property during crises: in-crisis correlation change and level results

in-crisis average correlation (ρ)	positive correlation and higher than 0.100	negative correlation	uncorrelated
change $\downarrow$ / level $\longrightarrow$	$\rho \geq 0.100$	$\rho < 0$	$0 \leq \rho < 0.100$
significant increase	Contagion (H4)	Higher interdependence Safe Haven (H3)	Weak contagion (H4) Safe Haven (H3)
insignificant increase	Higher interdependence	Higher interdependence Safe Haven (H3)	Higher weak interdependence Safe Haven (H3)
significant decrease	Lower interdependence	Flight-to-quality (H5) Safe Haven (H3)	Lower interdependence Safe Haven (H3)
insignificant decrease	Lower interdependence	Lower interdependence Safe Haven (H3)	Lower interdependence Safe Haven (H3)

Notes:

The Table presents an overview of the hypotheses we test in the statistical and macro sensitivity correlation analysis. Panel C reports the in-crisis correlation change and level combinations that indicate the interdependence types and safe haven property during crises.

4.3 Methodology and Data description

In this section, we are going to separate into two parts, the first part is going to explain this chapter's methodology (cDCC-MIDAS model and correlation regression analysis). For applying the cDCC-MIDAS model, we are going to estimate the daily assets' return via a trivariate specification for multi-asset combinations of global equity, real estate and commodity indices, so we have the estimated short- and long-run correlation from DCC-MIDAS. For the correlation regression analysis, we will use the estimated correlation (short- and long-run) to apply for the short and long-run macro variables and compute the correlation analysis and discover the macro determinants that influence three types of crisis shocks. the main aim of this chapter is to classify the hedging properties of assets and their independence, and also to define how the relationship between correlation and macroeconomic variables responds to the crisis. The second part of this section is a data description, we are going to present our data sets; firstly, the daily index prices (global benchmarks) for each asset, and the macro variables for the correlation determinants.

4.3.1 cDCC-MIDAS

This subsection is going to present the detail of the cDCC-MIDAS model, but based on the specification of the cDCC-MIDAS model, the estimation method is two steps; we need to introduce the conditional means and classify two types of errors first, then we can process to compute conditional variance (GARCH-MIDAS). Once we have the conditional variance, we can calculate the conditional correlation (from corrected DCC-MIDAS). The last part is the estimation method for corrected DCC-GARCH-MIDAS.

4.3.1.1 The conditional means

In the beginning, we need to define the daily index return as $\mathbf{r}_t = [r_{i,t}]_{1\leq i\leq N}$ at time t (high-frequency time scale), because we use trivariate corrected DCC-GARCH-MIDAS for our empirical analysis. Hence, we direct to use $r_{i,t}, i = 1, 2, 3$ to represent the return in this chapter for corrected DCC-GARCH-MIDAS. The conditional distribution of $r_{i,t}$ is given by $r_{it}\,|\Omega_{t-1} \sim i.i.d.\ N(\mu_i, \mathbf{H}_t)$, which means $r_{i,t}$ follows the normal distribution and given the condition which is the information at time $t-1$, denote as Ω_{t-1}. Based on the concept of $r_{i,t}$, the vector of the conditional mean rewrite as μ_i=$\mathbb{E}(r_{it}\,|\Omega_{t-1}), i = 1, 2, 3$ and we denotes the expectation operator $\mathbb{E}$. The following is the conditional variance matrix which is $\mathbf{H}_t \stackrel{def}{=} h_{ii,t} = \mathbb{V}ar(r_{it}\,|\Omega_{t-1})$. Meanwhile, the conditional covariances matrix present as: $h_{ij,t} = \mathbb{C}ov(r_{it}, r_{jt}\,|\Omega_{t-1}), \forall i \neq j$. Therefore, we can state our return in this chapter $r_{i,t}$ is as followed:

$$r_{it} = \mu_i + \varepsilon_t, \tag{4.1}$$

Based on this formula which can clearly see the error of $\varepsilon_{it} = r_{it} - \mu_i$. The next two sections are going to present the error ε_{it}, because based on two-step estimation, we need to define two types of errors.

4.3.1.2 The Errors

According to Colacito et al. (2011), they describe DCC-MIDAS is mixture of DCC and MIDAS model which can track short- and long-run component. Additionally, we can consider DCC-MIDAS model to be a *double* TV-GARCH (Time-Varying Multivariate GARCH) type of model. As previous section mentioned, our corrected DCC-MIDAS is based on DCC-MIDAS framework; it follows similar construction of DCC-MIDAS model. Hence, we still need to discuss the first ε_{it} for GARCH-MIDAS and introduce the second error $\mathbf{e}_{it}$ for the corrected DCC-GARCH-MIDAS.

The ε_t

As formula (4.1) state, the assumption of ε_t is defined by following the normal distribution with mean vector $\mathbf{0}_{3\times1}$ and the conditional variance $\mathbf{H}_t$; then we can state the covariance matrix $\mathbf{H}_t = [h_{ij,t}] = \mathbb{E}(\varepsilon_t\varepsilon_t'|\Omega_{t-1})$. The $\mathbf{h}_t$ is the vector of conditional variance, $\mathbf{h}_t = [h_{i,t}], h_{i,t} \stackrel{def}{=} h_{ii,t}$, it follows the GARCH-MIDAS progress (see the next section

4.3.1.3). For the following analysis, our estimation progress is separated into two steps. For estimation of the first step, we denote the notation $\widetilde{\mathbf{H}}_t = diag[\mathbf{h}_t]$ to represent $\widetilde{\mathbf{H}}_t$ is the main diagonal element of matrix $\widetilde{\mathbf{H}}_t$, and the off-diagonal is zero. Therefore, the error term ε_{it} can be expressed as $\varepsilon_{it} = \widetilde{\mathbf{H}}_t^{1/2}\widetilde{\mathbf{e}}_t$; we can also rewrite $\varepsilon_{it} = \sqrt{h_{it}}\widetilde{e}_t$. Hence, the conditional correlation matrix of ε_{it} is given by:

$$\mathbf{R}_t = \widetilde{\mathbf{H}}_t^{-1/2}\mathbf{H}_t\widetilde{\mathbf{H}}_t^{-1/2} \tag{4.2}$$

where $\mathbf{R}_t$ is the conditional correlation matrix, which denote $\mathbf{R}_t = [\rho_{ij,t}]$. Additionally, we can notice that $\mathbf{H}_t = \widetilde{\mathbf{H}}_t^{-1/2}\mathbf{H}_t\widetilde{\mathbf{H}}_t^{-1/2}$; hence, we can note that $|\rho_{ij,t}| \leq 1$.

The $\mathbf{e}_t$

For $\mathbf{e}_t$'s assumption, it is followed normal distribution with mean vector $\mathbf{0}_{3\times1}$ and conditional covariance matrix $\mathbf{Q}_t = [q_{ij,t}] = \mathbb{E}(\mathbf{e}_t\mathbf{e}_t^{'}|\Omega_{t-1})$. Hence, we can know that $\mathbf{e}_{it}|\Omega_{t-1} \sim i.i.d.\ N(\mathbf{0}_{3\times1}, \mathbf{Q}_t)$. In the second step of our estimation progress, we assume this $\mathbf{Q}_t$ follows the cDCC-MIDAS model. Therefore, we define $\mathbf{q}_t = [q_{ii,t}]$ and $\widetilde{\mathbf{Q}}_t = diag[\mathbf{q}_t]$; $\mathbf{q}_t$ is the vector with the conditional variances of $\mathbf{e}_t$, and $\widetilde{\mathbf{Q}}_t$ is the main diagonal elements from the matrix $\widetilde{\mathbf{Q}}_t$; meanwhile, the off-diagonal elements from matrix $\widetilde{\mathbf{Q}}_t$ are 0. Accordingly, the vector of *standardised* errors, $\widetilde{\mathbf{e}}_t = [\widetilde{e}_{it}]$, where $\widetilde{e}_{it} = e_{it}/\sqrt{q_{ii,t}}$ is given by $\widetilde{\mathbf{Q}}_t^{-1/2}\mathbf{e}_t$ and its conditional covariance matrix also denoted by $\mathbf{R}_t = [\rho_{ij,t}]$ where $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$. Therefore, our conditional correlation of the second error $\mathbf{e}_{it}$ is given by:

$$\mathbf{R}_t = \mathbb{E}(\widetilde{\mathbf{e}}_t\widetilde{\mathbf{e}}_t^{'}|\Omega_{t-1}) = \widetilde{\mathbf{Q}}_t^{-1/2}\widetilde{\mathbf{Q}}_t\widetilde{\mathbf{Q}}_t^{-1/2} \tag{4.3}$$

Regarding to the assumption of ε_t and $\mathbf{e}_t$, we can know the vector of *standardised* error $\widetilde{\mathbf{e}}_t$ is equal to the vector of the *devolatilised* errors, $\widetilde{\mathbf{H}}_t^{-1/2}\varepsilon_{it}$. Hence, we have $\widetilde{\mathbf{e}}_t = \widetilde{\mathbf{H}}_t^{-1/2}\varepsilon_{it}$. As previous stated, DCC-MIDAS needs to use two-steps estimation, so the $\mathbf{Q}_t$ follows cDCC-MIDAS model in the second step estimation. Then we can restructure from the formula 4.2 and 4.3, so the equation is as followed:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} = \frac{h_{ij,t}}{\sqrt{h_{it}}\sqrt{h_{jt}}}. \tag{4.4}$$

In the short conclusion, DCC-MIDAS model uses two-steps estimation. We can estimate the first errors ε_t and the conditional variances $\mathbf{h}_t$ via the GARCH-MIDAS model, both of them are vectors (Conrad & Loch 2015, Engle et al. 2013). On the second step, we can estimate the matrix of conditional covariances' *standardised* errors $\widetilde{e}_{it}$ and $\mathbf{Q}_{it}$ by using cDCC-MIDAS process. Therefore, the order of estimation is estimated $\mathbf{h}_t$ and $\mathbf{Q}_{it}$ at first, and then we can have estimated $\mathbf{R}_t$. The last two need to pay attention, it is the conditional correlations of error ($\mathbf{e}_t$ and ε_{it}) which obtain from the Eq. (4.4); and the second one is the estimated conditional covariances $\mathbf{H}_t$, which also can be calculated by second term in the Eq. (4.4) [14].

4.3.1.3 The Conditional Variances

cDCC-MIDAS is volatilities' model with two-components (short- and long-run) specification and it is similar as DCC-MIDAS model. Hence, we need to define two different time scales; the first time scale is high-frequency, it introduces in section 4.3.1.1 which is t. The second time scale is the low-frequency (i.e. monthly, quarterly, or biannual) which we denote by τ. We use σ_i and m_i to denote the components of short- and long-run variances for each asset i. The long-run component (MIDAS part) remain constant across the days of the month, quarter or half-year; so m_i is held fixed (i.e. month, quarter, or biannual) for the number of days, we denote this number of days as $K_v^{(i)}$. The superscript i means the specific asset, and subscript v is for variances; it also differentiates the similar scheme from the conditional correlation.

Now, we introduce two-components GARCH-MIDAS process to estimate the conditional variance $h_{i,t}$, and the composition of $h_{i,t}$ will be two parts (short- and long-run), it shows as below[15]:

$$h_{it} = m_{i\tau}\sigma_{it}, \text{for all } t = (\tau-1)K_v^{(i)}+1, \dots, \tau K_v^{(i)}, \tag{4.5}$$

where σ_{it} is short-run component, it follows a GARCH (1,1) process:

$$\sigma_{i,t} = (1-\alpha_i-\beta_i) + \alpha_i\xi_{i,t-1}^2\sigma_{i,t-1} + \beta_i\sigma_{i,t-1} \tag{4.6}$$

Based on the conditional mean from Eq. (4.1), we can rewrite $\varepsilon_{it} = r_{it} - \mu_i$, and then we can have $\varepsilon_{it}^2 = m_{i\tau}\sigma_{it}\xi_{it}^2$; equally, we can get $\xi_{i,t-1}^2\sigma_{i,t-1} = (r_{it}-\mu_i)^2/m_{i\tau}$. Turning

[14] Comte & Lieberman (2003), Ling & McAleer (2003), McAleer et al. (2008) discuss the two-step estimator's asymptotic properties, but all of them only focused on fixed-parameter DCC models. Additionally, Wang & Ghysels (2015) discuss the maximum likelihood estimation for GARCH-MIDAS. However, the problem of DCC-MIDAS's two-step estimation method is still an open question Colacito et al. (2011).

[15] Notice that GARCH-MIDAS is two-components model, normally we should present the notation $h_{it,\tau}$, but we take out the subscript τ for simplicity.

to the long-run (MIDAS) component $m_{i\tau}$, we mention that $m_{i,\tau}$ is a constant and also a weighted sum of $M_v^{(i)}$ of realised variances (RV) over a long horizon, so MIDAS is showed as below:

$$m_{i,\tau} = m_i + \theta_i \sum_{l=1}^{M_v^{(i)}} \varphi_l(\omega_v^{(i)}) RV_{i,\tau-l} \tag{4.7}$$

m_i is the constant in the MIDAS part, and $\varphi_l(\omega_v^{(i)})$ is so call beta weight. In this chapter, we only consider one ω[16], so our beta weight is defined as:

$$\varphi_l(\omega_v^{(i)}) = \frac{\left(1 - \frac{l}{M_v^{(i)}}\right)^{\omega_v^{(i)}-1}}{\sum_{j=1}^{M_v^{(i)}} \left(1 - \frac{j}{M_v^{(i)}}\right)^{\omega_v^{(j)}-1}}, \tag{4.8}$$

Additionally, the realised variances are equal to the sum $K_v^{(i)}$ squared returns:

$$RV_{i,\tau} = \sum_{t=(\tau-1)K_v^{(i)}+1}^{\tau K_v^{(i)}} r_{it}^2. \tag{4.9}$$

Firstly, we can notice GARCH-MIDAS progress that m_i can be pre-determined,

$$\mathbb{E}_{t-1}[(r_{i,t} - \mu_i)^2] = m_{i,\tau}\mathbb{E}_{t-1}(\sigma_{i,t}) = m_{i,\tau} \tag{4.10}$$

so, it point out the short-term (GARCH) can be $\mathbb{E}_{t-1}(\sigma_{i,t}) = 1$ in the starting point. Secondly, in Eq. (4.8), $\omega_v^{(i)}$'s size can determine the rate of decay in the beta weight, if $\omega_v^{(i)}$ is large value which will generate a rapidly decaying pattern; if it is small value, it will be opposite.

The last part of GARCH-MIDAS process needs to pay attention to which are the parameters $M_v^{(i)}$ and $K_v^{(i)}$, both of them are the same across different assets, which can represent as $M_v^{(i)} = M_v$ and $K_v^{(i)} = K_v$ for $i = 1, 2, 3$. In the short conclusion for GARCH-MIDAS model, the short-run component is using daily (squared) returns of each assets via a GARCH(1,1), and then the long-run component is based on monthly (quarterly or biannual) realised volatilities to compute (see Eq. (4.8 - 4.9))[17]. For K_v , if we want to

[16] According to Engle et al. (2013), they present two type of weighting schemes. We use the beta weight.

[17] Base on Engle et al. (2013), they notice $m_{i,\tau}$ can be constant in the fixed period or be constant during the rolling window period, but the estimation results between both of them are very closed. Additionally, Colacito et al. (2011) stated the case of correlation can consider neither fixed span or rolling window. However, we consider the fixed span can offer much general results, we remain the fixed span in our formulas' setting instead of including rolling window notation.

compute the monthly realised volatility we can set $K_v = 22$; if we want to have the quarterly case, which it can be $K_v = 66$. As τ varies, the time span that $m_{i\tau}$ is fixed (that is M_v) also changes. In other words, MIDAS lags represent the number of years, spanned in each MIDAS polynomial $m_{i,\tau}$. In our empirical analysis, we choose $m_{i,\tau}$ changes from one to four years; it means that if we select the monthly component for MIDAS part, $M_v = 12, 24, 36, 48, 60$. If our analysis is based on quarterly realised volatility which will be $M_v = 4, 8, 12, 16$.

Summarised for the number of parameters, we will have a parameter space as $\Theta = \{\mu_i, \alpha_i, \beta_i, m_i, \theta_i, \omega_v^{(i)}\}, i = 1, 2, 3$. Meanwhile, our parameters are fixed, so we can use different time span to compute the GARCH-MIDAS, then we compare the estimated parameters from different GARCH-MIDAS. Additionally, we follow the concept of Colacito et al. (2011), Engle et al. (2013) about GARCH-MIDAS, we use the log-likelihood function to estimate the conditional variance for short- and long-run. The next subsection will be the description of cDCC-MIDAS.

4.3.1.4 The Conditional Correlation

Before we are going to introduce cDCC-MIDAS model, we define two elements which is $\mathbf{\Omega}_c = [\omega_c^{(ij)}]$ and $\Phi_l(\mathbf{\Omega}_c) = [\varphi_l(\omega_c^{(ij)})]$; both of them are the matrices $N \times N$, $N = 3$ due to this chapter is trivariate cDCC-MIDAS progress.

Definition 4.1 *Let* $\mathbf{Z}_t = [z_{ij,t}] = \sum_{k=t-M_c}^{t} \widetilde{\mathbf{e}}_k \widetilde{\mathbf{e}}_k'$, *with* $M_c = \max_{ij} M_c^{(ij)}$, $\mathbf{z}_t = [z_{ii,t}]$ *and* $\widetilde{\mathbf{Z}}_t = diag[\mathbf{z}_t]$, *that is* $\widetilde{\mathbf{Z}}_t$ *is a diagonal matrix with i-th diagonal element* $\sum_{k=t-M_c}^{t} \widetilde{e}_{i,t}^2$. *Define* $\mathbf{C}_t = [c_{ij,t}]$ *as:* $\mathbf{C}_t = \widetilde{\mathbf{Z}}_t^{-1/2} \mathbf{Z}_t \widetilde{\mathbf{Z}}_t^{-1/2}$.

Using the vector of the residuals, $\mathbf{e}_t$ (and not of the *standardised* residuals, $\widetilde{\mathbf{e}}_t$, that is we use the cDCC-MIDAS: the MIDAS version of the corrected DCC model of Aielli (2013)), it is possible to obtain a matrix $\mathbf{Q}_t = [q_{ij,t}]$ as follows:

$$\mathbf{Q}_t = (1 - a - b)\overline{R}_t(\mathbf{\Omega}_r) + a\mathbf{e}_{t-1}\mathbf{e}_{t-1}' + b\mathbf{Q}_{t-1}, \tag{4.11}$$

where

$$\overline{R}_t(\mathbf{\Omega}_c) = \sum_{l=1}^{K_c} \Phi_l(\mathbf{\Omega}_c) \odot \mathbf{C}_{t-l}, \tag{4.12}$$

with $K_c = \underset{ij}{\max} K_c^{(ij)}$, and $\odot$ stands for the Hadamard product.[18] Meanwhile, if we write down the $ij-$th element of $\mathbf{Q}_t$ is given by:

$$q_{ij,t} = \overline{\rho}_{ij,\tau}(1-a-b) + ae_{i,t-1}e_{j,t-1} + bq_{ij,t-1}, \tag{4.13}$$

where the long-run competent (MIDAS with correlation) presents as below:

$$\overline{\rho}_{ij,\tau} = \sum_{l=1}^{K_c^{(ij)}} \varphi_l(\omega_c^{(ij)})c_{ij,\tau-l}. \tag{4.14}$$

In addition, $q_{ij,t}$ is the covariance (off-diagonal elements) in the correlation's matrix, so we can write the main diagonal elements of $q_{ii,t}$ is given by:

$$q_{ij,t} = (1-a-b) + ae_{i,t-1}^2 + bq_{ij,t-1}, \tag{4.15}$$

and, in view of the fact that in the cDCC $\mathbb{E}(e_{i,t}^2) = \mathbb{E}(q_{ij,t}) = q_{ii}$, it follows that q_{ii}=1.[19] In the Eq. (4.14), we need to set up the weights $\omega_c^{(ij)}$, lag lengths $M_c^{(ij)}$ and historical correlation's span lengths $K_c^{(ij)}$; based on these settings, we can differ across any pair of series. We use a single setting apply to all pairs of assets' combination, and our selection of these three elements are similar choice of MIDAS in the univariate models (in this chapter, the univariate model is GARCH-MIDAS). As previous stated, ω_c is the common decay parameter which it is independent selection for the pair of assets. From Eq. (4.13), we can notice the covariance matrices are positive definite; it means the matrix $\mathbf{Q}_t = [q_{ij,t}]$ is a weighted average of three matrices. Additionally, the matrix $\mathbf{R}_t = [\rho_{ij,t}]$ needs to remain semi-positive based on the assumption; another element needs to be positive semi-definite is the matrix $\boldsymbol{e}_t\boldsymbol{e}_t^{'}$ where the $\boldsymbol{e}_t = [e_{it}]$. Hence, the initial value $\mathbf{Q}_0$ defines to be a semi-positive matrix, then the $\mathbf{Q}_t$ must be the same as $\mathbf{Q}_0$ which is the semi-positive matrix at each time t (see Colacito et al. (2011) for the implication of a single parameter selection verse the multiple parameter for DCC-MIDAS).

[18]Note that in the formulation for $\overline{R}_t(\mathbf{\Omega}_c)$ we could have used simple cross-products, that is $\mathbf{Z}_t$ instead of $\mathbf{C}_t$, but, as pointed out by Colacito et al. (2011), the normalisation allows us to have regularity conditions in terms of correlation matrices.

[19]Following Aielli (2013) one could employ a correction in the long-run correlations, $\overline{R}_t(\mathbf{\Omega}_r)$, by using the vector of the residuals, $\mathbf{e}_t$, that is using: $\mathbf{Z}_t = [z_{ij,t}] = \sum_{k=t-M_c}^{t} \mathbf{e}_k\mathbf{e}_k'$.

Note that in the DCC estimator the estimator of the long-run correlations is computed only once in the first step, whereas, with the cDCC estimator, it will be recomputed at each evaluation of the objective function of the second step (see Definition 3.4 in Aielli (2013)). We leave this for future work.

In Eq. (4.4), we can notice the estimated long-run correlation can based on short-run correlation between asset i and j. Hence, we can relocate the 4.13 which shows as below:

$$q_{ij,t} - \overline{\rho}_{ij,\tau} = a(e_{i,t-1}e_{j,t-1} - \overline{\rho}_{ij,\tau}) + b(q_{ij,t-1} - \overline{\rho}_{ij,\tau}) \tag{4.16}$$

we can notice from this equation, short-run (daily) correlation and covariance are base on DCC scheme, and includes the slowly moving long-run correlation. According to Colacito et al. (2011), they wrote down : "short-lived effects on correlations will be captured by the autoregressive dynamic structure of DCC, with the intercept of the latter being a slowly moving process that reflects the fundamental or secular causes of a time variation in correlation". Before we head into the estimation method in this chapter, we need to collect the cDCC-MIDAS's parameter space which is $\Xi = \{a, b, \omega_c^{ij}\}$.

4.3.1.5 The Estimation method

As previous section stated, our estimation method for cDCC-MIDAS still remain two-steps progress from Engle (2002); it means our parameters are separated into two parts to estimate, so first step estimate the GARCH-MIDAS parameters (Θ) and second step estimate the cDCC-MIDAS (Ξ). Hence, the quasi- likelihood function QL can be:

$$\begin{aligned} QL(\Theta, \Xi) &= QL_1(\Theta) + QL_2(\Xi) \\ &\equiv -\sum_{t=1}^{T}(nlog(2\pi) + 2log|\widetilde{\mathbf{H}}_t| + \mathbf{r}_t^{'}\widetilde{\mathbf{H}}_t\mathbf{r}_t) - \sum_{t=1}^{T}(log|\mathbf{R}_t| + \widetilde{\mathbf{e}}_t^{'}\mathbf{R}_t^{-1}\widetilde{\mathbf{e}}_t + \widetilde{\mathbf{e}}_t^{'}\widetilde{\mathbf{e}}_t) \end{aligned} \tag{4.17}$$

4.3.2 Macro-sensitivity correlation analysis

As previously stated, the progress is estimated by the correlation from cDCC-MIDAS, and then we turn to the macro-sensitivity correlation analysis to classify the hedging properties and interdependence. Based on cDCC-MIDAS construction, we can have short- (daily) and long-run (monthly) estimated correlation, so we can examine different frequency data to the macro variables. Hence, we have two steps for the regression analysis; firstly, we will investigate all of the asset's time series graphs to define the asset's interdependence which is contagion (countercyclical) or flight-to-quality (pro-cyclical). Secondly, we use the regression analysis to study which key statistics will have a huge impact on the correlation during the sample period and the specific period (GFC, ESDC, COV); at the same time, we are based on the regression analysis to define the hedging properties. Additionally, we use two types of mean difference tests which are the Satterthwaite-Welch t-test and the Welch F-test in the crisis analysis. After these two tests, we use the crisis mean to compare with the pre-crisis mean; we can base it on the mean change (increase or decrease) from the pre-crisis to the crisis period to identify the hedging property to the assets. Meanwhile, the case of contagion is the positive in-crisis level and a significant increase from the pre-crisis to the crisis time; if the correlation level is negative in the crisis period and a significant decrease, this case will be the flight-to-quality. The safe haven property is also based on the in-crisis correlation when if the whole sample means classifies hedges or diversifies.

When we finished the statistical tests, we used regression analysis to examine the relationship between the correlation and macroeconomic elements, and then to determine which macroeconomic variable has a massive impact on the correlation. In section 4.2.2, we state that macro and news proxies will be independent variables for the regression analysis; then we use independent variables to explain the correlation performance. We apply the Fisher Z transformation of the correlation time series which can relax the correlation restriction bound ($[-1, 1]$). Hence, we denote the transformed short- and long-run correlations which are $\rho_{SR,t}$ and $\rho_{LR,t}$[20], then we can have $\rho_{SR,t} = log(\frac{1+q_{ij,t}}{1-q_{ij,t}})$ and $\rho_{LR,t} = log(\frac{1+\bar{\rho}_{ij,t}}{1-\bar{\rho}_{ij,t}})$[21].

The Fisher Z transformation allows the correlation performances better in the regression analysis, and the major macroeconomic variables are explained in the Hypothesis section 4.2.2. Our hypothesis points out our expectation about the correlations; if the regressors state economic deterioration for flight-to-quality, it means the lower correlations. hence, the case of contagion is the opposite situation; we expect this case to have higher correlations. Meanwhile, the regression for daily and monthly will estimate different economic factors due to the data availability (see the section of data description, the section 4.3.3 details the indices represented each macroeconomic factors).

The daily (short-run) correlation regression will be estimated with the following independent variables: economic policy uncertainty ($EPU_{SR,t}$), financial uncertainty ($FU_{SR,t}$),

[20] In the regression analysis, we drop down the subscript ij to simplify the notations.

[21] In the previous section, we use $q_{ij,t}$ as short-run correlation, $\rho_{ij,t}$ as long-run correlation

infectious disease news impact on financial volatility ($ID_{SR,t}$), financial stress ($FS_{SR,t}$), news sentiment ($NS_{SR,t}$), economic activity ($EC_{SR,t}$), freights ($FR_{SR,t}$), and foreign exchange rates ($FX_{SR,t}$). Hence, we can write down the short-run correlation regression as followed:

$$\begin{aligned}\rho_{SR,t} = \; & \zeta_0 + \zeta_1 \rho_{SR,t-1} + \zeta_2 EPU_{SR,t-1} + \zeta_3 FU_{SR,t-1} + \zeta_4 ID_{SR,t-1} + \zeta_5 FS_{SR,t-1} \\ & + \zeta_6 NS_{SR,t-1} + \zeta_7 EC_{SR,t-1} + \zeta_8 FR_{SR,t-1} + \zeta_9 FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{4.18}$$

with the constant term ζ_0 and the standard stochastic error term $u_{SR,t}$.

After we introduced the macroeconomic variables for the short-run correlation, so we turn to the long-run correlations' regression now. The long-run components are the monthly data; the independent variables for the regression of long-run correlations are economic policy uncertainty ($EPU_{LR,t}$), financial stress ($FS_{LR,t}$), sentiment/confidence ($SENT_{LR,t}$), economic activity ($EC_{LR,t}$), inflation ($INFL_{LR,t}$), and freights ($FR_{LR,t}$). To sum up, the long-run correlations' regressions are presenting as below:

$$\begin{aligned}\rho_{LR,t} = \; & \delta_0 + \delta_1 \rho_{LR,t-1} + \delta_2 EPU_{LR,t-1} + \delta_3 FS_{LR,t-1} + \delta_4 SENT_{LR,t-1} \\ & + \delta_5 EC_{LR,t-1} + \delta_6 INFL_{LR,t-1} + \delta_7 FR_{LR,t-1} + u_{LR,t}\end{aligned} \tag{4.19}$$

Similar to the short-run correlations' regression, the δ_0 is the constant term and $u_{LR,t}$ is the error term in the long-run regression. All the variables are the first lag and the regressions of correlation time series are according to the parameters' significance; additionally, we will use two classical information criteria: AIC (Akaike information criteria) and BIC (Schwartz Information Criteria), and the adjusted R^2 (the goodness of fit).

The next step of the macro sensitivity analysis examines the role of the uncertainty channel in the short-run correlations (long-run correlations).[22]. We discuss the impact of uncertainty on the business cycle in the hypothesis section 4.2.2, and we want to further investigate the uncertainty effect on short-run correlations; Additionally, we examine the uncertainty effect on the macroeconomic variables. According to Karanasos & Yfanti (2021), Pástor & Veronesi (2013), they found the higher EPU will increase the macroeconomic effect on the short-run correlation; Hence, our expectation for the regression related to EPU, which has similar results as them (Karanasos & Yfanti 2021, Pástor & Veronesi 2013). In addition, we study the indirect EPU effect on the macroeconomic

[22]Long-run correlations' results are similar, so we present the short-run results

variables based on EPU interaction terms. We use to use EPU variable to multiply each macroeconomic variable and news factor, then reconstruct the Eq. (4.18) which presents below:

$$\begin{aligned}\rho_{SR,t} &= \zeta_0 + \zeta_1 \rho_{SR,t-1} + \zeta_2 EPU_{SR,t-1} + (\zeta_3 + \zeta_3^{EPU} EPU_{SR,t-1}) FU_{SR,t-1} \\ &+ (\zeta_4 + \zeta_4^{EPU} EPU_{SR,t-1}) ID_{SR,t-1} + (\zeta_5 + \zeta_5^{EPU} EPU_{SR,t-1}) FS_{SR,t-1} \\ &+ (\zeta_6 + \zeta_6^{EPU} EPU_{SR,t-1}) NS_{SR,t-1} + (\zeta_7 + \zeta_7^{EPU} EPU_{SR,t-1}) EC_{SR,t-1} \\ &+ (\zeta_8 + \zeta_8^{EPU} EPU_{SR,t-1}) FR_{SR,t-1} + (\zeta_9 + \zeta_9^{EPU} EPU_{SR,t-1}) FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{4.20}$$

where we denote the superscript ^{EPU} to the interaction terms' coefficients.

The last part of this section is to study the crisis vulnerability of correlations to finish our macro sensitivity analysis in this chapter. In this part, we separate into two parts which the first part is crisis effect to the correlation; secondly, the indirect EPU and crisis effect to the macroeconomic regression. We examine how the relationship between the response of correlations and crisis shocks in the regression analysis. Because of the crisis is event, we treat each crisis as dummy variables and use crisis intercept; we compare and present each crisis's effect on the correlation levels and the macro factors' impact on the correlation.

Firstly, we denote $D_{C,t}$ to the three crisis dummies, and $C = GFC$, $ESDC$, COV; so we are based on the respective crisis time-line to classify the dummy variables 0 and 1. Therefore, we use $D_{C,t} = 1$ which it means the crisis period; if $D_{C,t} = 0$, then it will be the non-crisis period. We use the crisis dummy multiple to each macroeconomic variables, then we can calculate the slop dummies. We include the crisis dummies to the Eq. (4.18), then we can rewrite this formula which shows as below:

$$\begin{aligned}\rho_{SR,t} &= \zeta_0 + \zeta_0^C D_{C,t} + \zeta_1 \rho_{SR,t-1} + (\zeta_2 + \zeta_2^C D_{C,t-1}) EPU_{SR,t-1} + (\zeta_3 + \zeta_3^C D_{C,t-1}) FU_{SR,t-1} \\ &+ (\zeta_4 + \zeta_4^C D_{C,t-1}) ID_{SR,t-1} + (\zeta_5 + \zeta_5^C D_{C,t-1}) FS_{SR,t-1} + (\zeta_6 + \zeta_6^C D_{C,t-1}) NS_{SR,t-1} \\ &+ (\zeta_7 + \zeta_7^C D_{C,t-1}) EC_{SR,t-1} + (\zeta_8 + \zeta_8^C D_{C,t-1}) FR_{SR,t-1} + (\zeta_9 + \zeta_9^C D_{C,t-1}) FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{4.21}$$

Secondly, we want to investigate the indirect EPU effect on the correlation during the crisis period; so we use the similar approach with Eq. (4.20) which multiples the EPU interaction terms and the crisis dummies together. The regression is:

$$
\begin{aligned}
\rho_{SR,t} &= \zeta_0 + \zeta_1 \rho_{SR,t-1} + \zeta_2 EPU_{SR,t-1} \\
&+(\zeta_3 + \zeta_3^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FU_{SR,t-1} \\
&+(\zeta_4 + \zeta_4^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) ID_{SR,t-1} \\
&+(\zeta_5 + \zeta_5^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FS_{SR,t-1} \\
&+(\zeta_6 + \zeta_6^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) NS_{SR,t-1} \\
&+ + (\zeta_7 + \zeta_7^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) EC_{SR,t-1} \\
&+(\zeta_8 + \zeta_8^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FR_{SR,t-1} \\
&+ + (\zeta_9 + \zeta_9^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FX_{SR,t-1} + u_{SR,t}
\end{aligned} \tag{4.22}
$$

where we define the superscript $^{EPU\_C}$ to the EPU under crisis coefficients. The next section is the data description of this chapter.

4.3.3 Data Description

In this section, we are going to explain the assets and macroeconomic data for this chapter after we introduced our methodology (we report a table for the variables' definitions and sources in the Appendix's Table D.1). Based on our models' specification, we have two types of data; so our daily data is from 18/01/2005 to 27/07/2020, with a total of 4050 observations (daily assets' returns and daily macroeconomic variables). The monthly data (monthly realised volatility and monthly macroeconomic variables) are from 01/2005 to 07/2020, this data is 180 monthly observations. Based on our sections of literature and methodology, we apply global benchmarks of each asset's markets. Firstly, we will introduce three assets' returns, then we move to the macroeconomic variables. The last part will be the timeline for three crises (GFC, ESDC, COV).

The main three asset returns are the benchmark index of Equities (EQU), Real Estate (RE), and commodity (COM). The first asset EQU is peroxided by a global equities index, which called by MSCI World Equities index (MXWO); and, this index consists of the mid-and large-cap equities of 23 developed countries. The second asset is the Real Estate index, we decide to use the Dow Jones (DJ) Real Estate Investment Trusts index (REIT) which is the securities real estate investments, mainly this index includes all publicly US REITs the Dow Jones stock index. For the commodity index, we consider the Standard

& GSCI can track the global commodity prices, this index includes 24 commodities from five categories. Hence, these three assets will be our daily index return.

These three assets will estimate in the cDCC-MIDAS progress. Daily asset returns $r_{i,t}$ are calculated on each asset index as follow: $r_{i,t} = [\ln(P_{i,t}^{Close}) - \ln(P_{i,t-1}^{Close})] \times 100$, where $P_{i,t}^{Close}$ the daily closing price on day t. Additionally, we examine the unit root test for each asset return before the cDCC-MIDAS progress, and we discover all of them reject the null hypothesis which is not unit root in this series [23]. The descriptive statistics and the pairwise correlation are presented in table (4.3). From this table, we can notice the mean of these three assets, only the commodity is negative. Meanwhile, we notice that EQU has the lowest volatile and RE has the opposite situation; the pairwise correlation between EQU and RE has the highest (0.656), but the pair of RE and COM is the lowest (0.213). We notice these three pairs' correlation is positive from the table (4.3).

[23] We consider various tests about unit root, including the Augmented Dickey–Fuller test, Phillips-Perron test, etc. Then we figure out all of them are having the same conclusion, so only perform the ADF test.

Table 4.3: Summary statistics of asset returns and correlation

Panel A. Asset returns statistics.

	Mean	Median	Max	Min	Std.Dev.	ADF
EQU	0.0180	0.0596	9.0967	-10.4412	1.0350	-61.5468^{***}
RE	0.0137	0.0377	16.8063	-21.4858	1.9653	-79.4611^{***}
COM	-0.0241	0.0000	7.6166	-12.5224	1.4836	-67.9225^{***}

Panel B. Cross-asset correlation coefficients.

	EQU	RE	COM
EQU	1.000		
RE	0.656	1.000	
COM	0.445	0.213	1.000

Notes:

The table reports the summary statistics of each asset returns series: Mean, Median Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.), the Augmented Dickey-Fuller (ADF) test statistic (Panel A), and the pairwise cross-asset correlation coefficients (Panel B). The asset series notation is as follows: Equities (EQU), Real estate (RE), Commodities(COM). ***, **,* denote significance at the 0.01, 0.05, 0.10 level, respectively.

The next part is going to describe the macroeconomic factors. According to Eiling & Gerard (2015), they mention that the macroeconomic circumstance has various impacts on the cross-asset correlation, it also improves the connection of the different asset markets. As previous section's development for our hypotheses, we conclude the macroeconomic variables to be five types: 1. the investors' sentiment (EPU, FU, ID, SENT); 2. news (NS); 3. credit conditions (FS); 4. economic activity (EC); 5. prices (INFL, FR, FX). In addition, we mention that the short- (daily) and long-run (monthly) correlation macroeconomic regressions will have different macro effects due to the data available. Therefore, we can separate to introduce the daily and monthly macroeconomic factors which show in below:

EPU (daily and monthly): we decide to use the data from Baker et al. (2016), they introduce the newspaper-based US EPU indices; so we consider the US uncertainty as a global uncertainty proxy which also includes the low- and high- frequencies, we denoted $EPU_{d,t}$ for daily and $EPU_{m,t}$ for monthly. This index is based on information from newspapers, it can represent most of the investors' behaviour regarding uncertainty for the global economic environment and the policies. We believe this will have a powerful explanation for the global financial market and economic circumstances, and a couple of empirical analyses have similar opinions (Bernal et al. 2016, Pástor & Veronesi 2013).

FU (daily): we consider the data to represent financial uncertainty as the daily S&P500 implied volatility index, names $VIX_{d,t}$. This index is peroxided the financial uncertainty and global risk aversion; another reason for selecting this index is that it includes the cross-border and local effects for the financial uncertainty (Arghyrou & Kontonikas 2012, Bernal et al. 2016).

ID (daily): for infectious disease news effect on financial uncertainty, our analysis selects the data created by Baker et al. (2020) which calls the Infectious Disease Equity Market Volatility tracker (ID_EMV_t), and this is daily data. Additionally, this index is a news-based index which it presents the new effect of disease on the US stock market volatility (financial uncertainty). We expect this index will perform at a highly significant level to explain the cross-asset correlations because of the Covid-19 pandemic period; this period has a huge impact on the global economic environment and also the whole financial market.

FS (daily and monthly): the credit channel is peroxided by the monthly and daily financial stress index, which is also the main factor the cyclical economic fluctuations and it represents the data for credit and liquidity. For the financial stress index, our daily and monthly data are not the same index. Our short-run correlation regression is using OFR Financial Stress Index which includes 33 financial market data to consist of the daily market-based stress for the financial markets, this denotes FSI_t. On the other hand, we consider the monthly Kansas City Financial Stress Index ($KCFSI_t$) to apply in the long-run correlation regression (Hakkio et al. 2009); this data is constructed in two elements: one is yield spreads and the other is the asset prices' volatility. For this variable's analysis, we expect the higher FS to indicate tighter liquidity and credit condition for the economic environment during the turmoil period; the lower FS shows the opposite economic situation.

SENT (monthly): for the investors' confidence sentiment (SENT), we select the G7 Business Confidence Index growth ($gBCI_t$), which is a global survey-based confidence indicator, for our long-run correlation regression. This index tracks the aggregate sentiment with a positive effect on the long-run correlations (Breaban & Noussair 2018, Correa et al. 2021).

NS (daily): we select the News sentiment as the daily data because the short-run cross-assets correlation is significantly impacted by high-frequency daily news. According to Albuquerque & Vega (2009), they point out the different types of news will have different impacts on the investors' behaviour and the global assets' markets. For example, bad news released increases public concern about the economy and enhances the uncertainty in the assets market; if the news is about positive information it will improve the financial market participant confidence in the market. Therefore, we apply the data from San Francisco Fed, naming the daily US News Sentiment Index (NSI_t); this index is created by Shapiro et al. (2020) and Buckman et al. (2020). They are based on US newspapers, and they separate news from good and bad news via a sentiment-scoring lexical analysis.

EC (daily and monthly): economic activity has low- and high-frequency data. We apply the daily economic activity as the US yield curve slope which is based on the different 10 years minus 3-month US treasury yields, which we denote as $YCsl_t$. According to Estrella & Hardouvelis (1991), they state this data can well predict the real variable; an increase in this data can predict higher GDP growth. A decrease in this data leads to lower growth for GDP. In the long-run correlation regression, we apply the G7 Industrial Production growth (gIP_t) to indicate the economic activity.

INFL (monthly): we consider the monthly G7 Producer Price Index Growth ($gPPI_t$) to investigate the global inflation effect in the long-run correlation regression. However, the daily inflation data is not available.

FR (daily and monthly): freights can present trading activity around the world, and freights affect the correlation of cross-asset. Therefore, we consider the daily Baltic Dry Index, which measures the global cost of shipping products, to include in our short-run correlation regression, this index denotes BDI_t. We apply the monthly Cass Freight Index as freights effect to the long-run correlation regression.

FX (daily): we consider the index for foreign exchange rate calls the daily DXY index growth ($gDXY_t$), and this index is measured by the US dollar. It presents if the US dollar is strong and influences the other currencies' performance.

Overall, these macroeconomic factors include the short- and long-run correlation; we are expecting to have a significant influence on the correlations' analysis. Meanwhile, we sum up the summary statistics of the correlation determinants for the macroeconomic variables (daily in Panel A and monthly in Panel B) in table 4.4. We consider the US indices as indices as global proxies for each macro effect. In this table, we notice the daily macro variables have two negative means in the overall period which are FS (-0.2388) and EC (-0.0006); the monthly regressor only has one negative mean is SENT (-0.0132). All of the macroeconomic variables reject the null hypothesis of the unit root hypothesis (ADF - Augmented Dickey-Fuller tests), the aim of this test is to examine whether the data is stationary for the correlation regressions. Meanwhile, we also use the Variance Inflation Factors (VIF) multicollinearity tests which also reject the null hypothesis of multicollinearity; both of them make sure the suitability of the data for macro regressions.

Table 4.4: Summary statistics of the correlation determinants (macroeconomic variables)

Macro effect	Macro variable	Mean	Median	Max	Min	Std.Dev.	ADF
Panel A. Daily determinants.							
EPU	$EPU_{d,t}$	1.9258	1.9244	2.9072	0.5211	0.2902	-6.4871^{***}
FU	VIX_t	1.2352	1.1973	1.9175	0.9609	0.1655	-5.4444^{***}
ID	ID_EMV_t	0.1164	0.0000	6.8370	0.0000	0.5011	-3.1580^{**}
FS	FSI_t	−0.2388	−1.7460	29.320	−5.3340	4.7711	-2.9235^{**}
NS	NSI_t	0.0106	0.0307	0.4886	−0.7258	0.2252	-4.2380^{***}
EC	$\Delta YCsl_t$	−0.0006	−0.0015	1.1980	−0.6260	0.0705	-66.579^{***}
FR	BDI_t	3.2372	3.1741	4.0716	2.4624	0.3443	-2.6522^{*}
FX	$gDXY_t$	0.0016	0.0000	−2.5237	−3.0646	0.4847	-64.679^{***}
Panel B. Monthly determinants.							
EPU	$EPU_{m,t}$	1.9503	1.9253	2.7016	1.5713	0.1984	-3.9532^{***}
FS	$KCFSI_t$	0.0028	−0.4294	5.4128	−1.0397	1.1908	-2.5681^{*}
$SENT$	$gBCI_t$	−0.0132	−0.0030	0.8178	−1.0677	0.2361	-4.3833^{***}
EC	gIP_t	0.7782	2.1553	9.5047	−22.378	5.2441	-3.5847^{***}
$INFL$	$gPPI_t$	2.1531	2.7618	10.321	−7.6907	3.2531	-3.5205^{***}
FR	CFI_t	1.1326	1.1390	1.3470	0.8510	0.1044	-3.1211^{**}

Notes:

The table reports the summary statistics of the daily (Panel A) and monthly (Panel B)macro proxies (proxy of each macro effect) used as regressors in the short- and long-run correlations regressions: Mean, Median, Maximum (Max),Minimum (Min), Standard Deviation (Std.Dev.), and the Augmented Dickey-Fuller (ADF) test statistic. The macro variables reported are the following: the US EPU index (daily: $EPU_{d,t}$ and monthly: $EPU_{m,t}$), the S&P500 IV log-transformed index (VIX_t), the Infectious Disease Equity Market Volatility Tracker (ID_EMV_t), the global Financial Stress index (FSI_t), the US Financial Stress index of the Kansas City Fed ($KCFSI_t$), the G7 Business Confidence Index growth ($gBCI_t$), the News Sentiment Index (NSI_t), the daily change of the US Yield Curve slope ($\Delta YCsl_t$), the G7 Industrial Production index growth (gIP_t), the G7 inflation rate ($gPPI_t$), the Baltic Dry Index (BDI_t), the Cass Freight Index (CFI_t), and the DXY US Dollar index growth ($gDXY_t$). ***, **, * denote significance at the 0.01,0.05,0.1 level, respectively.

We classified ten economic effects in which we expect EPU, FU, ID, and FS to be positive signs under (*H6*) but they are negative signs under (*H7*); SENT, NS, EC, INFL, FR, FX are an opposite sign which is negative under (*H6*), and under (*H7*) are positive (see the detail in the table D.1, Panel B). These ten variables can reflect the economic pattern. If the economy becomes worse or a crisis happens, these variables (EPU, FU, ID, FS) will be higher uncertainty, the massive disease news released to influence the financial volatility and financial stress; the rest of the variables (SENT, NS, EC, INFL, FR, FX) perform lower confidence, news sentiment, activity, inflation, freights, and the US dollar is strong. Those events will increase the correlation due to the contagion under (*H6*) or decrease the correlation on the regressions due to flight-to-quality under (*H7*). On the opposite situation, economic expansion leads to lower uncertainty, and less disease news impact on financial volatility and financial stress; additionally, the rest of the variables present higher confidence, news sentiment, activity, inflation, and freights, but with the US dollar is weak; those events present the correlation will reduce (*H6*) or increase (*H7*). Consequently, the cross-asset correlation change is based on the hypothesis of contagion or flight-to-quality with weak economic fundamentals.

The last part of the data description is the timeline for the three crises. First crisis GFC, we are based on the Bank for International Settlements (BIS) and the Federal Reserve Bank of St. Louis timelines. Second crisis ESDC is based on the European Central Bank ESDC timeline. The last crisis COV is based on the World Health Organisation (WHO) COV pandemic chronology. Hence, we summarise these three sub-sample periods:

1. GFC subsample: 9/8/07 - 31/3/09. The GFC starting point was the suspension of certain BNP Paribas investment funds in August 2007 and it lasted until the first quarter of 2009.

2. ESDC subsample: 9/5/10 - 31/12/12. The Greek default in May 2010 established the beginning of ESDC, which lasted until the end of 2012.

3. COV subsample: 11/3/20 - 27/7/20. The COV started in March 2020, when the WHO characterised the Covid-19 outbreak as a pandemic and is still in place until the end of the whole sample.

The aim of separating the sub-sample crisis period from the whole sample period is to compare the correlation variation between the crisis and the pre-crisis period. On the other hand, we are also interested in studying the macroeconomic variables and how to influence the correlation during the actual crisis period. According to Karanasos & Yfanti (2021), they present the analysis of structural breaks for the correlation dynamics, but they did not explain the real crisis period and how to influence the correlation in the same period. Meanwhile, the structural break analysis might not match the official crisis

period. Therefore, we intend to study the actual crisis period rather than the structural break.
From most of crisis sub-sample, we notice that the fundamental economic environment deteriorated will shift the correlation. For example, the uncertainty increase, confidence decreases, diseases news impact on the financial volatilities. Hence, we expect higher contagion and less flight-to-quality in the correlations' regression analysis.

4.4 Empirical Analysis

In this section, we are going to explain the results from DCC-GARCH-MIDAS variance and correlation; then, we will focus on the correlation regression performed in the whole sample period, and examine the correlation shift during the three crisis periods.

4.4.1 Dynamic correlation estimation

As section 4.3.1 mentioned, DCC-GARCH-MIDAS presents the variance and correlation equations. Table 4.5 is the detail of the parameters of each variance equation and trivariate correlation equation. Additionally, our analysis is daily data in the short-run component and monthly data in the long-run component; so our empirical analysis selection for K_v is 22, and K_c is 22. Meanwhile, we examine the different lag for GARCH-MIDAS and DCC-GARCH-MIDAS; in the end, we use lag 48 for both of them, because we compare AIC (Akaike information criteria) and BIC (Schwarz information criteria) with different lag, lag 48 for variance and lag 48 for correlation are best fit to the model. From table 4.5 (Panel A variance equation), we notice that most of the parameters are significant in this table. The conditional means are significant to the EQU and RE, both of them are positive (0.0622 and 0.0577); but the conditional mean of COM is not significant in this sample period, it is still positive (0.0027). In the three variance equations for the arch(α) and garch(β), all of them are significant and all $\alpha_i + \beta_i < 1$ to make sure the short-run component is mean-reverting. However, the β of COM (0.9353) is higher than EQU (0.8187) and RE (0.8619), it presents COM with has high volatility than the other two. The section 4.3.1.1 discusses how the intercept m_i, the beta weight ω_v^i and parameter θ_i drive the variance equation's long-term component. θ are less than one, and m are around 0.5472 up to 1.3472; we select the monthly realised volatility as our long-run component, so the θ and m will be positive all the time. However, the beta weight is not quite stable which shows the RE is not significant (which is 3.6994) compare with the other two, and COM is flat which is only 1.001.

Table 4.5: DCC-MIDAS Variance and Correlation equation results

Panel A. Variance equation									
	μ_i	α_i	β_i	θ_i	ω_v^i	m	logL	AIC	BIC
EQU	0.0622***	0.1417***	0.8187***	0.1703***	6.3906***	0.5472***	-4720.40	9452.80	9492.03
	(0.0103)	(0.0094)	(0.0120)	(0.0122)	(1.3439)	(0.0505)			
RE	0.0577***	0.1242***	0.8619***	0.0996***	3.6994	1.2705***	-6443.62	12899.24	12938.47
	(0.0146)	(0.0073)	(0.0082)	(0.0262)	(2.6989)	(0.1705)			
COM	0.0027	0.0585***	0.9353***	0.1113**	1.001***	1.3472***	-6786.03	13584.05	13623.28
	(0.0187)	(0.0035)	(0.0041)	(0.0495)	(0.2384)	(0.2369)			

Panel B. Correlation equation						
	a	b	ω_c^{ij}	logL	AIC	BIC
EQU-RE-COM	0.0326***	0.9475***	4.4071***	-15833.914	31673.8278	31693.4423
	(0.0029)	(0.0067)	(1.0097)			

Notes:

The table reports the GARCH-DCC-MIDAS results of the trivariate cross-asset combinations. The number of MIDAS lags is 48 both for variance and correlation equation. The estimation of the variance equation for each asset series is the same for the trivariate models where the series is included (Panel A and B). Numbers in parentheses are standard errors ***, ** , * denote significance at the 0.01, 0.05, 0.10level, respectively. logL denote the log likelihood, AIC represents Akaike information criteria, and BIC is Schwarz information criterion.

Now, we turn to the correlation equation, our study is for the trivariate DCC-GARCH-MIDAS. Short-run correlation is derived by a and b, in which a is 0.0326 and b is 0.9475; their sum is lower than 1 which remains the short-run correlation mean-reversion to the long-term correlation. The last component is the lagged monthly realised correlations with the weight parameter is stable in this trivariate model which ω_c^{ij} is 4.4071 and significant in this pair. The following section will detail the estimated correlations from cDCC-MIDAS and how the correlation shift in the different crisis periods.

4.4.2 Short- and Long-run correlations

This section is going to extract the daily and monthly correlation to separate analysis of them. Due to the estimated correlation, we can have three pair of correlation group which is as follows:

1. Equities with the Real estate (one pair: EQU-RE);

2. Equities with Commodities (one pair: EQU-COM);
3. Real estate with Commodities (one pair: RE-COM).

These three pairs can explain how the connectedness between these three assets and figure 4.1 presents a cyclical variation of the cross-asset nexus. Based on our hypothesis, we mainly expect two types of interdependence dynamics. We use the red circle to state the crisis period, and we notice three correlation pairs are almost increasing during the crisis period. In another word, we can describe the countercyclical correlation increase during crises and procyclical decrease. However, the pair of real estate and commodities have different patterns compared with the other two in the GFC and ESDC. These pairs' correlation increases after GFC, but three of the pairs' correlations have a significant decrease after the ESDC period; however, we only observe the correlation increase during the COV. Additionally, the short-run correlation is more volatile than the long-run correlation in figure 4.1. From figure 4.1, most of the correlations are positive during our sample period, but the correlation between real estate and commodities is the smallest compared with the other two pairs; this pair's correlation is negative before the GFC.
Table 4.6 reports the statistics of short- and long-run correlation and all of them have positive mean in short- and long-run correlation. We can confirm the long-run correlation is more stable than the short-run correlation based on table 4.6 and figure 4.1. Meanwhile, we can also notice the highest correlation is the pair of EQU-RE, and the pair of RE-COM is the lowest correlation in this analysis. The pair of EQU and RE has the highest average correlation (short- and long-run) compare to the other two, and the lowest average correlation is the pair of RE-COM. It is interesting to see the minimum of pair EQU-RE is positive not only in the short- and long-run correlation (0.0876 and 0.2997), but the other two have the negative minimums.

Figure 4.1: Cross-asset Short- and Long-run Dynamic Correlations (short-run correlation: dotted grey line, long-run correlation: black solid line, crisis periods: red circled)

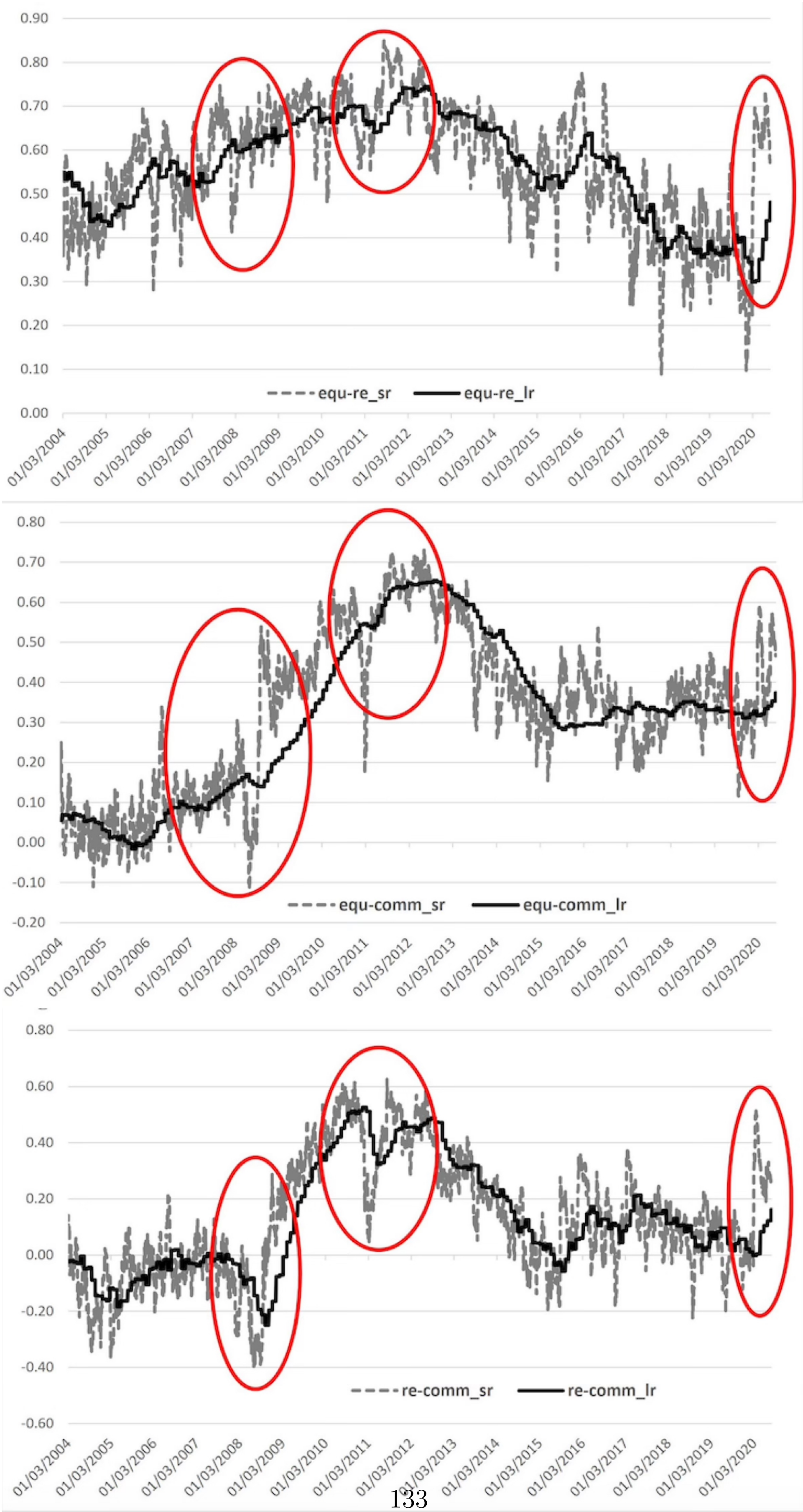


Table 4.6: Summary statistics of short- and long-run cross-asset dynamic correlations.

	Short-run correlations statistics					Long-run correlations statistics				
	Mean	Median	Max	Min	Std.Dev.	Mean	Median	Max	Min	Std.Dev.
EQU-RE	0.5661	0.5812	0.8499	0.0876	0.1337	0.5604	0.5653	0.7455	0.2997	0.1110
EQU-COM	0.3322	0.3499	0.7298	−0.1166	0.1968	0.3144	0.3272	0.6539	−0.0155	0.1915
RE-COM	0.1281	0.1042	0.6248	−0.4000	0.2152	0.1213	0.0836	0.5253	−0.2500	0.1908

Notes:

The table reports the summary statistics of the short- and long-run cross-asset dynamic correlation series computed by the trivariate cDCC-MIDAS models: Mean, Median, Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.). The asset series notation is as follows: Equities (EQU), Real estate (RE), Commodities(COM)

Based on table 4.6, we can classify these three pairs are which one hedging property under hypothesis *H1* and *H2*. All of the pairs' short- and long-run correlations' averages are positive and not close to 1, so all of them are under hypothesis *H1*; it means all the assets can act as diversifiers for the multi-asset portfolios. However, we did not detect any cross-asset correlation to satisfying hypothesis *H2* because the condition of *H2* needs the correlations to be close to zero (lower than 0.1) or the correlations are not negative. The next part is going to discuss the crisis sub-sample statistics under hypothesis *H3* - *H5*.

The crisis analysis is based on the sub-sample period's correlation mean and we use the mean difference tests (Satterthwaite-Welch t-test and Welch F-test). In this crisis analysis, we divide the crisis sub-sample into pre-crisis and in-crisis periods, and the pre-crisis is equal in length to the in-crisis time interval for the mean difference tests. Additionally, the crisis analysis separates into two parts based on two frequencies (daily and monthly); hence, we will focus on the short-run(daily), and then move to the crisis analysis for the long-run (monthly).

Table 4.7: Short-run (daily) dynamic correlation mean difference tests: pre-crisis vs. crisis subsamples.

	GFC				ESDC				COV			
	pre-crisis	in-crisis	mean diff.	t-test F-test	pre-crisis	in-crisis	mean diff.	t-test F-test	pre-crisis	in-crisis	mean diff.	t-test F-test
EQU-RE	0.547	0.633	$+^{***}$	-17.42 303.61	0.652	0.707	$+^{***}$	-14.99 224.55	0.298	0.651	$+^{***}$	-31.73 1006.5
EQU-COM	0.099	0.208	$+^{***}$	-13.73 188.57	0.312	0.594	$+^{***}$	-38.79 1504.9	0.331	0.448	$+^{***}$	-9.67 93.47
RE-COM	-0.023	-0.069	$-^{***}$	5.10 26.00	0.107	0.433	$+^{***}$	-30.65 939.49	0.028	0.318	$+^{***}$	-20.36 414.46

Notes:

The table reports the mean difference tests of the daily cross-asset correlations and the three crisis periods (GFC, ESDC, COV) under investigation. 'Pre-crisis' and 'in-crisis' columns report the correlation mean values in the pre-crisis and during crisis subsamples, respectively. 'Mean diff.' denotes the increase (+) or decrease (−) of the correlations during the crisis subsample. ***, **, * denote significance of the mean difference test at the 0.01, 0.05, 0.10 level, respectively. 't-test' and 'F-test' are the two mean difference test statistics, that is the Satterthwaite-Welch t-test and Welch F-test statistics,respectively.

Table 4.7 presents the short-run correlation in these three pairs short-run correlation in the crisis sub-sample period. The first pair EQU-RE are positive in three crisis periods, and this pair's correlation increased significantly during all the crises. Meanwhile, figure 4.1 presents this pair's short-run correlation as an overall increase during all crisis periods. If we combine table 4.7 and figure 4.1 together, we can consider this pair is under hypothesis *H4* in thee crisis period. Our conclusion for this pair's short-run correlation, which is supported by the related empirical evidence such as Case et al. (2012), Heaney & Sriananthakumar (2012), Hiang Liow (2012), Karanasos & Yfanti (2021)

Turning to the second pair of global equities and commodities, it is significantly positive in three crisis periods. Before the GFC, the correlation between these two assets are close to 0 which a mean is 0.099 in the pre-crisis period; and, the correlation's figure 4.1 shows this pairs' connection increase from March 2006 to March 2012, the short-run correlations hit the highest record is in the period of ESDC. However, the short-run correlation slightly increase in the COV period compared to the other periods. Hence, we can summarise this pair under hypothesis *H4* for all crisis periods. According to Huang & Zhong (2013), they present a large increase in the correlation between real estate and aggregate commodities during the GFC.

The short-run correlation of the last pair (RE-COM) presents quite different results compared to the other two. In this pair, we detect three hedging property which is safe-haven and flight-to-quality in the GFC, and Contagion in the ESCD and COV. We found the short-run correlation of RE-COM is negative correlation during the GFC period, it is also significantly decreasing in the GFC. From figure 4.1, we notice this pair's short-run correlation decreased at the beginning of the crisis, the lowest correlation in this pair which is around March 2019. Hence, we can summarise this pair's short-run correlation in the GFC under hypothesis *H3* and *H5*. This pair's short-run correlation remains positive and significantly increases during ESDC and COV, so we consider this pair is contagion (*H4*) in these two crisis periods.

Table 4.8: Long-run dynamic correlation mean difference tests: pre-crisis vs. crisis sub-samples.

	GFC				ESDC				COV			
	pre-crisis	in-crisis	mean diff.	t-test F-test	pre-crisis	in-crisis	mean diff.	t-test F-test	pre-crisis	in-crisis	mean diff.	t-test F-test
EQU-RE	0.544	0.605	$+^{***}$	-7.96 63.29	0.633	0.697	$+^{***}$	-7.44 55.32	0.363	0.367	$+$	-0.75 0.56
EQU-COM	0.060	0.150	$+^{***}$	-8.32 69.28	0.214	0.578	$+^{***}$	-18.21 331.73	0.319	0.335	$+^{*}$	-2.33 5.42
RE-COM	-0.029	-0.090	$-^{***}$	3.28 10.77	-0.043	0.444	$+^{***}$	-11.38 129.51	0.035	0.070	$+$	-1.34 1.80

Notes:

The table reports the mean difference tests of the long-run cross-asset correlations and the three crisis periods (GFC, ESDC, COV) under investigation. 'Pre-crisis' and 'in-crisis' columns report the correlation mean values in the pre-crisis and during crisis subsamples, respectively. 'Mean diff.' denotes the increase (+) or decrease (−) of the correlations during the crisis subsample. ***, **, * denote significance of the mean difference test at the 0.01, 0.05, 0.10 level, respectively. 't-test' and 'F-test' are the two mean difference test statistics, that is the Satterthwaite-Welch t-test and Welch F-test statistics, respectively.

Table 4.8 shows the long-run correlation performance in these three pairs during three crisis periods. We notice GFC and ESDC are the same results for the short- and long-run correlation mean different tests in these three pairs. As previously stated, the long-run correlation is more stable than the short-run correlation.

The pair of EQU-RE remains the positive and significant increase in the long-run correlation during the period GFC and ESDC, so we can conclude this pair's long-run correlation is under hypothesis *H4* in the first and second crisis. However, the difference between the short- and long-run is the COV period, we find this pair's long-run correlation is not significantly increasing which we can conclude this period is higher interdependence because the pre-crisis is 0.363 and the in-crisis period is 0.367; both of them are higher than 0.1.

In the second pair EQU and COM, its long-run correlation remains positive and also significantly increase in the three crisis period; this pair's long-run correlation has the same conclusion as the short-run correlation which all of them fit the hypothesis *H4*. Meanwhile, figure 4.1 presents this pair correlation has been a stable increase from GFC to ESDC crisis period. However, this figure also indicates the long-run correlation does not rapidly increase during the COV period. Combined figure 4.1 and table 4.10, we can conclude this pair's long-run correlation is still contagious during the COV period.

The pair of RE-COM long-run correlation presents similar results as the short-run correlation, in which the first crisis is under hypothesis *H3* and *H5* due to the negative correlation and correlation decrease during the crisis period; the second crisis is under hypothesis *H4* (Contagion) because pre-crisis and in-crisis remain positive and the mean different test shows the long-run correlation significantly increase. However, we also notice the COV period shows different results compared with the short-run correlation. The long-run correlation is 0.035 in the pre-crisis period and 0.07 in the in-crisis period both of them are lower than 0.1; meanwhile, it is no significant increase in the COV period. Therefore, we can conclude this pair's long-run correlation is Higher than weak interdependence and also it fits the hypothesis *H3*.

Table 4.9: Short- and Long-run interdependences and safe haven property.

	Panel A: Short-run (daily) correlations			Panel B: Long-run (monthly) correlations		
	GFC	ESDC	COV	GFC	ESDC	COV
EQU-RE	Contagion	Contagion	Contagion	Contagion	Contagion	Higher int.
EQU-COM	Contagion	Contagion	Contagion	Contagion	Contagion	Contagion
RE-COM	Flight-to-quality Safe Haven	Contagion	Contagion	Flight-to-quality Safe Haven	Contagion	Higher weak int. Safe Haven

Notes:

The table recaps the interdependence phenomena and safe haven property identified in the short- and long-run correlations statistical analysis (Tables 4 and 5) across the three crisis subsamples (GFC, ESDC, COV). The in-crisis interdependence types are as follows: Contagion, Flight-to-quality, Higher Interdependence (Higher Int.), and Lower Interdependence (Lower Int.).

Table 4.10 is the summary of the three pairs' short- and long-run correlation with their hedging properties. Overall, EQU-RE and EQU-COM present contagion in the GFC, but the pair of RE-COM is the flight-to-quality during the GFC. Meanwhile, these three pairs are contagion in the short- and long-run correlation during the ESDC period. However, all of their short-run correlation shows the contagion during the COV period; the long-run correlation presents quite different results. Hence, we can conclude the correlation of short-run and long-run are different in the three pairs, the investors and policy markets should pay attention to this difference.

4.5 Sensitivity Analysis of Dynamic Correlations

After the estimation of correlation, we turn to the relationship between cross-asset correlation and macroeconomic factors. This section, we separate into two parts. Firstly, we examine the daily and monthly Fisher-transformed correlations on the high- and low-frequency regression Eq. (4.18) and (4.19); we also investigate the relationship between financial assets correlation and macroeconomic variable performance when the economic uncertainty involved Eq. (4.20). Secondly, we analyse the crisis impact on the correlation determinants based on Eq. (4.21) and (4.22).

4.5.1 Correlations' Macroeconomic analysis

Motived by correlation estimation, we also want to examine how macroeconomic factors influence the financial assets' correlation. Hence, we apply different macroeconomic variables separate from low- and high-frequency correlation regressions. We use the Fisher Z transformation to apply the estimation correlations from DCC-GARCH-MIDAS; then, the transformed correlations (daily and monthly) and all the macroeconomic variables (daily and monthly) reject the null hypothesis of the unit root test (ADF test). Therefore, our data are suitable for the regressions of Eq. (4.18) and (4.19).

The purpose of short-run correlations with macroeconomic variable analysis is to discover the early warning signals for the crisis. Meanwhile, we notice the long-run correlations are more stable compared to the short-run correlations from the previous section analysis. Low-frequency correlation regression can provide the distance of the global economy.

The short-run correlations regressions

Table 4.10 present the daily correlations regression Eq. (4.18), we notice the short-run correlation depends on the previous data; three of them are around 0.969 up to 0.9727.

Table 4.10: Short-run (daily) cross-asset correlations regressions on macro fundamentals, Eq. (4.18).

	ζ_0	$\rho_{SR,t-1}$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$	AIC / BIC	DW / R^2
EQU-RE	0.4469*** (0.0334)	0.9690*** (0.0022)	0.0015*** (0.0005)	0.0885*** (0.0198)	0.0026* (0.0015)	0.0021*** (0.0008)	−0.0318*** (0.0131)	−0.0073*** (0.0030)	−0.0239** (0.0120)	−0.0009* (0.0005)	−5.1203	2.0186
											−5.1039	0.9817
EQU-COM	0.4845*** (0.1306)	0.9727*** (0.0188)	0.0030** (0.0013)	0.0111** (0.0053)	0.0022* (0.0013)	0.0103*** (0.0026)	−0.0343** (0.0153)	−0.0036*** (0.0010)	−0.0587* (0.0350)	−0.0004** (0.0002)	−4.7710	2.0799
											−4.7517	0.9878
RE-COM	0.1478 (0.1016)	0.9619*** (0.0019)	0.0020*** (0.0006)	0.0392** (0.0181)	0.0016 (0.0011)	0.0032** (0.0015)	−0.0193* (0.0110)	−0.0115*** (0.0044)	−0.0290*** (0.0078)	−0.0006*** (0.0001)	−5.0601	2.0737
											−5.0408	0.9852

Notes:

The table reports the estimation results of the daily correlations regressions on daily macro factors for each pairwise cross-asset combination. Each correlation series is explained by a constant (ζ_0), the first autoregressive term ($\rho_{SR,t-1}$), and the macro regressors (eq. (4.18)). The numbers in parentheses are standard errors. ***, **, * 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. $\overline{R}^2$ is the adjusted R^2.

From this table, we find out all macroeconomic variables have a different impact on the pair of EQU-RE and EQU-COM, excluding the pair of RE-COM; the ID is not significant in the daily macroeconomic regression.

For the pair of EQU-RE, we notice the EPU has the lowest positive impact on this pair's correlation (0.0015); Financial uncertainty has the highest positive contribution to this correlation (0.0885). EPU, FU, ID, and FS confirm the hypothesis *H6*, these four macro elements contribute to improving the short-run correlation in the case of contagion with the weak economic condition. Additionally, the rest of the macro variables (NS, EC, FR and FX) are significantly negative to the pair of EQU-RE short-run correlations, and they are under hypothesis *H6*.

The second pair of EQU-COM's short-run correlation regression has a similar conclusion as the pair of EQU-RE which all of the macro determinants are under *H6*; it means EPU, FU, ID, and FS increase the correlation between equities and commodities, and NS, EC, FR, FX reduce this pair's correlation. However, financial uncertainty contributes the highest positive impact on this pair's short-run correlation, and the ID is the smallest positive influence on this pair. The result indicates the US dollar strength is the smallest negative act on this pair's correlation, but the freight rate presents the highest negative impact on the short-run correlation of this pair.

The last short-run correlation pair shows similar results as the previous two pairs, but ID presents insignificant in this regression. Additionally, the rest of the macro variables are under *H6*. The results show that the macro variables are less impact on this pair, such as the highest positive impact on this pair is FU only got 0.0392. We are not surprised to find out that the freight rate has the highest negative impact on this pair.

The long-run correlations regressions

Turning to the long-run correlation regression, the table 4.11 present these results for three pairs. As previously stated, the long-run correlation regression is different to the short-run one due to the data available. Long-run correlation has less related to the previous date $_{t-1}$, such as the pair of EQU-RE only has 0.384, and the constant of this pair is also negative. the other two are more dependent on the previous data which are 0.7289 (EQU-COM) and 0.7107 (RE-COM), their constants are positive in the long-run correlation regressions. Meanwhile, all the parameters are significant in the long-run correlation.

Table 4.11: Long-run cross-asset correlations regressions on macro fundamentals, eq.(4.19).

	δ_0	$\rho_{LR,t-1}$	$EPU_{LR,t-1}$	$FS_{LR,t-1}$	$SENT_{LR,t-1}$	$EC_{LR,t-1}$	$INFL_{LR,t-1}$	$FR_{LR,t-1}$	AIC BIC	DW R^2
EQU-RE	−0.0095 (0.0090)	0.3840*** (0.0724)	0.0035* (0.0018)	0.0011* (0.0006)	−0.0148** (0.0067)	−0.0004*** (0.0002)	−0.0002* (0.0001)	−0.0061*** (0.0023)	−7.2805 −7.0777	2.0141 0.4071
EQU-COM	0.0169 (0.0420)	0.7289*** (0.0468)	0.0066*** (0.0030)	0.0020*** (0.0010)	−0.0079** (0.0035)	−0.0005* (0.0003)	−0.0003** (0.0001)	−0.0147* (0.0088)	−7.2022 −6.9993	2.1211 0.7353
RE-COM	0.0575 (0.0496)	0.7107*** (0.0529)	0.0016*** (0.0004)	0.0013*** (0.0005)	−0.0324*** (0.0108)	−0.0007*** (0.0003)	−0.0003*** (0.0001)	−0.0199*** (0.0012)	−6.9856 −6.7813	2.0780 0.7266

Notes:

The table reports the estimation results of the long-run correlations regressions on monthly macro factors for each pairwise cross-asset combination. Each correlation series is explained by a constant (δ_0), the first autoregressive term ($\rho_{LR,t-1}$), and the macro regressors (eq. (4.19))). The numbers in parentheses are standard errors. ***, **, * 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. $\overline{R}^2$ is the adjusted R^2.

All pairs' macroeconomic variables are under hypothesis *H6*; EPU and FS are a positive impact on the three pairs' long-run correlation, FS has a small impact on the pair of EQU-RE, but it is the highest influence on the pair of EQU-COM. The result shows that economic policy uncertainty has less impact on the correlation between real estate and commodities (0.0016), the pair of EQU-COM is the opposite situation (0.0066). The rest of the macro determinates reduce the correlation in the case of contagion (*H6*). Inflation is the lowest negative influence on all pairs; news factors have the highest impact on the pairs of EQU-RE and RE-COM, but it is the second highest impact on the EQU-COM. Unlike the short-run correlation results, the frights rate seems to have more impact on the long-run correlation.

The uncertainty channel of the economy

Now, we can progress to the next interesting point which is the role of the uncertainty channel in the short-run correlations (see Eq. 4.20). As a previous state, we expect the EPU can enhance the macroeconomic variables' performance in the short-run correlation regression. Meanwhile, our results on the short- and long-run macro correlation regression suggest that economic policy uncertainty is always significant and has the highest impact on the correlation. Hence, we consider EPU as a powerful correlation determinant which can enhance the contagion or flight-to-quality during the crisis period. Especially, wider researchers suggest the EPU influence the financial and economic environment (Costantini & Sousa 2022, Pástor & Veronesi 2013). We use the EPU interaction with each macroeconomic variable to discover the EPU impact.

Table 4.12: The EPU effect on the macro drivers of daily cross-asset correlations, eq. (4.20).

$EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0018^{*} (0.0010)	0.0011^{*} (0.0006)	0.0005^{**} (0.0002)	-0.0120^{***} (0.0044)	-0.0029^{***} (0.0010)	-0.0044^{***} (0.0020)	-0.0005^{**} (0.0002)
EQU-COM	0.0012^{**} (0.0005)	0.0007 (0.0005)	0.0013^{***} (0.0005)	-0.0073^{***} (0.0030)	-0.0026^{**} (0.0013)	-0.0050^{***} (0.0018)	-0.0002^{*} (0.0001)
RE-COM	0.0122^{*} (0.0066)	0.0005 (0.0005)	0.0003^{***} (0.0001)	-0.0062^{***} (0.0019)	-0.0059^{***} (0.0022)	-0.0085^{**} (0.0042)	-0.0003^{*} (0.0002)

Notes:

The table reports the EPU effect on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each EPU interaction term, estimated separately, are displayed. The EPU interaction terms are calculated by the multiplication of EPU ($EPU_{SR,t-1}\times$) with each macro regressor. The numbers in parentheses are standard errors.

***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table 4.12 shows the EPU effect on the macroeconomic variables in the short-run correlation. From this table, EPU enhances FU and FS performance in these three pairs' short-run correlations; especially, FU has the largest increase in the pair of RE-COM. However, we did not find any evidence of an indirect EPU effect to increase the ID coefficient in the short-run correlation regression (EQU-COM and RE-COM). On the negative impact, macroeconomics determines, the results present NS magnifies its effect on the short-run correlation with the EPU effect, but the US dollar strength has less influenced by the economic policy uncertainty. Therefore, we can conclude that EPU can improve the macroeconomic variables on the three pairs' correlation regressions.

4.5.2 Correlations' crisis vulnerability

In this section, we will discuss our least interest in correlation determinants with the crisis-sensitive analysis. Motived by the macroeconomic analysis for the whole sample period, we want to identify how the crisis shock act on the correlation regressions. Hence, we use Eq. (4.21) and (4.22) to discover the correlation reaction during the crisis period; we denote the crisis intercept dummies as ($D_{C,t}$), and estimate the regressions with the crisis interception term. Meanwhile, we have a similar expectation of crisis parameters as the EPU effect which means crisis existence can enhance the macroeconomic regressors on the correlations.

In the previous section 4.4.2, we present how the correlations shift during the crisis period and their hedging properties. Meanwhile, the results suggest these three pairs are contagion cases in the crisis period, excluding the pair of RE-COM. In the case of contagion, we expect the crisis can magnify the macro effect on the correlations which shows similar results as Karanasos & Yfanti (2021); for example, the positive macro factors (EPU, FU, ID, FS) become more positive, and the negative macro regressors (NS, EC, FR, FX) become more negative. Hence, the table 4.13 shows the results satisfied our expectation which all the macroeconomic regressors remain the same sign as the last section.

Firstly, we focus on the first crisis period (GFC). For the positive case of macro regressors, all of them remain the same signs, but ID is not significant during the GFC. For the negative case, the sign of macro regressors remain the same, but the pair of RE-COM only has one significant macro regressor during the crisis period GFC; unfortunately, our results cannot suggest EC, FR and FX can reduce the correlation during the crisis period GFC.

Table 4.13: The Crisis effect on the macro drivers of daily cross-asset correlations, eq. (4.21).

Panel A . The Crisis (GFC) effect on the macro drivers of daily cross-asset correlations

$D_{GFC,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0025^{*}	0.0031^{***}	0.0003	0.0004^{***}	-0.0430^{***}	-0.0161^{**}	-0.0036^{***}	-0.0013^{*}
	(0.0013)	(0.0010)	(0.0029)	(0.0000)	(0.0106)	(0.0069)	(0.0011)	(0.0007)
EQU-COM	0.0027^{***}	0.0025^{***}	0.0002	0.0053^{***}	-0.0080^{***}	-0.0039^{***}	-0.0030^{**}	-0.0009^{**}
	(0.0010)	(0.0008)	(0.0008)	(0.0006)	(0.0032)	(0.0010)	(0.0015)	(0.0004)
RE-COM	0.0027^{***}	0.0034^{***}	0.0066	0.0006^{*}	-0.0191^{***}	-0.0152	-0.0009	-0.0003
	(0.0009)	(0.0006)	(0.0056)	(0.0003)	(0.0055)	(0.0146)	(0.0008)	(0.0010)

Panel B. The Crisis (ESDC) effect on the macro drivers of daily cross-asset correlations

$D_{ESDC,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0028^{***}	0.0298^{***}	0.0289^{***}	0.0013^{***}	-0.0773^{**}	-0.0022^{***}	-0.0137^{**}	-0.0013^{*}
	(0.0011)	(0.0122)	(0.0107)	(0.0002)	(0.0390)	(0.0007)	(0.0060)	(0.0008)
EQU-COM	0.0108^{***}	0.0032^{**}	0.0374^{***}	0.0078^{***}	-0.0065^{**}	-0.0208^{**}	-0.0046^{**}	-0.0015^{*}
	(0.0040)	(0.0015)	(0.0121)	(0.0017)	(0.0031)	(0.0107)	(0.0024)	(0.0009)
RE-COM	0.0039^{***}	0.0075^{***}	0.0260^{***}	0.0018^{***}	-0.0627^{***}	-0.0043^{***}	-0.0055^{*}	-0.0004^{**}
	(0.0004)	(0.0010)	(0.0094)	(0.0003)	(0.0251)	(0.0010)	(0.0030)	(0.0002)

Panel C. The Crisis (COV) effect on the macro drivers of daily cross-asset correlations

$D_{COV,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0073^{***}	0.0136^{***}	0.0039^{**}	0.0023^{***}	-0.2159^{***}	-0.0112^{***}	-0.0101^{*}	-0.0045^{**}
	(0.0020)	(0.0046)	(0.0020)	(0.0009)	(0.0853)	(0.0049)	(0.0056)	(0.0021)
EQU-COM	0.0094^{***}	0.0424^{***}	0.0028^{***}	0.0062^{***}	-0.0969^{***}	-0.0335^{***}	-0.0087^{**}	-0.0030^{***}
	(0.0040)	(0.0082)	(0.0011)	(0.0020)	(0.0362)	(0.0129)	(0.0041)	(0.0012)
RE-COM	0.0077^{***}	0.0347^{***}	0.0040^{***}	0.0043^{*}	-0.1465^{***}	-0.0078^{***}	-0.0074^{***}	-0.0021^{*}
	(0.0019)	(0.0082)	(0.0012)	(0.0026)	(0.0519)	(0.0011)	(0.0010)	(0.0011)

Notes: The table reports the crisis effect on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each crisis slope dummy, estimated separately, are displayed. The crisis slope dummies are calculated by the multiplication of the respective dummy for each crisis period (GFC dummy: $D_{GFC,t-1}\times$, ESDC dummy: $D_{ESDC,t-1}\times$, COV dummy: $D_{COV,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Turning to table 4.13 (Panel B and Panel C), we notice the crisis ESDC and COV remain similar conclusions for the macroeconomic regressors. EPU, FU, ID and FS are positively increasing two pairs' correlations, and NS, EC, FR, and FX are negatively reducing these two pairs' correlations during the crisis period ESDC and COV. Overall, we can conclude crisis shock can expand most of the macro determinants' effect on the cross-asset correlations.

The last interest of us is to study how macroeconomic variables influence in the correlation between the crisis shock and economic policy uncertainty, we estimate eq.(4.22) to examine our interest. Table 4.14 presents the EPU effect on the macro factors during three crisis periods. In addition, the result indicates that EPU and crisis shock can enlarge the macroeconomic fundamentals on the cross-assets correlation. However, we could not find significant results on the ID during the GFC, which is similar to the table 4.13. We also notice fright rate becomes insignificant in the pair of RE-COM during the ESDC period.

Table 4.14: The EPU effect on the macro drivers of daily cross-asset correlations during crises Eq. (4.22)

Panel A. The EPU effect on the macro drivers of daily cross-asset correlations during crises (GFC)

$D_{GFC,t-1}EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0087^{***} (0.0035)	0.0009 (0.0008)	0.0004^{**} (0.0002)	-0.0092^{*} (0.0048)	-0.0078^{**} (0.0032)	-0.0020^{***} (0.0007)	-0.0006^{***} (0.0001)
EQU-COM	0.0010^{***} (0.0003)	0.0024 (0.0025)	0.0012^{**} (0.0006)	-0.0047^{***} (0.0015)	-0.0026^{**} (0.0003)	-0.0008^{***} (0.0003)	-0.0004^{**} (0.0002)
RE-COM	0.0020^{***} (0.0003)	0.0009 (0.0014)	0.0004^{*} (0.0003)	-0.0073^{***} (0.0015)	-0.0075 (0.0100)	-0.0001 (0.0003)	-0.0002 (0.0005)

Panel B. The EPU effect on the macro drivers of daily cross-asset correlations during crises (ESDC)

$D_{ESDC,t-1}EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0066^{**} (0.0030)	0.0134^{***} (0.0048)	0.0011^{**} (0.0006)	-0.0295^{**} (0.0142)	-0.0008^{*} (0.0004)	-0.0065^{*} (0.0036)	-0.0005^{*} (0.0003)
EQU-COM	0.0030^{**} (0.0015)	0.0171^{**} (0.0070)	0.0020^{***} (0.0007)	-0.0060^{***} (0.0026)	-0.0102^{**} (0.0049)	-0.0009^{***} (0.0003)	-0.0007^{*} (0.0004)
RE-COM	0.0011^{***} (0.0003)	0.0140^{***} (0.0055)	0.0009^{***} (0.0002)	-0.0200^{***} (0.0071)	-0.0020^{***} (0.0006)	-0.0009 (0.0010)	-0.0009^{*} (0.0005)

Panel C. The EPU effect on the macro drivers of daily cross-asset correlations during crises (COV)

$D_{COV,t-1}EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0124^{**} (0.0061)	0.0015^{**} (0.0008)	0.0012^{***} (0.0004)	-0.0780^{***} (0.0259)	-0.0030^{***} (0.0010)	-0.0042^{***} (0.0014)	-0.0015^{**} (0.0008)
EQU-COM	0.0139^{***} (0.0063)	0.0008^{***} (0.0002)	0.0060^{***} (0.0021)	-0.0481^{***} (0.0202)	-0.0155^{*} (0.0080)	-0.0026^{***} (0.0009)	-0.0014^{*} (0.0010)
RE-COM	0.0177^{***} (0.0062)	0.0015^{***} (0.0005)	0.0015^{*} (0.0010)	-0.0673^{**} (0.0347)	-0.0069^{**} (0.0034)	-0.0057^{***} (0.0022)	-0.0014^{**} (0.0007)

Notes: The table reports the EPU effect during crises on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each EPU interaction term under crisis, estimated separately, are displayed. The EPU interaction terms under crisis are calculated by the multiplication of the respective dummy for each crisis period and EPU (GFC dummy: $D_{GFC,t-1} \times EPU_{SR,t-1}\times$, ESDC dummy: $D_{ESDC,t-1} \times EPU_{SR,t-1}\times$, COV dummy: $D_{COV,t-1} \times EPU_{SR,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

In this section, we examine the macro sensitivity analysis to confirm our last two hypotheses during the whole sample period, and we further discover how the EPU and three crises influence cross-assets correlation. Long-run co-movements are less volatile, and they are less related to the previous date. Short-run correlations reflect the market's attitude and investors' confidence in the markets. In addition, our analysis presents similar results as Karanasos & Yfanti (2021) during the GFC.

4.6 Discussion and implications

Overall, our results indicate that investors and policymakers should pay attention to the cross-asset interdependences between these three asset markets. In particular, they should consider the short- and long-run correlation separately; our evidence indicates the long-run correlations are less volatile compared to the short-run correlation. Meanwhile, the type of crisis is important to the cross-assets hedging property and their independence. For example, all cross-correlation results on the ESDC present contagion property, and the COV period presents different hedging properties. Based on our estimation results, we can conclude to consider the pair of RE-COM can act as flight-to-quality during the crisis in the investment portfolio. Meanwhile, investors need to pay attention to the crisis type in order to minimise their lost. In our empirical evidence, we notice the type of crisis shifts the cross-asset hedging property such as the RE-COM. Additionally, we also suggest considering their investment strategy separately in the short- and long-run.
During the macroeconomic sensitivity test, our evidence also provides that macro regressors have a significant impact on correlation regressions. Meanwhile, we also include the indirect EPU effect and crisis shock into the macro correlation regressions. Most of the results from the macro correlation are highly significant in these three markets, so investors and market participants should consider the macroeconomic factors that influence their investment plans in these markets.

4.7 Conclusion

In conclusion, this chapter examines the relationship between cross assets, we discover combinations of three assets in the short- and long-run correlation; meanwhile, we also indicate their hedging properties during three crises period. In addition, we propose a new corrected DCC-MIDAS specification to estimate the cross-assets correlation. Based on the estimation correlation, our study presents these three pairs are contagion phenomena that imperil the whole financial stability. Additionally, our results suggest the pair of RE-COM is the flight-to-quality property during the GFC. For the macroeconomic sensitivity analysis, we further discover the macro factors expand their effect under the impact of economic policy uncertainty during the crisis period.
This chapter contributes to examining the short- and long-run co-movements between

three assets (global equities, real estate and aggregate commodities). Moreover, our study presents the stable macroeconomic environment is important to the financial assets market. However, we only study three assets in this chapter, our analysis does not consider the disaggregate commodities such as energy commodities and agriculture. Hence, in the next chapter, we are going to separate the aggregate commodities into a couple of types of commodities, and continue to analyse the co-movement between financial and 'financialised' Assets.

4.8 Appendix

Table D.1: Variable definitions

Panel A. Assets		Panel B. Macro-financial and news variables		
Variable	Definition	Variable	Definition	Macro effect description
EQU	Equities	$EPU_{d/m,t}$	US Economic policy uncertainty index (d/m)	EPU: Economic policy uncertainty
RE	Real estate	VIX_t	S&P 500 Implied Volatility index (d)	FU: Financial uncertainty
COM	Commodities	ID_EMV_t	Infectious Disease Equity Market Volatility tracker (d)	ID: Infectious disease news impact
		FSI_t	Global Financial Stress index (d)	FS: Financial Stress
		$KCFSI_t$	US Financial Stress index of the Kansas City Fed (m)	FS: Financial Stress
		$\Delta YCsl_t$	US Yield Curve slope (or term spread) daily change (d)	EC: Economic activity
		gIP_t	G7 Industrial Production index growth (m)	EC: Economic activity
		$gBCI_t$	G7 Business Confidence Index growth (m)	SENT: Sentiment / Confidence
		NSI_t	News sentiment index (d)	NS: News sentiment
		$gPPI_t$	G7 inflation rate (m)	INFL: Inflation
		BDI_t	Baltic Dry Index (d)	FR: Freights
		CFI_t	Cass Freight Index (m)	FR: Freights
		$gDXY_t$	DXY US Dollar index growth (d)	FX: Foreign Exchange rates

Notes:

The table reports the definitions of the data variables (assets & macro data). The asset series (Panel A) are downloaded from Refinitiv Eikon Datastream. The sample is common for daily assets and macro variables (1/3/2004 - 27/7/2020). The sample of the monthly macro variables spans from 01/2007 until 07/2020. Daily / monthly macro variables are denoted by (d) and (m), respectively. The macro data (Panel B) sources are as follows: EPU and ID_EMV indices are sourced from www.policyuncertainty.com. Implied Volatility indices, Yield Curve slope, BDI, and DXY are downloaded from Refinitiv Eikon Datastream. KCFSI is retrieved from the FRED database and NSI from San Francisco Fed. IP, PPI, and BCI are sourced from the OECD database. CFI and FSI are downloaded from Cass Information Systems Inc. and the Office of Financial Research, respectively.

Table D.2: The Crisis effect on daily cross-asset correlations, eq. (4.21)

	$D_{GFC,t}$	$D_{ESDC,t}$	$D_{COV,t}$
EQU-RE	0.0215^{*} (0.0118)	0.0064^{***} (0.0026)	0.0087^{***} (0.0032)
EQU-COM	0.0033^{***} (0.0009)	0.0032^{***} (0.0007)	0.0443^{***} (0.0031)
EQU-COM	0.0033^{***} (0.0009)	0.0032^{***} (0.0007)	0.0443^{***} (0.0031)

Notes: The table reports the crisis effect on daily cross-asset dynamic correlations (eq. (4.21)). The coefficients of the crisis intercept dummies, estimated separately from the crisis slope dummies, are displayed. The three dummies corresponding to each crisis subsample are the GFC dummy: $D_{GFC,t}$, the ESDC dummy: $D_{ESDC,t}$, and the COV dummy: $D_{COV,t}$. The numbers in parentheses are standard errors. ***, **, *denote significance at the $0.01, 0.05, 0.10$ level, respectively.

5 Short- and Long-run co-movement between financial and 'financialised' asset in the cDCC-MIDAS

5.1 Introduction

Financial contagion has been a wider discussion over two decades, but the recent health crisis rekindles researchers' interest. Meanwhile, most research works related to financial contagion are focusing on stock markets or equity markets (de Goeij & Marquering 2009, Pineda et al. 2022). Additionally, non-financial markets can be a potent threat to the global financial market even the world economy. Many researchers point out that episodes of economic turmoil are trigged by endogenous and exogenous factors (Allen et al. 2012, Iwanicz-Drozdowska et al. 2021). For the endogenous factors, we can think of financial stress conditions to trigger the crisis such as the credit crunch in the 2008 sub-prime crisis and the sovereign defaults in the 2010 European sovereign debt crisis; both of them are crushed in the financial system firstly then spill to the whole economy. For the exogenous factors, the recent COV health crisis causes economic activity to be reduced and climate change influences the economic environment. In addition, the exogenous factors have a significant impact on the real economy (Baur 2012, Samitas et al. 2022). Therefore, such spillover effects are characterised as contagion. Most investors and policymakers do not pay attention to the contagion during the strong economic condition due to the market its independence. However, the economic market and financial system become tighter due to globalisation and financial liberalisation in real economic terms; this is the one of reasons causes the financial crisis happened frequently during these decades. Especially, the contagion effect caused by the weak fundamental economic environment contributed to expanding the size of crises such as the well-known global financial crisis of 2008.

In this vein, the purpose of this chapter is to study time-varying interconnectedness among economic and financial markets; but in this chapter focuses on the interconnection of 'financial' assets. In addition, the non-financial assets have been attributed by the investors due to the risk transmission during the crisis period. The previous chapter studied the connection between financial and 'financialised' assets (global equities, real estate and commodities), but we only focused on the three benchmark indexes. Hence, this chapter wants to investigate the correlation between the two benchmarks and the major categories of commodities (energy commodities, precious metals, industrial metals, agriculture and livestock. Meanwhile, we apply the cDCC-MIDAS specification [24] specification, a novel extension of the DCC-GARCH-MIDAS model of Colacito et al. (2011), modified by the correction of Aielli (2013) on the classic DCC of Engle (2002). The aim of using the cDCC-MIDAS model is to calculate the estimation of short- and long-run dynamic correlations among these asset indexes. After we have the estimation correlation, we use the pairwise combinations' correlation to identify the hedging properties and assets' interdependence. Furthermore, our empirical analysis covers the correlation's movement and examines cross-asset hedging properties during the crisis period. Motived by the correlation shift during the crisis, we continue to confirm the fundamental economic factors' impact on the cross-assets co-movements during the whole sample period and also the crisis period.

Our empirical analysis suggests the contagion phenomena appear in most cross-asset pairs and the crisis period. There are a few cases the flight-to-quality from the pairs of real estate - commodities, but this phenomenon only happens in one crisis. These pairs are also acting as safe-haven property at the same time. Additionally, if the combination is with precious metals, these pairs most of the time act as safe-heaven property in the crisis period. Based on our analysis, we find a significant differentiation in our cross-asset pairs during three different crisis periods (the 2008 global financial crisis [GFC], the European sovereign debt crisis [ESDC], and the Covid-19 crisis [COV]). Overall combinations pair are significantly increasing during the three crisis periods, but the real estate - commodities pairs decrease during the GFC. Furthermore, the intra-commodities pairs significantly decrease during the ESDC. Moreover, the three pairs of precious metals' correlation increased on average in the short-run correlation during the COV period. In this chapter, we also conclude the fundamental economic factors which have a significant effect on the assets' co-movement; especially, the weak economic condition expands the crisis effect on the assets' correlation.

This chapter's contributions are four parts. Firstly, this chapter is given evidence about the financial contagion; unlike the last chapter only focuses on the three benchmark in-

[24] *c* stands for corrected, *DCC* for Dynamic Conditional Correlations, *GARCH* for Generalised Autoregressive Conditional Heteroskedasticity, and *MIDAS* for Mixed-Data Sampling.

dexes, we expand our asset selections which include the disaggregate commodities indexes. In this chapter, our empirical analysis not only covers financial assets' co-movement but also includes the 'financialised' asset combinations (total is 20 pairs). Meanwhile, we continue to apply the cDCC-GARCH-MIDAS model to investigate the short- and long-run correlation among these assets. The second contribution is to identify the hedging properties (hedge and diversifier) of cross-assets during the crisis period, and we furthermore investigate the cross-assets interdependence during the crisis period. In addition, we signify the co-movement between different asset combinations during the pre-crisis and in-crisis periods. The third contribution is about the macro-sensitive investigation, we consider the macroeconomic fundamentals which have a significant impact on the short- and long-run correlation during our sample period. At the same time, we are also interested in the crisis expanding the weak economic condition impact on the cross-assets co-movements. Motived by Karanasos & Yfanti (2021), we select the macroeconomic variables to confirm our macro-sensitive investigation. In this contribution, we emphasise the uncertainty channel magnifies the crisis and the macro factors on the contagion dynamics. Meanwhile, this chapter uses the real timeline instead of the structural breaks which are calculated by statistical identification. In our last contribution in this chapter which is for the financial econometrics literature, we apply the DCC-MIDAS with (Aielli 2013) correlation on the correlation estimation.

To our best knowledge, this chapter is the first existing literature on the cross-assets co-movements to include a detailed breakdown of commodities. In addition, our study provides novel findings on two directions which are the cross-assets hedging properties and their interdependence type. Due to our cDCC-MIDAS specification, we can estimate the short- and long-run correlation horizon, this model allows us to study the macro sensitivity test with high- and low-frequency data to compare in the chapter. Our empirical evidence presents that investors and policymakers should pay more attention to the cross-asset combination because a well-construct portfolio can reduce the crisis effect. Especially, this chapter focuses on the intra-commodities instead of the benchmark indexes; this chapter will provide a more general idea about asset allocation and hedging strategies to the investors and regulatory authorities. The investors can based on our analysis select the correct cross-assets combination which to reduce the risk in the investment portfolios. For the regulator authorities and policy markers, they can use our results to consider the problem of financial stability and systemic risk. Equivalently, this chapter shows the correlations have significantly increased during the crisis period; higher interdependence creates a massive loss to the investors' and market participants' investment portfolios and even influences the financial systems and the whole economic environment. Hence, we believe the correlation determinates can be the woke up call and early warning alarms of imminent crisis episodes. The safe-haven assets can be one of the solutions to prevent crisis damage to the financial system for investors and policy markers. In the last part of this chapter, our analysis suggests that cross-asset connectedness can contribute to designing the micro and macro policies for regulator authorities.

The remainder of this chapter is structured as follows. The section 5.2 will be the theoretical background which contains literature reviews and hypotheses development; the part of the hypotheses details our seven hypotheses for assets' hedging properties and interdependence and our expectation of macro effect on the correlations. The following section 5.3 introduces our model framework cDCC-MIDAS and the correlation regressions for macroeconomic sensitivity investigation. The section 5.4 presents our empirical analysis of estimation correlation; this section will include the results from cDCC-MIDAS and also the difference test for the estimation correlation during the crisis periods. The next section is the macroeconomic sensitivity investigation which we separate 20 cross-assets pairs to detect the macroeconomic effect in the sample period and also the separated crisis periods. The last two are the discussion and conclusion of this chapter.

5.2 Theoretical background

At the end of the introduction presented, this section introduces the Literature Review and our development of hypotheses. The literature review will provide previous evidence on the financial markets co-movements. The following subsection describes how we consider our hypothesis to examine the cross-asset hedging properties and their interdependence.

5.2.1 Literature Review

Financial integration and tight interconnection are direct outcomes of the previous three decades of progressive liberalisation, deregulation, and globalisation. Meanwhile, a lot of evidence shows many markets and economics are interdependent (Eiling & Gerard

2015). Meanwhile, the financial contagion significantly increases the correlation because the crisis shock improves the cross-assets connection Forbes & Rigobon (2002). Turning to the cross-asset dimension of financial interconnectedness, empirical research has demonstrated either contagion or flight-to-quality conditions during crises for several asset pairs. For example, sovereign bonds or precious metals are considered safe havens. In market stress times, they attract investors who quit or hedge positions in riskier assets such as stocks. Equities and real estate investment vehicles mostly experience common contagious shocks, while several financial assets are highly correlated with certain commodities given their financialisation in the last two decades (Büyükşahin & Robe 2014, Henderson et al. 2015). In addition, a large number of studies have investigated the interdependence between stocks and commodities (Bekiros et al. 2017, Creti et al. 2013), intra-commodity co-movements (Alquist et al. 2020, Flori et al. 2021) alongside several other asset combinations at the global or regional level (Apostolakis & Papadopoulos 2015, Huang & Zhong 2013).

There is a lot of evidence about the cross-asset connection between equities and commodities. However, we notice there are few kinds of literature about the relationship between real estate and commodities. We believe this connection is also important. For example, Breitenfellner et al. (2015) states that energy commodities is an important role in real estate development through the housing cost, investors' income, monetary policy, and financial markets channels. Meanwhile, oil and industrial metal prices also influence the housing market Huang & Zhong (2013). Further research relates to the connection between oil and the housing market (residential properties). According to Kilian & Zhou (2022), Nguyen et al. (2021), Rehman et al. (2020), their research provides evidence on both negative and positive correlations sensitive to time (increased connectedness as financialisation progresses), regional factors (e.g., oil-producers vs. oil-importers) and market conditions (crises or other extreme events exacerbate correlations). The next section is the hypothesis of this chapter.

5.2.2 Hypotheses

This chapter's hypotheses are similar to the previous chapter, but our empirical analysis are focusing on three groups (global equities - disaggregate commodities, real estate - disaggregate commodities, and intra-commodities). Hence, our analysis involves two important aspects. We first scrutinise the anatomy of the pairwise correlation time series computed by the trivariate cDCC-GARCH-MIDAS system to conclude on the hedging properties of the assets (diversifier or hedge or safe haven) and the type of interdependence (contagion or flight-to-quality). Second, we proceed with the macro sensitivity exercise, which unveils the major drivers of cross-asset connectedness in the macroeconomic environment.

In the correlation time series statistical analysis, we follow Forbes & Rigobon (2002) and Baur & Lucey (2009, 2010) to identify the hedging properties of the assets and to distinguish between contagion, flight-to-quality, or simple interdependence (Table 5.1, Panel A). Moreover, we are based on the special case of correlations increasing to positive but low levels during crises (uncorrelated assets with average dynamic correlations between 0 and 0.100) the assets are safe havens and we define the interdependence types as i) weak contagion if the change is significant and ii) higher weak interdependence if the change is insignificant (see also table 5.2, Panel C, for the in-crisis correlation change and level combinations indicative of each interdependence type and safe haven property during crises). Hence, we can observe safe haven properties when correlations are positive but very low, close to zero ($0 < \rho < 0.100$), regardless of whether we have (weak) contagion or higher interdependence. Against this backdrop, we test the following hypotheses on the dynamics of the short- and long-run cross-asset correlations extracted from the cDCC-GARCH-MIDAS estimations:

Hypothesis 1(*H1*): Positively, but not perfectly, correlated (on average) assets act as *diversifier* (whole sample: $+, < 1$).

Hypothesis 2 (*H2*): Uncorrelated or negatively correlated (on average) assets act as *hedges* (whole sample: 0 or $-$).

Hypothesis 3 (*H3*): In-crisis uncorrelated or negatively correlated assets act as *safe havens* (in-crisis: 0 or $-$).

Hypothesis 4 (*H4*): Significant positive change and level of correlations during crises mean *contagion* (in-crisis: $\uparrow, +$).

Hypothesis 5 (*H5*): Significant negative change and level of correlations during crises mean *flight-to-quality* (in-crisis: $\downarrow, -$).

In the second step of the macroeconomic investigation, we intend to attribute the correlation pattern to economic fluctuations. Motivated by the well-documented rising interdependences during crises (contagion) and lower negative correlations for flight-to-quality in turbulent times (safe haven assets), we expect that weak economic conditions, indicative of market stress, lead to contagion or flight-to-quality for safe havens. Conversely, strong fundamentals drive most cross-asset correlations down, increasing the diversification benefits for investors. Therefore, our hypothesis about the macro analysis of correlations is below (see also Table 5.1 Panel B, for the expected signs of each macro effect under each type of interdependence according to our last two hypotheses):

Hypothesis 6 (*H6*): Weak economic fundamentals increase correlations in the case of contagion.

Hypothesis 7 (*H7*): Weak economic fundamentals decrease correlations in the case of flight-to-quality.

Table 5.1 and table 5.2 present our hypotheses and expected results on the macroeconomic sensitivity exercise. These two tables' Panel A and Panel C are the detail of our hypotheses (*H1* - *H5*). Panel B is the expectation signs in the macroeconomic correlation regressions for our macroeconomic sensitive investigation (*H6* - *H7*).

Table 5.1: Overview of hypotheses and expected results

Panel A. Hedging properties & interdependence hypotheses			Panel B. Macro sensitivity (correlation determinants)		
	Hedging property			Expected sign	
Correlation pattern	Interdependence	Hypothesis	Macro effect on correlations	H6	H7
Positively, but not perfectly, correlated	Diversifier	H1	Economic policy uncertainty (EPU)	$+$	$-$
(whole sample average: $+, < 1$)			Financial uncertainty (FU)	$+$	$-$
Uncorrelated or negatively correlated	Hedge	H2	Infectious disease news impact (ID)	$+$	$-$
(whole sample average: 0 or $-$)			Financial Stress (FS)	$+$	$-$
In-crisis uncorrelated or negatively	Safe haven	H3	Sentiment / Confidence (SENT)	$-$	$+$
correlated (in-crisis: 0 or $-$)			News sentiment (NS)	$-$	$+$
In-crisis increase & positive level	Contagion	H4	Economic activity (EC)	$-$	$+$
(in-crisis: $\uparrow, +$)			Inflation (INFL)	$-$	$+$
In-crisis decrease & negative level	Flight-to-quality	H5	Freights (FR)	$-$	$+$
(in-crisis: $\downarrow, -$)			Foreign Exchange rates (FX)	$-$	$+$

Notes:

The Table presents an overview of the hypotheses we test in the statistical and macro sensitivity correlation analysis. Panel A illustrates the correlation pattern features, characterising each hedging property and interdependence phenomenon (H1 - H5). Panel B recaps the expected signs of each macro effect on correlation evolution under H6 and H7.

Table 5.2: Overview of hypotheses and expected results

Panel C. Interdependence types and safe haven property during crises: in-crisis correlation change and level results			
in-crisis average correlation (ρ)	positive correlation and higher than 0.100	negative correlation	uncorrelated
change $\downarrow$ / level $\longrightarrow$	$\rho \geq 0.100$	$\rho < 0$	$0 \leq \rho < 0.100$
significant increase	Contagion (H4)	Higher interdependence Safe Haven (H3)	Weak contagion (H4) Safe Haven (H3)
insignificant increase	Higher interdependence	Higher interdependence Safe Haven (H3)	Higher weak interdependence Safe Haven (H3)
significant decrease	Lower interdependence	Flight-to-quality (H5) Safe Haven (H3)	Lower interdependence Safe Haven (H3)
insignificant decrease	Lower interdependence	Lower interdependence Safe Haven (H3)	Lower interdependence Safe Haven (H3)

Notes:

The Table presents an overview of the hypotheses we test in the statistical and macro sensitivity correlation analysis. Panel C reports the in-crisis orrelation change and level combinations that indicate the interdependence types and safe haven property during crises.

5.3 Methodology and Data description

This section separates into two parts, the first part is Methodology which we will introduce our framework of the corrected DCC-MIDAS model, and also this chapter's correlation analysis and macroeconomic correlation regression. Additionally, we include the Data description in this section.

5.3.1 Framework of cDCC-MIDAS

This subsection is going to present the detail of cDCC-MIDAS model, but based on the specification of cDCC-MIDAS model, the estimation method is two-steps; we need to introduce the conditional means, and to classify two type of errors at first, then we can process to compute conditional variance (GARCH-MIDAS). Once we have the conditional variance, we can calculate the conditional correlation (from cDCC-MIDAS). The last part is the estimation method for cDCC-GARCH-MIDAS.

5.3.1.1 The conditional means

Similar as previous chapters, the first element that we are interested on is the daily index return, $\mathbf{r}_t = [r_{i,t}]_{1 \leq i \leq N}$ at time t (high-frequency time scale), because we use trivariate corrected DCC-GARCH-MIDAS for our empirical analysis. We direct to use $r_{i,t}, i = 1, 2, 3$ to represent the return in this chapter for corrected DCC-GARCH-MIDAS. The conditional distribution of $r_{i,t}$ is given by $r_{it} \,|\Omega_{t-1} \sim i.i.d.\ N(\mu_i, \mathbf{H}_t)$, which means $r_{i,t}$ follows the normal distribution and given the condition which is the information at the previous time $t-1$, denote as Ω_{t-1}. Due to the assumption of $r_{i,t}$, the vector of the conditional mean presents as μ_i=$\mathbb{E}(r_{it} \,|\Omega_{t-1}), i = 1, 2, 3$; here expectation operator defines $\mathbb{E}$. The following is the conditional variance matrix which is $\mathbf{H}_t \stackrel{def}{=} h_{ii,t} = \mathbb{V}ar(r_{it} \,|\Omega_{t-1})$. The following interested element of this study, which is the conditional covariances matrix present as: $h_{ij,t} = \mathbb{C}ov(r_{it}, r_{jt} \,|\Omega_{t-1}), \forall i \neq j$. Therefore, we can state our return in this chapter $r_{i,t}$ is as followed:

$$r_{it} = \mu_i + \varepsilon_t, \tag{5.1}$$

From this equation, we can clearly notice the error can be reconstructed as $\varepsilon_{it} = r_{it} - \mu_i$. Hence, we compute the definition of condition mean, we can continue to introduce the error terms of cDCC-MIDAS.

5.3.1.2 The Errors

As previous section mentioned, our corrected DCC-MIDAS is based on DCC-MIDAS framework; it follows similar construction of DCC-MIDAS model. Additionally, we can consider DCC-MIDAS model to be a *double* TV-GARCH (Time-Varying Multivariate

GARCH) type of model. Therefore, we need to explain two types of errors: ε_{it} for GARCH-MIDAS and $\mathbf{e}_{it}$ for the corrected DCC-GARCH-MIDAS.

The ε_t

As formula (5.1) state, the assumption of ε_t is defined by following the normal distribution with mean vector $\mathbf{0}_{3\times1}$ and the conditional variance $\mathbf{H}_t$; then we can state the covariance matrix $\mathbf{H}_t = [h_{ij,t}] = \mathbb{E}(\varepsilon_t\varepsilon_t^{'}|\Omega_{t-1})$. The $\mathbf{h}_t$ is the vector of conditional variance, $\mathbf{h}_t = [h_{i,t}], h_{i,t} \overset{def}{=} h_{ii,t}$, it follows the GARCH-MIDAS progress (see the next section 5.3.1.3). For the following analysis, our estimation progress is separated into two steps. For estimation of the first step, we denote the notation $\widetilde{\mathbf{H}}_t = diag[\mathbf{h}_t]$ to represent $\widetilde{\mathbf{H}}_t$ is the main diagonal element of matrix $\widetilde{\mathbf{H}}_t$, and the off-diagonal is zero. Therefore, the error term ε_{it} can be expressed as $\varepsilon_{it} = \widetilde{\mathbf{H}}_t^{1/2}\widetilde{\mathbf{e}}_t$; we can also rewrite $\varepsilon_{it} = \sqrt{h_{it}}\widetilde{e}_t$. Hence, the conditional correlation matrix of ε_{it} is given by:

$$\mathbf{R}_t = \widetilde{\mathbf{H}}_t^{-1/2}\mathbf{H}_t\widetilde{\mathbf{H}}_t^{-1/2} \tag{5.2}$$

where $\mathbf{R}_t$ is the conditional correlation matrix, which denote $\mathbf{R}_t = [\rho_{ij,t}]$. Additionally, we can notice that $\mathbf{H}_t = \widetilde{\mathbf{H}}_t^{-1/2}\mathbf{H}_t\widetilde{\mathbf{H}}_t^{-1/2}$; hence, we can note $|\mathbf{R}_t| \leq 1$.

The $\mathbf{e}_t$

Regarding to $\mathbf{e}_t$, this error is for the cDCC-MIDAS, it is also followed normal distribution with mean vector $\mathbf{0}_{3\times1}$ and conditional covariance matrix $\mathbf{Q}_t = [q_{ij,t}] = \mathbb{E}(\mathbf{e}_t\mathbf{e}_t^{'}|\Omega_{t-1})$. Hence, we can know that $\mathbf{e}_{it}|\Omega_{t-1} \sim i.i.d.\ N(\mathbf{0}_{3\times1}, \mathbf{Q}_t)$. In the second step of our estimation progress, we assume this $\mathbf{Q}_t$ follows the cDCC-MIDAS model. Therefore, we define $\mathbf{q}_t = [q_{ii,t}]$ and $\widetilde{\mathbf{Q}}_t = diag[\mathbf{q}_t]$; $\mathbf{q}_t$ is the vector with the conditional variances of $\mathbf{e}_t$, and $\widetilde{\mathbf{Q}}_t$ is the main diagonal elements from the matrix $\widetilde{\mathbf{Q}}_t$; meanwhile, the off-diagonal elements from matrix $\widetilde{\mathbf{Q}}_t$ are 0. Accordingly, the vector of *standardised* errors, $\widetilde{\mathbf{e}}_t = [\widetilde{e}_{it}]$, where $\widetilde{e}_{it} = e_{it}/\sqrt{q_{ii,t}}$ is given by $\widetilde{\mathbf{Q}}_t^{-1/2}\mathbf{e}_t$ and its conditional covariance matrix also denoted by $\mathbf{R}_t = [\rho_{ij,t}]$ where $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$. Therefore, our conditional correlation of the second error $\mathbf{e}_{it}$ is given by:

$$\mathbf{R}_t = \mathbb{E}(\widetilde{\mathbf{e}}_t\widetilde{\mathbf{e}}_t^{'}|\Omega_{t-1}) = \widetilde{\mathbf{Q}}_t^{-1/2}\widetilde{\mathbf{Q}}_t\widetilde{\mathbf{Q}}_t^{-1/2} \tag{5.3}$$

If we consider the assumption of ε_t and $\mathbf{e}_t$, we can notice that the vector of *standardised* error $\widetilde{\mathbf{e}}_t$ is equal to the vector of the *devolatilised* errors, $\widetilde{\mathbf{H}}_t^{-1/2}\varepsilon_{it}$. Hence, we have $\widetilde{\mathbf{e}}_t = \widetilde{\mathbf{H}}_t^{-1/2}\varepsilon_{it}$.

As previous stated, DCC-MIDAS needs to use two-steps estimation, so the $\mathbf{Q}_t$ follows cDCC-MIDAS model in the second step estimation. Then we can restructure from the formula (5.2) and (5.3), so the equation is as followed:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} = \frac{h_{ij,t}}{\sqrt{h_{it}}\sqrt{h_{jt}}}. \tag{5.4}$$

In the short conclusion, DCC-MIDAS model uses two-steps estimation. We can estimate the first errors ε_t and the conditional variances $\mathbf{h}_t$ via the GARCH-MIDAS model, both of them are vectors (Conrad & Loch 2015, Engle et al. 2013). On the second step, we can estimate the matrix of conditional covariances' *standardised* errors $\widetilde{e}_{it}$ and $\mathbf{Q}_{it}$ by using cDCC-MIDAS process. Therefore, the order of estimation is estimated $\mathbf{h}_t$ and $\mathbf{Q}_{it}$ at first, and then we can have estimated $\mathbf{R}_t$. The last two need to pay attention, it is the conditional correlations of error ($\mathbf{e}_t$ and ε_{it}) which obtain from the Eq. (4.4); and the second one is the estimated conditional covariances $\mathbf{H}_t$, which also can be calculated by second term in the Eq. (5.4) [25].

5.3.1.3 The Conditional Variances

Since we finished the introduction of conditional means and the errors, now we can turn to the conditional variances. As previous mentioned, GARCH-MIDAS progress needs to define two time scale. The first time scale is high-frequency (which it is daily data in this chapter), and it presents in section 5.3.1.1 which is t. The second time scale is the low-frequency (it is monthly in this chapter) which we define this one as τ. Hence, we can denote σ_i and $m_{i,\tau}$ to represent the short- and long-run variances for each asset i. In addition, the long-run component (MIDAS part) remain constant across the days of the month, quarter or half-year, $m_{i,\tau}$ is fixed held fixed (i.e. month, quarter, or biannual) for the number of days, we denote this number of days as $K_v^{(i)}$. We use the superscript i to indicate the specific asset, and subscript v is for the conditional variances; so, it differentiates the similar scheme from the conditional correlation.

[25] Comte & Lieberman (2003), Ling & McAleer (2003), McAleer et al. (2008) discuss the two-step estimator's asymptotic properties, but all of them only focused on fixed-parameter DCC models. Additionally, Wang & Ghysels (2015) discuss the maximum likelihood estimation for GARCH-MIDAS. However, the problem of DCC-MIDAS's two-step estimation method is still an open question Colacito et al. (2011).

The conditional variance $h_{i,t}$ [26] separates into two parts (short- and long-run). The formula of the conditional variances present as below:

$$h_{it} = m_{i\tau}\sigma_{it}, \text{for all } t = (\tau-1)K_v^{(i)} + 1, \dots, \tau K_v^{(i)}, \tag{5.5}$$

where σ_{it} is short-run component and $m_{i\tau}$ is the long-run component. Turning to the σ_{it}, it follows a GARCH (1,1) process:

$$\sigma_{i,t} = (1-\alpha_i-\beta_i) + \alpha_i\xi_{i,t-1}^2\sigma_{i,t-1} + \beta_i\sigma_{i,t-1} \tag{5.6}$$

Considering the conditional mean from Eq. (5.1), we can rewrite $\varepsilon_{it} = r_{it} - \mu_i$, so we can get $\varepsilon_{it}^2 = m_{i\tau}\sigma_{it}\xi_{it}^2$. In addition, based on the same concept, we will have $\xi_{i,t-1}^2\sigma_{i,t-1} = (r_{it}-\mu_i)^2/m_{i\tau}$. Since we finished the description of short-run component's model GARCH, then we can focus on the long-run (MIDAS) component $m_{i\tau}$, we mention that $m_{i,\tau}$ is a constant and also a weighted sum of $M_v^{(i)}$ of realised variances (RV) over a long horizon, so MIDAS part is showed as below:

$$m_{i,\tau} = m_i + \theta_i \sum_{l=1}^{M_v^{(i)}} \varphi_l(\omega_v^{(i)}) RV_{i,\tau-l} \tag{5.7}$$

we can clearly notice that m_i is the constant in the MIDAS part, and $\varphi_l(\omega_v^{(i)})$ is so call beta weight. In this chapter, we only consider one ω similar as previous chapter.[27], so our beta weight is defined as:

$$\varphi_l(\omega_v^{(i)}) = \frac{\left(1-\frac{l}{M_v^{(i)}}\right)^{\omega_v^{(i)}-1}}{\sum_{j=1}^{M_v^{(i)}}\left(1-\frac{j}{M_v^{(i)}}\right)^{\omega_v^{(j)}-1}}, \tag{5.8}$$

The last part of MIDAS is the realised variances are equal to the sum $K_v^{(i)}$ squared assets' returns:

$$RV_{i,\tau} = \sum_{t=(\tau-1)K_v^{(i)}+1}^{\tau K_v^{(i)}} r_{it}^2. \tag{5.9}$$

On one hand, based on the concept of GARCH-MIDAS, the m_i can be pre-determined, it can present as below:

$$\mathbb{E}_{t-1}[(r_{i,t}-\mu_i)^2] = m_{i,\tau}\mathbb{E}_{t-1}(\sigma_{i,t}) = m_{i,\tau} \tag{5.10}$$

[26]Notice that GARCH-MIDAS is two-components model, so we should use the notation $h_{it,\tau}$, but we drop the subscript τ for notational simplicity.

[27]According to Engle et al. (2013), they present two type of weighting schemes. We use the beta weight.

so, it point out the short-term (GARCH) can be $\mathbb{E}_{t-1}(\sigma_{i,t}) = 1$ in the starting point. On the other hand, $\omega_v^{(i)}$ in the Eq. (5.8),its size can determine the rate of decay in the beta weight, if $\omega_v^{(i)}$ is large value which will generate a rapidly decaying pattern; so if the $\omega_v^{(i)}$ is small value, it will be opposite situation.

Setting up $M_v^{(i)}$ and $K_v^{(i)}$ are the important problems for the conditional variance (GARCH-MIDAS process), they are the key to estimate MIDAS part. For K_v , if we want to compute the monthly realised volatility we can set $K_v = 22$; if we want to have the quarterly case, which it can be $K_v = 66$. For M_v, it will base on K_v, if K_v is the monthly realised volatility, then the selection of M_v will be 12,24,36,48,60; if we select K_v to be the quarterly case, the M_v will be 4,8,12,16.

Overall, the conditional variance is based on daily (squared) returns of each assets via a GARCH(1,1), and then the long-run component is using monthly (quarterly or biannual) realised volatilities to compute (see Eq. (5.8 - 5.9))[28].

Summarised for the number of parameters, we will have a parameter space as $\Theta = \{\mu_i, \alpha_i, \beta_i, m_i, \theta_i, \omega_v^{(i)}\}, i = 1, 2, 3$. Meanwhile, our parameters are fixed, so we can use different time span to compute the GARCH-MIDAS, then we compare the estimated parameters from different GARCH-MIDAS. Additionally, we follow the concept of Colacito et al. (2011), Engle et al. (2013) about GARCH-MIDAS, we use the log-likelihood function to estimate the conditional variance for short- and long-run. The next subsection will be the description of cDCC-MIDAS.

5.3.1.4 The Conditional Correlation

Before we are going to introduce cDCC-MIDAS model, we define two elements which is $\mathbf{\Omega}_c = [\omega_c^{(ij)}]$ and $\Phi_l(\mathbf{\Omega}_c) = [\varphi_l(\omega_c^{(ij)})]$; both of them are the matrices $N \times N$, $N = 3$ due to this chapter is trivariate cDCC-MIDAS progress.

Definition 5.1 *Let* $\mathbf{Z}_t = [z_{ij,t}] = \sum_{k=t-M_c}^{t} \widetilde{\mathbf{e}}_k \widetilde{\mathbf{e}}_k'$, *with* $M_c = \max_{ij} M_c^{(ij)}$, $\mathbf{z}_t = [z_{ii,t}]$ *and* $\widetilde{\mathbf{Z}}_t = diag[\mathbf{z}_t]$, *that is* $\widetilde{\mathbf{Z}}_t$ *is a diagonal matrix with i-th diagonal element* $\sum_{k=t-M_c}^{t} \widetilde{e}_{i,t}^2$.

[28]Base on Engle et al. (2013), they notice $m_{i,\tau}$ can be constant in the fixed period or be constant during the rolling window period, but the estimation results between both of them are very closed. Additionally, Colacito et al. (2011) stated the case of correlation can consider neither fixed span or rolling window. However, we consider the fixed span can offer much general results, we remain the fixed span in our formulas' setting instead of including rolling window notation.

Define $\mathbf{C}_t = [c_{ij,t}]$ *as:* $\mathbf{C}_t = \widetilde{\mathbf{Z}}_t^{-1/2}\mathbf{Z}_t\widetilde{\mathbf{Z}}_t^{-1/2}$.

Using the vector of the residuals, $\mathbf{e}_t$ (and not of the *standardised* residuals, $\widetilde{\mathbf{e}}_t$, that is we use the cDCC-MIDAS: the MIDAS version of the corrected DCC model of Aielli (2013)), it is possible to obtain a matrix $\mathbf{Q}_t = [q_{ij,t}]$ as follows:

$$\mathbf{Q}_t = (1-a-b)\overline{R}_t(\mathbf{\Omega}_r) + a\mathbf{e}_{t-1}\mathbf{e}'_{t-1} + b\mathbf{Q}_{t-1}, \tag{5.11}$$

where

$$\overline{R}_t(\mathbf{\Omega}_c) = \sum_{l=1}^{K_c} \Phi_l(\mathbf{\Omega}_c) \odot \mathbf{C}_{t-l}, \tag{5.12}$$

with $K_c = \max_{ij} K_c^{(ij)}$, and $\odot$ stands for the Hadamard product.[29] Meanwhile, if we write down the $ij-$th element of $\mathbf{Q}_t$ is given by:

$$q_{ij,t} = \overline{\rho}_{ij,\tau}(1-a-b) + ae_{i,t-1}e_{j,t-1} + bq_{ij,t-1}, \tag{5.13}$$

where the long-run competent (MIDAS with correlation) presents as below:

$$\overline{\rho}_{ij,\tau} = \sum_{l=1}^{K_c^{(ij)}} \varphi_l(\omega_c^{(ij)})c_{ij,\tau-l}. \tag{5.14}$$

In addition, $q_{ij,t}$ is the covariance (off-diagonal elements) in the correlation's matrix, so we can write the main diagonal elements of $q_{ii,t}$ is given by:

$$q_{ij,t} = (1-a-b) + ae_{i,t-1}^2 + bq_{ij,t-1}, \tag{5.15}$$

and, in view of the fact that in the cDCC-MIDAS $\mathbb{E}(e_{i,t}^2) = \mathbb{E}(q_{ij,t}) = q_{ii}$, it follows that q_{ii}=1.[30] In the Eq. (5.14), we need to set up the weights $\omega_c^{(ij)}$, lag lengths $M_c^{(ij)}$ and historical correlation's span lengths $K_c^{(ij)}$; based on these settings, we can differ across any pair of series. We use a single setting apply to all pairs of assets' combination, and our selection of these three elements are similar choice of MIDAS in the univariate

[29]Note that in the formulation for $\overline{R}_t(\mathbf{\Omega}_c)$ we could have used simple cross-products, that is $\mathbf{Z}_t$ instead of $\mathbf{C}_t$, but, as pointed out by Colacito et al. (2011), the normalisation allows us to have regularity conditions in terms of correlation matrices.

[30]Following Aielli (2013) one could employ a correction in the long-run correlations, $\overline{R}_t(\mathbf{\Omega}_r)$, by using the vector of the residuals, $\mathbf{e}_t$, that is using: $\mathbf{Z}_t = [z_{ij,t}] = \sum_{k=t-M_c}^{t} \mathbf{e}_k\mathbf{e}'_k$.

Note that in the DCC estimator the estimator of the long-run correlations is computed only once in the first step, whereas, with the cDCC estimator, it will be recomputed at each evaluation of the objective function of the second step (see Definition 3.4 in Aielli (2013)). We leave this for future work.

models (in this chapter, the univariate model is GARCH-MIDAS). As previous stated, ω_c is the common decay parameter which it is independent selection for the pair of assets. From Eq. (5.13), we can notice the covariance matrices are positive definite; it means the matrix $\mathbf{Q}_t = [q_{ij,t}]$ is a weighted average of three matrices. Additionally, the matrix $\mathbf{R}_t = [\rho_{ij,t}]$ needs to remain semi-positive based on the assumption; another element needs to be positive semi-definite is the matrix $\boldsymbol{e}_t\boldsymbol{e}_t^{'}$ where the $\boldsymbol{e}_t = [e_{it}]$. Hence, the initial value $\mathbf{Q}_0$ defines to be a semi-positive matrix, then the $\mathbf{Q}_t$ must be the same as $\mathbf{Q}_0$ which is the semi-positive matrix at each time t (see Colacito et al. (2011) for the implication of a single parameter selection verse the multiple parameter for DCC-MIDAS).

In Eq. (5.4), we can notice the estimated long-run correlation can based on short-run correlation between asset i and j. Hence, we can relocate the Eq. (5.13) which shows as below:

$$q_{ij,t} - \overline{\rho}_{ij,\tau} = a(e_{i,t-1}e_{j,t-1} - \overline{\rho}_{ij,\tau}) + b(q_{ij,t-1} - \overline{\rho}_{ij,\tau}) \tag{5.16}$$

we can notice from this equation, short-run (daily) correlation and covariance are base on DCC scheme, and includes the slowly moving long-run correlation. According to Colacito et al. (2011), they wrote down : "short-lived effects on correlations will be captured by the autoregressive dynamic structure of DCC, with the intercept of the latter being a slowly moving process that reflects the fundamental or secular causes of a time variation in correlation". Before we head into the estimation method in this chapter, we need to collect the cDCC-MIDAS's parameter space which is $\Xi = \{a, b, \omega_c^{ij}\}$.

5.3.1.5 The Estimation method

As previous section stated, our estimation method for cDCC-MIDAS still remain two-steps progress from Engle (2002); it means our parameters are separated into two parts to estimate, so first step estimate the GARCH-MIDAS parameters (Θ) and second step estimate the cDCC-MIDAS (Ξ). Hence, the quasi- likelihood function QL can be:

$$\begin{aligned} QL(\Theta, \Xi) &= QL_1(\Theta) + QL_2(\Xi) \\ &\equiv -\sum_{t=1}^{T}(nlog(2\pi) + 2log|\widetilde{\mathbf{H}}_t| + \mathbf{r}_t^{'}\widetilde{\mathbf{H}}_t\mathbf{r}_t) - \sum_{t=1}^{T}(log|\mathbf{R}_t| + \widetilde{\mathbf{e}}_t^{'}\mathbf{R}_t^{-1}\widetilde{\mathbf{e}}_t + \widetilde{\mathbf{e}}_t^{'}\widetilde{\mathbf{e}}_t) \end{aligned} \tag{5.17}$$

5.3.2 Correlation analysis and macro correlation regression

Once we have the estimation correlations (short- and long-run) from the cDCC-MIDAS model, we can progress to our next analysis. In this section, we will introduce two parts for the correlation analysis. Firstly, we will use the mean difference tests for the estimation correlation to test our hypotheses. Secondly, we will apply the regression analysis to examine the fundamental macro of how to influence the correlation performance during our sample period and the crisis period.

5.3.2.1 Correlation analysis

The purpose of correlation analysis is to find the cross-assets hedging properties and interdependence (our hypothesis *H1 - H5*) during the crisis period. Based on the cDCC-MIDAS specification, we can have two frequency correlations at the same time which allows us to compare both of their performance during the crisis period. Hence, we denote the short- and long-run cross-asset pairwise correlation for each pair, ij: the short-run (daily) and the long-run (monthly) correlation time series extracted are denoted as $\rho_{ij,t}$ and $\overline{\rho}_{ij,t}$, respectively.[31] In the correlation analysis, we first examine the cross-assets time series graphs; the graphs will provide the cyclical variation of cross-assets pairs to define their hedging properties which are contagion(countercyclical) or flight-to-quality(procyclical). The time series graphs only offer common characteristics, so our second step uses the mean different test to confirm cross-assets hedging properties and interdependence in our sample period and the real crisis period (GFC, ESDC, COV). The mean difference tests will be the Satterthwaite-Welch t-test and the Welch F-test. Hence, we can compare the in-crisis mean with the pre-crisis mean and then the difference test will provide the correlation mean change (decrease or increase) from the pre-crisis level to the in-crisis level which is statistically significant. The case of contagion is the significant increase in association with a positive in-crisis level; if the cross-assets correlation is flight-to-quality, the correlation is a significant decrease in association with a negative in-crisis level. Meanwhile, the safe haven property will be based on the in-crisis correlation mean, while the whole sample means will bring the conclusion to the hedges or diversifiers.

[31] The correlation analysis separates the short- and long-run correlation, so t only represents the time for each correlation regression. In other words, $\rho_{ij,t}$'s t means daily;$\overline{\rho}_{ij,t}$'s t means monthly.

5.3.2.2 Macro correlation regression

Once we determine the hedging properties and interdependence, our interest will focus on how the macro factors influence the short- and long-run correlations, so the estimation correlations will be the dependent variables and the macroeconomic factors will be the independent variables. Before we introduce our macro correlation regression, we need to apply the Fisher Z transformation of the correlation; because our estimation correlation is bounded by $[-1, 1]$. The fisher Z transformation allows the correlations to overcome this problem, so our transformation of daily and monthly correlation will be: $\rho_{SR,t} = log(\frac{1+q_{ij,t}}{1-q_{ij,t}})$ and $\rho_{LR,t} = log(\frac{1+\overline{\rho}_{ij,t}}{1-\overline{\rho}_{ij,t}})$.[32] The following up step is to discover the results from the macro correlation regression, to confirm the explanatory variables' effect on the correlations, then we can confirm our Hypothesis (*H6* and *H7*) in this part. Our expectation is that if the macro regressors higher (lower) correlation under economic deterioration with the cast of contagion (flight-to-quality). The short- and long-run regressors are not the same due to the data availability (see the next subsection 5.4.2 Data description). All of the regressors (short- and long-run) are in their first lag and the macro regressions for each correlation time series are selected according to the parameters' significance, the information criteria (AIC: Akaike and BIC: Schwartz Information Criteria), and the goodness of fit (adjusted $R^2[\overline{R}^2]$).

Turning to introduce our daily (short-run) correlation regression, it will be estimated with the following independent variables: economic policy uncertainty ($EPU_{SR,t}$), financial uncertainty ($FU_{SR,t}$), infectious disease news impact on financial volatility ($ID_{SR,t}$), financial stress ($FS_{SR,t}$), news sentiment ($NS_{SR,t}$), economic activity ($EC_{SR,t}$), freights ($FR_{SR,t}$), and foreign exchange rates ($FX_{SR,t}$). Hence, we can write down the short-run correlation regression is as followed:

$$\begin{aligned}\rho_{SR,t} = \;& \zeta_0 + \zeta_1\rho_{SR,t-1} + \zeta_2 EPU_{SR,t-1} + \zeta_3 FU_{SR,t-1} + \zeta_4 ID_{SR,t-1} + \zeta_5 FS_{SR,t-1} \\ & +\zeta_6 NS_{SR,t-1} + \zeta_7 EC_{SR,t-1} + \zeta_8 FR_{SR,t-1} + \zeta_9 FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{5.18}$$

with the short-run correlation is the dependent variables. ζ_0 is the constant term, and $u_{SR,t}$ is the error term of this macro short-run correlation regressions.

Then our long-run macro long-run correlation regression is using following as: economic policy uncertainty ($EPU_{LR,t}$), financial stress ($FS_{LR,t}$), sentiment / confidence

[32]In the regression analysis, we drop down the subscript ij to simplify the notations.

($SENT_{LR,t}$), economic activity ($EC_{LR,t}$), inflation ($INFL_{LR,t}$), and freights ($FR_{LR,t}$). To sum up the long-run correlations' regressions are presenting as below:

$$\begin{aligned}\rho_{LR,t} &= \delta_0 + \delta_1 \rho_{LR,t-1} + \delta_2 EPU_{LR,t-1} + \delta_3 FS_{LR,t-1} + \delta_4 SENT_{LR,t-1} \\ &\quad + \delta_5 EC_{LR,t-1} + \delta_6 INFL_{LR,t-1} + \delta_7 FR_{LR,t-1} + u_{LR,t}\end{aligned} \tag{5.19}$$

with the long-run correlation is the dependent variables. δ_0 is the constant term, and $u_{LR,t}$ is the error term of this macro long-run correlation regressions. From these two regressions, we can define how the macro factors influence the correlations under the weak economic conditions.

After identifying the correlation determinants, we progress the next step of macro sensitivity analysis which investigate the uncertainty channel impact on the short-run correlation. Similar from the previous chapter, our expect the uncertainty channel will have significant impact on the correlation such as higher EPU expands the macroeconomic factors on the correlation. Therefore, we consider the interaction term EPU multiple with each maco regressors, this will indicate the indirect EPU effect on the macro regressors. Now, our new regression include the interaction term EPU will present as :

$$\begin{aligned}\rho_{SR,t} &= \zeta_0 + \zeta_1 \rho_{SR,t-1} + \zeta_2 EPU_{SR,t-1} + (\zeta_3 + \zeta_3^{EPU} EPU_{SR,t-1}) FU_{SR,t-1} \\ &\quad + (\zeta_4 + \zeta_4^{EPU} EPU_{SR,t-1}) ID_{SR,t-1} + (\zeta_5 + \zeta_5^{EPU} EPU_{SR,t-1}) FS_{SR,t-1} \\ &\quad + (\zeta_6 + \zeta_6^{EPU} EPU_{SR,t-1}) NS_{SR,t-1} + (\zeta_7 + \zeta_7^{EPU} EPU_{SR,t-1}) EC_{SR,t-1} \\ &\quad + (\zeta_8 + \zeta_8^{EPU} EPU_{SR,t-1}) FR_{SR,t-1} + (\zeta_9 + \zeta_9^{EPU} EPU_{SR,t-1}) FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{5.20}$$

where the coefficients of the interaction terms are denoted with the superscript ^{EPU}, with the similar structure as previous regression (5.18), ζ_0 remains constant term and $u_{SR,t}$ remains the error term in this short-run macro regression. The last part of the macro sensitivity analysis with the correlations' crisis vulnerability; we consider the crisis impact on the correlation regression. Therefore, we define the three crisis dummies are denoted by $D_{C,t}$ where $C = GFC, ESDC, COV$; it means $D_{C,t}$ during the crisis period will be 1 and the non-crisis period will be 0. The slope dummies are calculated by the crisis dummy multiplication with each macro regressor. Hence, we rewrite our regression

(5.18) as followed:

$$\begin{aligned}\rho_{SR,t} &= \zeta_0 + \zeta_0^C D_{C,t} + \zeta_1 \rho_{SR,t-1} + (\zeta_2 + \zeta_2^C D_{C,t-1}) EPU_{SR,t-1} + (\zeta_3 + \zeta_3^C D_{C,t-1}) FU_{SR,t-1} \\ &+ (\zeta_4 + \zeta_4^C D_{C,t-1}) ID_{SR,t-1} + (\zeta_5 + \zeta_5^C D_{C,t-1}) FS_{SR,t-1} + (\zeta_6 + \zeta_6^C D_{C,t-1}) NS_{SR,t-1} \\ &+ (\zeta_7 + \zeta_7^C D_{C,t-1}) EC_{SR,t-1} + (\zeta_8 + \zeta_8^C D_{C,t-1}) FR_{SR,t-1} + (\zeta_9 + \zeta_9^C D_{C,t-1}) FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{5.21}$$

where the crisis coefficients are denoted by the superscript ^{C}.

The last part of the macro regression analysis, we want to investigate the indirect EPU effect on the correlation during the crisis period; so we use the similar approach with Eq. (5.20) which multiples the EPU interaction terms and the crisis dummies together. The regression is:

$$\begin{aligned}\rho_{SR,t} &= \zeta_0 + \zeta_1 \rho_{SR,t-1} + \zeta_2 EPU_{SR,t-1} \\ &+ (\zeta_3 + \zeta_3^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FU_{SR,t-1} \\ &+ (\zeta_4 + \zeta_4^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) ID_{SR,t-1} \\ &+ (\zeta_5 + \zeta_5^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FS_{SR,t-1} \\ &+ (\zeta_6 + \zeta_6^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) NS_{SR,t-1} \\ &+ + (\zeta_7 + \zeta_7^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) EC_{SR,t-1} \\ &+ (\zeta_8 + \zeta_8^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FR_{SR,t-1} \\ &+ + (\zeta_9 + \zeta_9^{EPU\_C} D_{C,t-1} EPU_{SR,t-1}) FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{5.22}$$

where we define the superscript $^{EPU\_C}$ to the EPU under crisis coefficients. In our hypotheses (H6 and H7), they explain the macro sensitivity tests for the markets' interdependence, so our expectation for three parts in the macroeconomic correlation regressions. Firstly, the crisis shock magnifies (the absolute terms of crisis coefficients increase) the correlation level change (crisis intercept dummies' variables). Secondly, we believe the crisis shock enhances the macro effect on the correlations (crisis slope dummies). Thirdly, the indirect EPU effect influences the cross-assets correlation in the macroeconomic regression(crisis slope dummies multiple EPU interactions).

5.3.3 Data Description

In this section, we are going to explain the assets and macroeconomic data for this chapter after we introduced our methodology (we report a table for the variables' definitions and sources in the Appendix's Table E.1). Based on our models' specification, we have two types of data; so our daily data is from 18/01/2005 to 27/07/2020, with a total of 4050 observations (daily assets' returns and daily macroeconomic variables). The monthly data (monthly realised volatility and monthly macroeconomic variables) are from 01/2005 to 07/2020, this data is 180 monthly observations. In this chapter, we are going to apply the three global benchmark indexes and also the disaggregate commodities.

The table E.2 reports our eight asset's return in this chapter; we explain the detail about the benchmark index in the last chapter, so here we focus on the disaggregate commodities (five sub-index responding to each category): Energy Commodities (NRG), Precious Metals (PRM),Industrial Metals (INM),Agriculture (AGR), and Livestock (LIV).

The asset variables are included in the cDCC-MIDAS in their return form. Daily asset returns $r_{i,t}$ are calculated on each asset index as follow: $r_{i,t} = [\ln(P_{i,t}^{Close}) - \ln(P_{i,t-1}^{Close})] \times 100$, where $P_{i,t}^{Close}$ the daily closing price on day t. Additionally, we examine the unit root test for each asset return before the cDCC-MIDAS progress, and we discover all of them reject the null hypothesis which is not unit root in these series [33]. The descriptive statistics and the pairwise correlation are presented in table (E.2). From this table, we can notice the NRG, AGR and LIV are negative means in our sample period. Especially, the energy price returns the lowest negative mean (-0.0375) compare with the other assets, and it's always the most volatile among all assets. Although the mean of livestock return is negative, it has the lowest volatility (the standard deviation is 0.9552).

Table E.2 (Panel B) of the appendix presents the cross-asset pairwise correlation coefficients between 23 pairs. The highest correlation pair is still EQU-RE (0.656), but the pair RE-PRM is the lowest correlation (0.035) among all the pairs. We observe Equities-commodities are more connected than the real estate-commodities pairs (0.445 > 0.21). In addition, the intra-commodity pairs are all below 0.5; we notice the pair PRM-LIV is the lowest correlation (0.045), and the pair NRG-INM is the highest correlation (0.368) among the intra-commodities pairs. Overall, we do not detect any negative correlation between all the pairs during our sample period; but only a few cases such as RE-PRM and PRM-LIV are very close to 0.

[33] We consider various tests about unit root, including the Augmented Dickey–Fuller test, Phillips-Perron test, etc. Then we figure out all of them are having the same conclusion, so only perform the ADF test.

Now, we turn to describe our macro fundamentals (high and low frequency); the purpose of studying the macroeconomic factors on the correlations is to examine how significant impact of economic effects on the global asset markets' performance and their connectedness. We are based on our hypotheses' summary table (5.2.2), we are separated into five sectors: 1. investors' sentiment (EPU, FU, ID, SENT); 2. news(NS); 3. credit conditions (FS); 4. economic activity (EC); 5. prices (INFL, FR, FX). Meanwhile, our short- and long-run macro correlation regressions are not using the same data sets, due to the data availability (see Eq. (5.18) and (5.19)). Hence, the following indices are presenting as below:

EPU (daily and monthly): daily and monthly data of economic policy uncertainty is from Baker et al. (2016).

FU (daily): financial uncertainty is the daily S&P500 implied volatility index.

ID (daily): the infectious disease news effect on financial uncertainty is from Baker et al. (2020) which only has the daily data.

FS (daily and monthly): daily financial stress index is from OFR Financial Stress Index, and monthly financial stress index is using monthly Kansas City Financial Stress Index ($KCFSI_t$).

SENT (monthly): the investors' confidence sentiment (SENT) is the monthly data which is G7 Business Confidence Index growth ($gBCI_t$).

NS (daily): the News sentiment is the daily data which is based on San Francisco Fed which they called this index is the daily US News Sentiment Index (NSI_t). This index is created by Shapiro et al. (2020) and Buckman et al. (2020).

EC (daily and monthly): economic activity has low- and high-frequency data. The daily economic activity is from US yield curve slope which is based on the different 10 years minus 3-month US treasury yields, which we call it as $YCsl_t$. The monthly economic activity is monthly G7 Industrial Production growth(gIP_t).

INFL (monthly): The the global inflation effect is the monthly data which is monthly G7 Producer Price Index Growth ($gPPI_t$).

FR (daily and monthly): daily freight rate is daily Baltic Dry Index, and monthly freight rate is monthly Cass Freight Index.

FX (daily): the foreign exchange rate is using the daily DXY index growth ($gDXY_t$).

These are the descriptions of macroeconomic variables that will use in our macroeconomic sensitivity investigation. Before we continue to our following analysis, we need to confirm the data is suitable to apply to the short- and long-run macro correlation's regressions. Therefore, all the macro regressors confirm there are no multicollinearity and unit root problems among these variables, and they best fit into the correlation regressions; because we use the Variance Inflation Factors for testing the multicollinearity problem, and the Augmented Dickey-Fuller tests for the unit root problem. Both of them reject the null hypothesis. Meanwhile, we report the summary statistics of these variables in the last chapter (see also the Appendix table E.2). Moreover, our hypothesis reports our expectation of the macroeconomic variables (see also the summary table 5.2.2).

The last part of this section is about our sub-sample crisis timeline, the aim of the crisis sub-sample period to define cross-assets hedging properties and their interdependences. In addition, our crisis sub-sample period will base on the real crisis timeline. GFC is based on International Settlements (BIS) and the Federal Reserve Bank of St. Louis timelines. ESDC is based on the European Central Bank ESDC timeline; the last one crisis is from World Health Organisation (WHO) COV pandemic chronology. The three crisis sub-sample presents below:

1. GFC subsample: 9/8/07 - 31/3/09

2. ESDC subsample: 9/5/10 - 31/12/12.

3. COV subsample: 11/3/20 - 27/7/20.

The real crisis date will allow us to study the full picture of crisis shock on the cross-assets correlation. Based on the real crisis date, we are expecting the cross-assets co-movement effect magnifies such as the case of contagion becoming a higher correlation and the case of flight-to-quality on the lower correlations. Moreover, we expect the commodities indexes to be more volatile during the crisis periods.

5.4 Empirical analysis of correlation dynamics

In this section, we separate into two parts; firstly, we focus on the cDCC-MIDAS estimation results; secondly, we will base our on estimation correlations from cDCC-MIDAS to confirm our hypothesis.

5.4.1 cDCC-MIDAS analysis

We first explain the variance equation in table 5.3, then we move to our results of cDCC-MIDAS in table 5.4 which includes our night trivariate models. Compared with different lags in the cDCC-MIDAS model, we use AIC and BIC to compare the best lag for our model; in the end, we select lag 48 for the variance equation and lag 48 for the correlation equation in this chapter.

Table 5.3: Variance equation (GARCH-MIDAS)

	EQU	RE	NRG	PRM	INM	AGR	LIV
μ_i	0.0622***	0.0577***	0.0126	0.0296*	0.0128	-0.0221	-0.0125
	(0.0103)	(0.0146)	(0.0247)	(0.0154)	(0.0179)	(0.0163)	(0.0134)
α_i	0.1417***	0.1242***	0.069***	0.0466***	0.0525***	0.053***	0.0551***
	(0.0094)	(0.0073)	(0.0034)	(0.0026)	(0.0058)	(0.0051)	(0.0073)
β_i	0.8187***	0.8619***	0.9241***	0.9398***	0.922***	0.9364***	0.909***
	(0.0120)	(0.0082)	(0.0041)	(0.0040)	(0.0105)	(0.0062)	(0.0166)
θ_i	0.1703***	0.0996***	0.1027*	0.1696***	0.1833***	0.1749***	0.1866***
	(0.0122)	(0.0262)	(0.0555)	(0.0161)	(0.0115)	(0.0262)	(0.0189)
ω_v^i	6.3906***	3.6994	1.001***	1.001***	3.4415***	1.0557**	6.4361**
	(1.3439)	(2.6989)	(0.2684)	(0.0749)	(1.2688)	(0.4108)	(3.2203)
m_i	0.5472***	1.2705***	1.9665***	0.6848***	0.5568***	0.7275***	0.4525***
	(0.0505)	(0.1705)	(0.3459)	(0.1151)	(0.1192)	(0.1797)	(0.1269)
logL	-4720.40	-6443.62	-8029.00	-6085.85	-6685.83	-6317.16	-5243.70
AIC	9452.80	12899.24	16070.00	12183.70	13383.65	12646.33	10499.41
BIC	9492.03	12938.47	16109.23	12222.93	13422.88	12685.55	10538.64

Notes:

The table reports the GARCH-cDCC-MIDAS results of the ten trivariate cross-asset combinations. The number of MIDAS lags is 48 for variance equation. The estimation of the variance equation for each asset series is the same for all trivariate models where the series is included (Panel A). Numbers in parentheses are standard errors ***, ** , * denote significance at the 0.01,0.05, 0.10. level, respectively. $logL$ denote the log likelihood, AIC represents Akaike information criteria, and BIC is Schwarz information criterion.

Table 5.3 reports the parameters of eight variance equations. Most of the parameters are significant, but the conditional means from GARCH-MIDAS are not significant in most of the commodities' assets excluding the PRM. In addition, the arch (α_i) and garch (β_i) are significant in the short-run variance dynamics in all the cases, and with a sum lower than the unity $\alpha_i + \beta_i < 1$. This setting allows the short-run component to be mean-reverting to the long-run trajectory (Conrad et al. 2014). EQU and RE are less volatile than the other commodities' assets whose β_i are 0.8187 and 0.8619; the commodities' assets β_i is more than 0.9. Turning to the long-run components' analysis, we notice most of the MIDAS parameters are highly significant during our sample period. However, RE has the insignificant ω_v^i which is 3.6994. We are using the realised volatility as our long-run components which cause all of θ to be around 0.0966 up to 0.1866. Additionally, our smoothing weights ω_v^i are varying considerably between 1.001 and 6.4361; but the intercepts m_i of MIDAS components are similar across our assets (between 0.4525 and 1.9665).

Table 5.4: Correlation equation (cDCC-MIDAS)

	a	b	ω_c^{ij}	logL	AIC	BIC
EQU-RE-NRG	0.0325***	0.9481***	4.0318***	-15915.547	31837.0938	31856.7084
	(0.0028)	(0.0062)	(0.9449)			
EQU-RE-PRM	0.0381***	0.9344***	1.9895***	-16160.761	32327.5215	32347.136
	(0.0029)	(0.0068)	(0.5139)			
EQU-RE-INM	0.03***	0.9491***	3.5806***	-15834.449	31674.8986	31694.5131
	(0.0030)	(0.0072)	(0.9749)			
EQU-RE-AGR	0.0284***	0.9447***	2.5484***	-16179.071	32364.1429	32383.7574
	(0.0032)	(0.0086)	(0.7143)			
EQU-RE-LIV	0.0237***	0.9522***	1.869***	-16255.646	32517.2922	32536.9067
	(0.0024)	(0.0081)	(0.5957)			
NRG-PRM-INM	0.027***	0.939***	3.5009***	-16544.207	33094.4142	33114.0287
	(0.0028)	(0.0092)	(0.6345)			
NRG-AGR-LIV	0.0089***	0.9867***	2.2551*	-16982.62	33971.2398	33990.8543
	(0.0015)	(0.0043)	(1.2470)			
PRM-AGR-LIV	0.0162***	0.9359***	3.1362***	-17093.231	34192.4624	34212.0769
	(0.0039)	(0.0246)	(0.8177)			
INM-AGR-LIV	0.0088***	0.9813***	3.3497**	-17009.785	34025.5698	34045.1843
	(0.0020)	(0.0102)	(1.3690)			

Notes:

The table reports the GARCH-cDCC-MIDAS results of the ten trivariate cross-asset combinations.

The number of MIDAS lags is 48 for variance equation, and the number of MIDAS lags is 48 for correlation equation.

The correlation equation is estimated for ten trivariate combinations (Panel B) and computes three pairwise dynamic correlation series for each trivariate system. Numbers in parentheses are standard errors . ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. $logL$ denote the log likelihood, AIC represents Akaike information criteria, and BIC is Schwarz information criterion.

Table 5.4 presents the coefficient of parameters in our cDCD-MIDAS model. The short-run correlation dynamics are determined by the a and b; all of them are highly significant in this table. Moreover, the sum of a and b are always lower than unity, denoting the short-term correlation mean-reversion to the long-term correlation trend. Turning to the long-run correlation component, all of ω_c^{ij} are significant in this table but we notice the pair of EQU-RE- PRM and EQU-RE-LIV have the lowest figure in the long-run components. It means these two pairs are more related to the short-run correlation rather than the long-run correlation. The next part is going to discuss the estimation of short- and long-run correlations from the cDCC-MIDAS model.

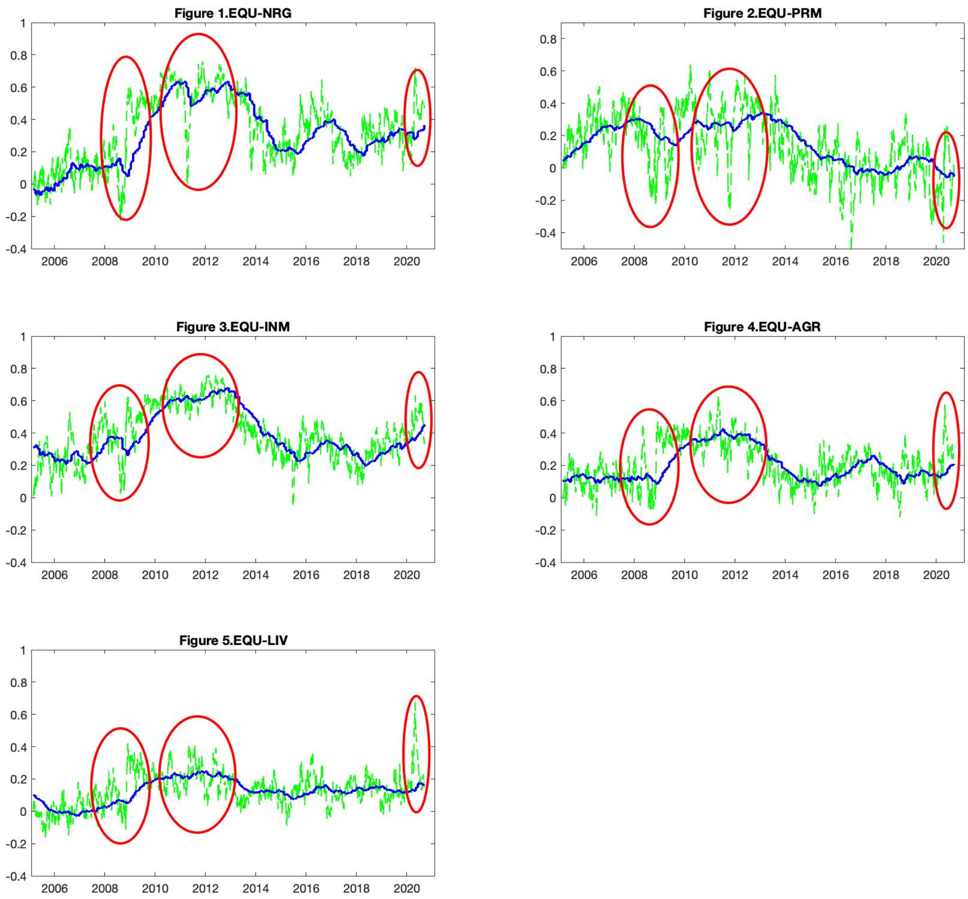
5.4.2 Estimated Short- and Long-run Correlation

In this section, we are going to analyse our estimated correlation from the cDCC-MIDAS model, and we further determine the hedging properties of cross-assets based on our hypotheses. Due to we have twenty unique asset pairs (for each pair one daily and one monthly correlation is extracted), we classified them into the three following groups:

1. equities with commodities (five pairs)
2. real estate with commodities (five pairs)
3. intra-commodities (ten pairs)

Meanwhile, the correlation graphs (figure 5.1 - 5.3) present a cyclical variation of the cross-asset nexus; we mainly notice two different types of interdependence dynamic. Based on the graphs, we mainly notice two different types of interdependence dynamics. The equities and most commodities are countercyclical correlations, which means these cross-assets correlations move in opposite directions during the crisis periods. In addition, the pairs of precious metals are the procyclical correlation which follows the business cycle. Overall, figure 5.1 - 5.3 shows that if the pairs are the countercyclical correlation, it means the crisis period brings the cross-assets correlation increase. Equivalently, if the pairs are procyclical correlations, these pairs' correlation reduces during the crisis period. Our correlation graphs show the cyclical property of each correlation series can differ across time and the type of crisis influence cross-assets correlation. For example, most of the pairs from the second group are countercyclical correlation during the COV period, the correlation increase significantly from the graphs; but these pairs' correlation fall in the GFC.

Figure 5.1: Cross-asset Short- and Long-run Dynamic Correlations (first group: Equities - intra-commodities)

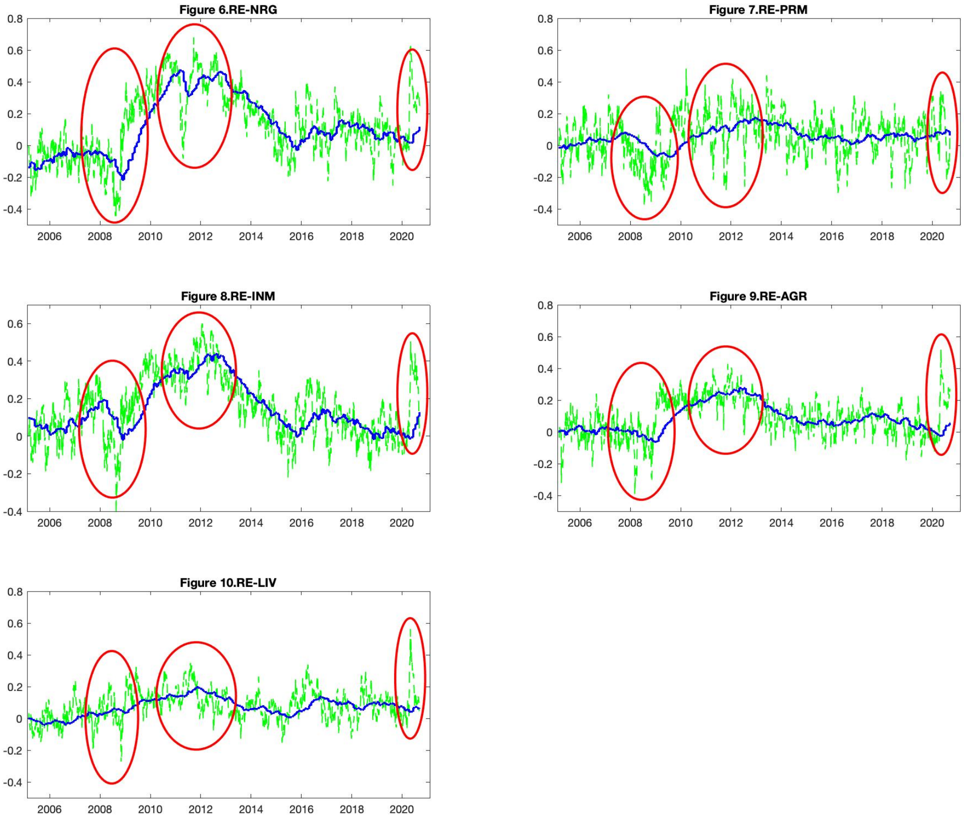


Note:

short-run correlation: dotted green line, long-run correlation: blue solid line, crisis periods: red circled

Now, we focus on the pair of equities and intra-commodities. The pair of EQU and NRG are procyclical correlations in the GFC and ESDC, but this pair is the typical example to show the cyclical property change in different periods. The EQU-PRM, EQU-INM and EQU-AGR are similar patterns in the GFC and ESDC, but only the EQU-PRM correlation reduces in the COV. However, the EQU-LIV are more stable than the other pairs. Compared with the short-run correlations and long-run correlations, the short-run correlation EQU-PRM is more volatile than the long-run correlation. Especially, all the pairs' short-run correlations have a significant increase during the COV period.

Figure 5.2: Cross-asset Short- and Long-run Dynamic Correlations (second group: Real estate - intra-commodities)

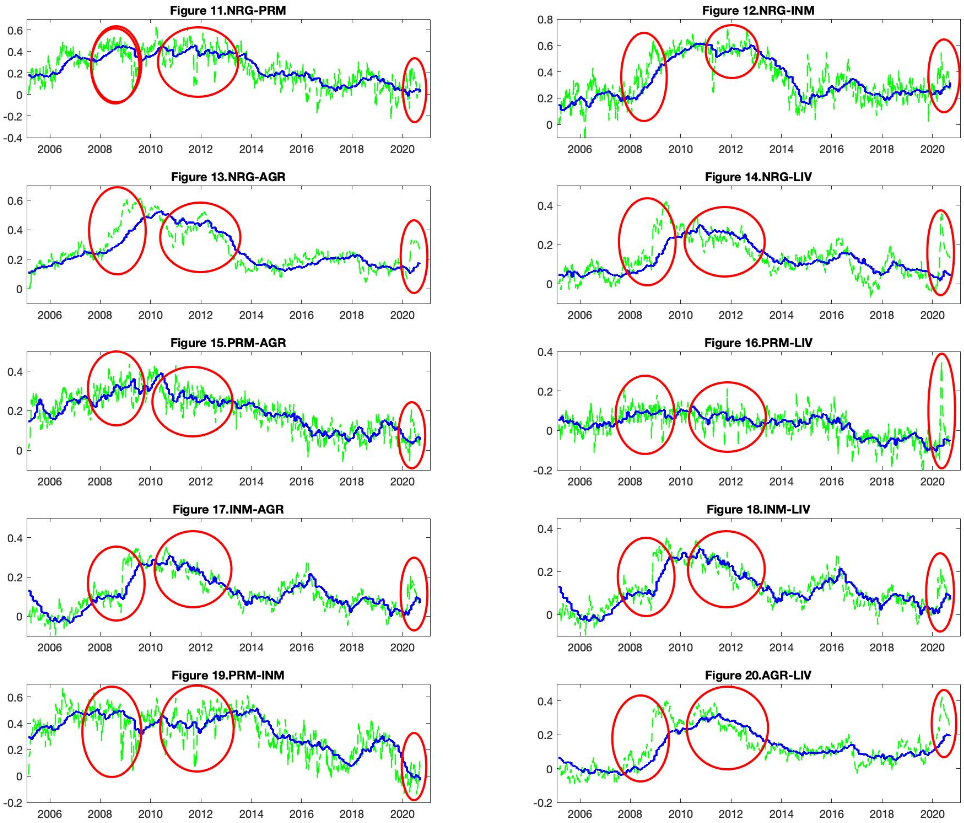


Note:

short-run correlation: dotted green line, long-run correlation: blue solid line, crisis periods: red circled

Figure 5.2 is the second group which is the pairs of real estate and intra-commodities correlations. The special case is the pair of RE-LIV is the most stable compared to other pairs in this group during our sample period, excluding the COV period. Meanwhile, the short-run correlation of EQU-PRM is the most volatile among all the pairs in this group. Similar to the correlations from the first groups' cross-assets, all of them have a significant increase in the COV period, and the short-run correlation is also more volatile than the long-run correlation among all the pairs in the second group.

Figure 5.3: Cross-asset Short- and Long-run Dynamic Correlations (third group: intra-commodities)



Note:

short-run correlation: dotted green line, long-run correlation: blue solid line, crisis periods: red circled

Figure 5.3 is the intra-commodities pairs' correlations. The combination of energy commodities and other commodities are sharing the same pattern during the GFC and COV period, but the pairs of NRG-PRM and NRG-INM slightly increase during the ESDC. On the opposite, the rest of the energy commodities' combinations with the other two commodities are the procyclical correlation in the ESDC period. In addition, most of the intra-commodities combinations' correlation present a significant increase in the COV period, but only the pair of PRM-INM correlations reduce in this period.

Overall, we can conclude the short-run correlation is more volatile compared to the long-run correlation; additionally, we confirm the cyclical property will change based on different time-line. Then the next part, we will combine the summary statistics of short-and long-run correlations and the graphs to conclude our pairs' hedging properties.

Table 5.5: Summary statistics of short- and long-run cross-asset dynamic correlations.

	Short-run correlations statistics					Long-run correlations statistics				
	Mean	Median	Max	Min	Std.Dev.	Mean	Median	Max	Min	Std.Dev.
EQU-NRG	0.2985	0.3003	0.7350	−0.2131	0.2113	0.2824	0.2831	0.6136	−0.0434	0.1904
EQU-PRM	0.1471	0.1485	0.6594	−0.5427	0.1904	0.1488	0.1710	0.3417	−0.1496	0.1315
EQU-INM	0.3848	0.3616	0.7424	0.0306	0.1465	0.3758	0.3015	0.6573	0.2488	0.1312
EQU-AGR	0.1961	0.1733	0.6182	−0.0839	0.1205	0.1911	0.1396	0.4355	0.0531	0.1018
EQU-LIV	0.1260	0.1269	0.5445	−0.1491	0.0959	0.1210	0.1229	0.2668	−0.0355	0.0718
RE-NRG	0.1148	0.0945	0.6400	−0.4110	0.2153	0.1073	0.0754	0.5018	−0.2342	0.1849
RE-PRM	0.0615	0.0650	0.3751	−0.2742	0.0994	0.0546	0.0548	0.2016	−0.0832	0.0610
RE-INM	0.1490	0.1394	0.5591	−0.3578	0.1409	0.1490	0.1040	0.4181	0.0040	0.1115
RE-AGR	0.0804	0.0718	0.3974	−0.3265	0.1086	0.0773	0.0509	0.2728	−0.0561	0.0854
RE-LIV	0.0726	0.0710	0.3803	−0.1966	0.0848	0.0700	0.0666	0.2052	−0.0409	0.0560
NRG-PRM	0.2441	0.2320	0.6242	−0.2740	0.1585	0.2466	0.2080	0.4575	−0.0207	0.1308
NRG-INM	0.3232	0.2898	0.7154	−0.0774	0.1525	0.3142	0.2559	0.5914	0.0680	0.1525
NRG-AGR	0.2596	0.2253	0.6376	−0.0033	0.1297	0.2515	0.2183	0.6116	0.0588	0.1426
NRG-LIV	0.1224	0.0990	0.3720	−0.0723	0.0925	0.1207	0.0894	0.3546	−0.0285	0.0923
PRM-AGR	0.1935	0.2017	0.4157	−0.0234	0.0905	0.1939	0.1997	0.3860	0.0437	0.0882
PRM-LIV	0.0272	0.0355	0.1880	−0.1567	0.0581	0.0277	0.0368	0.1060	−0.0908	0.0489
INM-AGR	0.2316	0.1946	0.4787	0.0262	0.1189	0.2270	0.1791	0.4698	0.0786	0.1152
INM-LIV	0.1158	0.1020	0.3191	−0.0755	0.0829	0.1165	0.1102	0.2794	−0.0026	0.0733
PRM-INM	0.3257	0.3307	0.6074	−0.1163	0.1514	0.3261	0.3798	0.4806	0.0501	0.1262
AGR-LIV	0.1148	0.0940	0.3857	−0.1113	0.1017	0.1127	0.0865	0.3326	−0.0466	0.0997

Notes:

The table reports the summary statistics of the short- and long-run cross-asset dynamic correlation series computed by the trivariate cDCC-MIDAS models: Mean, Median, Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.). The asset series notation is as follows: Equities (EQU), Real estate (RE), Commodities (COM), Energy (NRG), Precious metals (PRM), Industrial metals (INM), Agriculture (AGR), and Livestock (LIV).

The summary statistics (table 5.5) gave us detailed statistics about our estimate correlations from the cDCC-MIDAS framework. For most combinations, the mean values of the short- and long-run times series are quite close, while the long-term component is less volatile which also matches our graphs' conclusion. We notice that the minimums of short-run cross-assets correlations are negative excluding EQU-INM and INM-AGR. However, the minimums of long-run correlations are half positive and half negative.

If we compare the mean with the first group and second group, the connection between the equity market and commodity market is strong than the combination of the real estate market and commodity market; these results are similar to the previous chapter. The highest short- and long-run correlation's mean in these two groups are the pairs of EQU-INM. Turning to the intra-commodities pairs, we find the weakest connection is the correlation between precious metals and agriculture which is 0.0272 (short-run) and 0.0277 (long-run). Meanwhile, we are not surprised to see that precious metals and industrial metals are the strongest correlations, which are 0.3257 (short-run) and 0.3261 (long-run), among the intra-commodities pairs.

In short conclusion, we notice all of the pairs' means are positive in the short- and long-run correlation during our sample period, but few correlations' means are close to 0. Therefore, we can based on the whole sample correlation mean to confirm two hedging properties for 20 pairs correlations (short- and long-run) under *H1* and *H2*. As we point out, all the whole sample correlations' mean are positive, but they are not close to unity (on average); hence, we can confirm all the assets are under our first hypothesis *H1* which the assets involved can serve as diversifiers when included in pairs in multi-asset portfolios. Meanwhile, we also detect a few cases under the second hypothesis *H2*, which are the RE-PRM, RE-AGR, RE-LIV and PRM-LIV, based on four of which are very close to 0 (lower than 0.1). The whole sample statistics of both short- and long-run correlations give identical conclusions for diversifiers and hedges. In sharp contrast, the crisis subsample statistics will reveal differences among daily and monthly patterns, further asset properties, and the correlations' time-varying behaviour.

The following is the discussion about two mean difference tests (Satterthwaite- Welch t-test and Welch F-test, reported in the tables 5.6 and 5.7) about the short and long-run correlation's mean in the pre-crisis and in-crisis. In this discussion, we compare the pre-crisis and in-crisis correlation mean and conclude whether the mean differences are statistically significant. As the previous section 5.4.2 mentioned, our crisis timeline are following the real crisis period; we are based on the observations of the in-crisis period to consider the pre-crisis time interval. Then, we can progress to examine the next three hypotheses (*H3*, *H4*, *H5*) to indicate whether our cross-assets are safe-haven property and contagion or flight-to-quality phenomena.

Table 5.6: Short-run (daily) dynamic correlation mean difference tests: pre-crisis vs. crisis subsamples

	GFC				ESDC				COV			
	pre-crisis	in-crisis	mean diff.	F-test t-test	pre-crisis	in-crisis	mean diff.	F-test t-test	pre-crisis	in-crisis	mean diff.	F-test t-test
EQU-NRG	0.092	0.179	$+^{***}$	87.84 −9.37	0.316	0.560	$+^{***}$	655.06 −25.59	0.285	0.458	$+^{***}$	173.74 −13.18
EQU-PRM	0.300	0.162	$-^{***}$	224.10 14.97	0.227	0.284	$+^{***}$	37.87 −6.15	−0.152	−0.016	$+^{***}$	115.76 −10.76
EQU-INM	0.265	0.348	$+^{***}$	154.52 −12.43	0.430	0.613	$+^{***}$	1021.0 −31.95	0.369	0.461	$+^{***}$	185.71 −13.63
EQU-AGR	0.121	0.174	$+^{***}$	64.64 −8.04	0.245	0.360	$+^{***}$	384.25 −19.60	0.187	0.278	$+^{***}$	73.25 −8.56
EQU-LIV	0.013	0.100	$+^{***}$	289.78 −17.02	0.140	0.217	$+^{***}$	325.29 −18.04	0.151	0.241	$+^{***}$	49.69 −7.05
RE-NRG	−0.052	−0.081	$-^{***}$	10.08 3.18	0.091	0.411	$+^{***}$	862.27 −29.37	0.029	0.300	$+^{***}$	376.70 −19.41
RE-PRM	0.062	−0.037	$-^{***}$	212.11 14.56	0.014	0.129	$+^{***}$	324.74 −18.02	0.108	0.037	$-^{***}$	30.75 5.55
RE-INM	0.114	0.061	$-^{***}$	53.17 7.29	0.155	0.351	$+^{***}$	797.35 −28.24	0.004	0.222	$+^{***}$	624.52 −24.99
RE-AGR	0.008	0.001	$-$	1.22 1.10	0.070	0.232	$+^{***}$	903.28 −30.06	−0.011	0.166	$+^{***}$	357.73 −18.91
RE-LIV	0.014	0.051	$+^{***}$	59.99 −7.75	0.086	0.148	$+^{***}$	279.46 −16.72	0.037	0.146	$+^{***}$	71.57 −8.46
NRG-PRM	0.322	0.404	$+^{***}$	202.64 −14.24	0.411	0.387	$-^{***}$	20.36 4.51	0.016	0.068	$+^{***}$	18.38 −4.29
NRG-INM	0.185	0.328	$+^{***}$	572.70 −23.93	0.396	0.551	$+^{***}$	1024.9 −32.01	0.264	0.310	$+^{***}$	39.21 −6.26
NRG-AGR	0.245	0.404	$+^{***}$	504.42 −22.46	0.461	0.339	$-^{***}$	484.92 22.02	0.150	0.344	$+^{***}$	1317.9 −36.30
NRG-LIV	0.055	0.140	$+^{***}$	413.77 −20.34	0.259	0.224	$-^{***}$	78.19 8.47	0.028	0.110	$+^{***}$	70.66 −8.41
PRM-AGR	0.237	0.302	$+^{***}$	764.90 −27.66	0.317	0.260	$-^{***}$	832.69 28.86	0.054	0.074	$+^{***}$	34.28 −5.86
PRM-LIV	0.028	0.087	$+^{***}$	532.76 −23.08	0.084	0.057	$-^{***}$	263.24 16.23	−0.077	−0.032	$+^{***}$	42.23 −6.50
INM-AGR	0.174	0.286	$+^{***}$	453.61 −21.30	0.352	0.402	$+^{***}$	147.95 −12.16	0.108	0.194	$+^{***}$	1069.3 −32.70
INM-LIV	0.032	0.125	$+^{***}$	582.55 −24.14	0.179	0.214	$+^{***}$	93.79 −9.685	0.057	0.135	$+^{***}$	140.74 −11.86
PRM-INM	0.413	0.425	$+^{*}$	3.03 −1.74	0.430	0.417	$-^{**}$	5.54 2.35	−0.010	0.055	$+^{***}$	84.03 −9.17
AGR-LIV	−0.026	0.070	$+^{***}$	557.81 −23.62	0.147	0.267	$+^{***}$	685.86 −26.19	0.161	0.221	$+^{***}$	113.62 −10.66

Notes:

The table reports the mean difference tests of the daily cross-asset correlations and the three crisis periods (GFC, ESDC, COV) under investigation. 'Pre-crisis' and 'in-crisis' columns report the correlation mean values in the pre-crisis and during crisis subsamples, respectively. 'Mean diff.' denotes the increase (+) or decrease (−) of the correlations during the crisis subsample. ***, **, * denote significance of the mean difference test at the 0.01, 0.05, 0.10 level, respectively. 't-test' and 'F-test' are the two mean difference test statistics, that is the Satterthwaite-Welch t-test and Welch F-test statistics, respectively.

Table 5.7 presents the short-run dynamic correlation means. The first group of equity and intra-commodities are a significant increase from the pre-crisis to the in-crisis among the three crisis periods, but only the EQU-PRM has a different pattern compared with others. This pair's correlation remains positive but it significantly decreases in the GFC; meanwhile, the correlation is negative but also increases during the COV period. Therefore, we can conclude our first groups' short-run correlation are mostly contagion *H4* among three crises periods, our results show a similar conclusion with the related literature (Heaney & Sriananthakumar 2012, Huang & Zhong 2013, Yang et al. 2012); the EQU-PRM is lower interdependence in the GFC, and it is higher interdependence and also safe haven in the COV.

Turning to the second group, we notice that most of the pairs of real estate and commodities are the negative correlation mean in the GFC, but only the RE-LIV significant increase in this period. We notice the pair of RE-AGR are insignificant in the same period. During the following ESDC and COV crises period, most of the pairs in this group significant increases excluding the RE-PRM in the COV period. Hence, we can conclude this group is safe haven property *H3* during GFC; the pair of RE-NRG and RE-PRM are also flight-to-quality *H5* in this period. Equivalently, the pair RE-INM and RE-AGR are lower independent, although the correlation means of RE-AGR insignificant reduction in the GFC. The last pair RE-LIV is under hypothesis *H4* in this period. Most of the cases are contagion *H4* in ESDC and COV period, excluding the pair of RE-PRM is safe-haven property *H3* and lower interdependence.

Now, we focus on the last group short-run co-movement. The intra-commodities types present interesting results. The GFC presents short-run correlations significant increase in this group from the pre-crisis to in-crisis period; especially, we notice most of the pairs are higher interconnectedness in this period, a similar conclusion can find in the Le Pen & Sévi (2018), Zhang & Broadstock (2020). Hence, we can conclude most of the pairs of this group is contagion *H4*. However, there are two pairs that should be paid attention to which are PRM-LIV and AGR-LIV; PRM-LIV is very close to 0 in this period which is 0.021 in the pre-crisis level and move to 0.084. AGR-LIV has a negative correlation mean at the pre-crisis level, but it approaches 0.045. Both of them are safe haven *H3* and weak contagion *H4*.

In the ESDC and COV periods, the intra-commodities pairs' performances are different. Firstly, the NRG-PRM presents different signs in these two periods; this pair's correlation is significantly decreased in the ESDC, so we can summarise this pair is lower interdependence. Meanwhile, this pair's short-run correlation means a significantly increased in the COV period, so this pair is weak contagion *H4* and safe haven property *H3* in this period. The short-run correlation's pair of NRG-INM, INM-AGR, INM-LIV, and AGR-LIV are significant and increase in the ESDC and COV period, so we can conclude these four pairs are contagion in these two periods.

The next two pairs (NRG-AGR and NRG-LIV) significantly decrease in the ESDC period and significantly increase during the COV, so these two pairs are low interdependence in the ESDC and contagion *H4* in the COV. The pairs of PRM-AGR and PRM-INM are significantly reduced in the ESDC, and their correlations also significantly increase in the COV; the results clearly show they are low interdependence in the ESDC; and they are weak contagion *H4* and safe-haven property *H3* in the COV because both of them are lower than 0.1 at the in-crisis level. The last case is the PRM-LIV which this pair is significantly negative in the ESDC, which means this pair is lower interdependence and safe haven property *H3* in the second crisis period; however, this pair is a negative correlation means during the COV and also this pair is a positive increase in this period; our conclude for the last pair in the COV period which is higher interdependence and safe haven property *H3*.

Overall, most pairs' short-run correlations mean different tests are significant, only the pair of RE-AGR is insignificant. Meanwhile, most cases in the short-run correlations' pairs are contagion, but also real estate and commodities pairs are safe-haven properties in the GFC period.

Now, we can move to the last part of this section which is the long-run correlation analysis. Compare with the table 5.6 and 5.7, we notice the long-run correlation results from mean difference tests are less significant figures than the short-run correlation. This is also evidence to present that the long-run correlation is more stable than the short-run correlation.

Regarding the first group (the combination of equity and commodities), EQU-NRG and EQU-INM remain positive and with significant increases in the GFC both of them still remain contagion *H4* in the long-run; similar to EQU-PRM remain low interdependence. The last two pairs have a different conclusion in the long-run correlation; EQU-AGR's long-run correlation mean increases during GFC, but it is not significant in the mean difference test. For this pair, we summarise the higher interdependence in this period. EQU-LIV has a negative correlation mean at the pre-crisis level, but these pairs increase

Table 5.7: Long-run dynamic correlation mean difference tests: pre-crisis vs. crisis subsamples

	GFC				ESDC				COV			
	pre-crisis	in-crisis	mean diff.	F-test t-test	pre-crisis	in-crisis	mean diff.	F-test t-test	pre-crisis	in-crisis	mean diff.	F-test t-test
EQU-NRG	0.051	0.119	$+^{***}$	46.85 −6.85	0.200	0.562	$+^{***}$	312.12 −17.67	0.297	0.315	$+^{*}$	5.26 −2.29
EQU-PRM	0.265	0.253	$-$	0.75 0.87	0.226	0.289	$+^{***}$	29.62 −5.44	0.004	−0.043	$-^{**}$	9.17 3.03
EQU-INM	0.263	0.301	$+^{***}$	51.06 −7.15	0.348	0.595	$+^{***}$	265.99 −16.31	0.295	0.331	$+^{***}$	14.79 −3.85
EQU-AGR	0.121	0.128	$+$	1.53 −1.24	0.194	0.381	$+^{***}$	132.67 −11.52	0.125	0.166	$+^{**}$	11.72 −3.42
EQU-LIV	−0.014	0.052	$+^{***}$	50.39 −7.10	0.105	0.223	$+^{***}$	85.04 −9.22	0.134	0.172	$+^{***}$	23.19 −4.82
RE-NRG	−0.053	−0.106	$-^{***}$	14.48 3.81	0.011	0.419	$+^{***}$	172.91 −13.15	0.034	0.060	$+$	2.09 −1.45
RE-PRM	0.052	0.018	$-^{***}$	14.25 3.78	0.006	0.115	$+^{***}$	75.73 −8.70	0.087	0.074	$-^{**}$	9.54 3.09
RE-INM	0.078	0.099	$+^{***}$	14.58 −3.82	0.117	0.325	$+^{***}$	186.08 −13.64	0.014	0.025	$+$	1.81 −1.35
RE-AGR	0.012	−0.017	$-^{***}$	21.51 4.64	0.031	0.234	$+^{***}$	236.47 −15.38	−0.001	0.005	$+$	0.25 −0.50
RE-LIV	−0.014	0.046	$+^{***}$	105.95 −10.29	0.070	0.152	$+^{***}$	125.60 −11.21	0.062	0.070	$+$	2.71 −1.65
NRG-PRM	0.299	0.397	$+^{***}$	27.79 −5.27	0.385	0.393	$+$	0.70 −0.83	0.019	0.030	$+$	0.95 −0.97
NRG-INM	0.181	0.246	$+^{***}$	28.45 −5.33	0.313	0.569	$+^{***}$	240.63 −15.51	0.214	0.251	$+^{***}$	22.36 −4.73
NRG-AGR	0.243	0.337	$+^{***}$	18.40 −4.29	0.458	0.411	$-^{***}$	20.79 4.56	0.124	0.153	$+^{***}$	13.87 −3.73
NRG-LIV	0.054	0.112	$+^{***}$	13.68 −3.70	0.244	0.231	$-$	0.42 0.65	0.006	0.036	$+^{*}$	3.61 −1.90
PRM-AGR	0.230	0.292	$+^{***}$	29.03 −5.39	0.310	0.266	$-^{***}$	24.51 4.95	0.074	0.058	$-$	2.65 1.63
PRM-LIV	0.021	0.084	$+^{***}$	236.86 −15.39	0.084	0.061	$-^{***}$	33.01 5.75	−0.078	−0.062	$+^{**}$	10.43 −3.23
INM-AGR	0.156	0.224	$+^{***}$	41.09 −6.41	0.276	0.433	$+^{***}$	140.99 −11.87	0.111	0.113	$+$	0.17 −0.41
INM-LIV	0.015	0.057	$+^{***}$	22.86 −4.78	0.115	0.238	$+^{***}$	71.86 −8.48	0.036	0.062	$+^{***}$	32.46 −5.70
PRM-INM	0.391	0.461	$+^{***}$	26.50 −5.15	0.444	0.403	$-^{***}$	38.26 6.19	0.147	0.114	$-^{***}$	9.04 3.01
AGR-LIV	−0.029	0.045	$+^{***}$	24.58 −4.96	0.130	0.272	$+^{***}$	45.69 −6.76	0.126	0.204	$+^{***}$	33.28 −5.77

Notes:

The table reports the mean difference tests of the long-run cross-asset correlations and the three crisis periods (GFC, ESDC, COV) under investigation. 'Pre-crisis' and 'in-crisis' columns report the correlation mean values in the pre-crisis and during crisis subsamples, respectively. 'Mean diff.' denotes the increase (+) or decrease (−) of the correlations during the crisis subsample. ***, **, * denote significance of the mean difference test at the 0.01, 0.05, 0.10 level, respectively. 't-test' and 'F-test' are the two mean difference test statistics, that is the Satterthwaite-Welch t-test and Welch F-test statistics, respectively.

significantly in the GFC. Hence, this pair is weak contagion *H4* and also safe haven *H3*. We also notice that this group's long-run correlation has the same conclusion as the short-run correlation during the ESDC period, so all the pairs are contagion *H4* in this period. The COV period has a similar conclusion in the long-run correlation, but EQU-PRM's correlation means is positive but close to 0 and its in-crisis mean turns to negative; this pair concludes as flight-to-quality *H5* and safe haven *H3* during the COV period.

Moving to the second group, we notice the long-run correlation during the ESDC has the same conclusion as the short-run correlation, which means all the pairs of the second group are contagion *H3* in this period. However, the long-run correlation has different results compared to the short-run correlation in the other two crises. For GFC, RE-NRG and RE-LIV remain the same conclusion both of them are flight-to-quality *H5* and safe-haven *H3*. The rest of them are still safe haven property. RE-PRM is positive but this pair's long-run correlation significantly decreases, so this pair is lower interdependence in this crisis period. Although RE-INM significantly increases correlation during GFC, the pre-crisis and in-crisis level is close to 0; this pair shows weak contagion *H3* in this crisis period. The last pair is RE-AGR become the flight-to-quality *H5* because this pair's long-run correlation significantly reduces during the GFC. For COV, most of the pairs have different conclusions excluding RE-PRM; this pair is still under our hypothesis safe haven *H3* and low interdependence. The rest of the pairs change from contagion to safe haven *H3* and higher weak interdependence. Because most of the long-run correlations in this group are very close to 0 and have insignificant increases, only the pair of RE-PRM long-run correlations reduce during the COV period.

The intra-commodities' long-run correlation has a slightly different conclusion to the short-run correlation, which is similar to the previous two groups. We notice the pairs from this group during GFC, which are highly significant and the long-run correlation increase from the pre-crisis period to the in-crisis level. Meanwhile, most of the pairs' long-run correlation remains the similar conclusion as the short-run correlation, in which the combination with the energy commodities, PRM-AGR and PRM-INM are contagion *H4*; PRM-LIV and AGR-LIV are still weak contagion *H4* and safe haven *H3*. Only one pair should be noticed which is INM-LIV, this pair's pre-crisis and in-crisis means are close to 0, and it also significant increase during this crisis; hence, we conclude this pair's long-run correlation is weak contagion *H4* and safe haven *H3*. Similar situation to the second crisis ESDC, most of the pairs remain the same results, but there is one pair that should pay attention which is NRG-PRM. This pair is higher interdependence in the long-run correlation in this crisis period due to this pair's long-run correlation insignificant increase.

Regarding the last crisis COV, only five pairs have the same results as the short-run, in which NRG-INM, NRG-AGR and AGR-LIV are still contagion *H4* and PRM-LIV are higher interdependence and safe haven *H3*. The long-run correlation of NRG-PRM is close to 0 at the pre-crisis and in-crisis levels. This pair is not significant during this period, and it becomes higher weak independence and also safe haven *H3*. The next pair is NRG-LIV, this pair's pre-crisis and in-crisis correlation means are close to 0 and it is also a significant increase in this crisis period; so this pair is weak contagion *H4* and safe haven *H3*. PRM-AGR become low interdependence and safe haven *H3* due to this pair's correlation being close to 0 and this pair's correlation reduction, the mean difference tests are also insignificant in this crisis period. INM-AGR is different from the short-run correlation, it slightly increased during this crisis period; so we can conclude this pair is higher interdependences. The combination of industrial metals and livestock are weak contagion *H4* and safe haven *H3*. The last pair is PRM-INM which is lower interdependences based on the correlation reduction significantly during the COV.

Table 5.8 is the summary of short- and long-run correlation interdependences and safe haven property. If we compare from this table, we observe most of the cases are under contagion. The combination of real estate and commodities are safe haven during the GFC period and also the COV period (only long-run correlation). In addition, the pair of PRM-LIV is safe haven in the short- and long-run correlation during three crises.

Overall, beyond the contagion phenomena that dominate our cross-asset combinations, flight-to-quality arises in the following cases: 1. during GFC: two real estate - commodity pair; 2. during COV: EQU-PRM (long-run only). Although the flight-to-quality is rare according to the narrow definition of (*H5*), there are further cases where correlations decrease even with positive or close to zero in-crisis levels. Therefore, not only flights but also lower interdependence cases can partly contribute to financial stability, contrary to the contagion's destabilising impact for the whole financial system. Interestingly, during the ESDC, stocks, real estate, and commodities combinations always increase significantly while the intra-commodity dependences mostly decrease. Despite the sample evidence on the safe haven property of precious metals in combination with stocks and other risky assets (see, among others, Li & Lucey (2017), and the literature therein), we provide novel results on the equities-real estate-commodities and intra-commodity correlations. These asset co-movements have not been investigated yet for their response to three crises, the daily and long-term components, and their macro sensitivity. Hence, the next section is the macroeconomic sensitivity investigation.

Table 5.8: Short- and Long-run interdependences and safe haven property.

	Panel A: Short-run (daily) correlations			Panel B: Long-run (monthly) correlations		
	GFC	ESDC	COV	GFC	ESDC	COV
EQU-NRG	Contagion	Contagion	Contagion	Contagion	Contagion	Contagion
EQU-PRM	Lower int.	Contagion	Higher int. Safe Haven	Lower int.	Contagion	Flight-to-quality Safe Haven
EQU-INM	Contagion	Contagion	Contagion	Contagion	Contagion	Contagion
EQU-AGR	Contagion	Contagion	Contagion	Higher int.	Contagion	Contagion
EQU-LIV	Contagion	Contagion	Contagion	Weak contagion Safe Haven	Contagion	Contagion
RE-NRG	Flight-to-quality Safe Haven	Contagion	Contagion	Flight-to-quality Safe Haven	Contagion	Higher weak int. Safe Haven
RE-PRM	Flight-to-quality Safe Haven	Contagion	Lower int. Safe Haven	Lower int. Safe Haven	Contagion	Lower int. Safe Haven
RE-INM	Lower int. Safe Haven	Contagion	Contagion	Weak contagion Safe Haven	Contagion	Higher weak int. Safe Haven
RE-AGR	Lower int. Safe Haven	Contagion	Contagion	Flight-to-quality Safe Haven	Contagion	Higher weak int. Safe Haven
RE-LIV	Weak contagion Safe Haven	Contagion	Contagion	Weak contagion Safe Haven	Contagion	Higher weak int. Safe Haven
NRG-PRM	Contagion	Lower int.	Weak contagion Safe Haven	Contagion	Higher int.	Higher weak int. Safe Haven
NRG-INM	Contagion	Contagion	Contagion	Contagion	Contagion	Contagion
NRG-AGR	Contagion	Lower int.	Contagion	Contagion	Lower int.	Contagion
NRG-LIV	Contagion	Lower int.	Contagion	Contagion	Lower int.	Weak contagion Safe Haven
PRM-AGR	Contagion	Lower int.	Weak contagion Safe Haven	Contagion	Lower int.	Lower int. Safe Haven
PRM-LIV	Weak contagion Safe Haven	Lower int. Safe Haven	Higher int. Safe Haven	Weak contagion Safe Haven	Lower int. Safe Haven	Higher int. Safe Haven
INM-AGR	Contagion	Contagion	Contagion	Contagion	Contagion	Higher int.
INM-LIV	Contagion	Contagion	Contagion	Weak contagion Safe Haven	Contagion	Weak contagion Safe Haven
PRM-INM	Contagion	Lower int.	Weak contagion Safe Haven	Contagion	Lower int.	Lower int.
AGR-LIV	Weak contagion Safe Haven	Contagion	Contagion	Weak contagion Safe Haven	Contagion	Contagion

Notes:

The table recaps the interdependence phenomena and safe haven property identified in the short- and long-run correlations statistical analysis (Tables 5.6 and 5.7) across the three crisis subsamples (GFC, ESDC, COV). The in-crisis interdependence types are as follows: Contagion, Flight-to-quality, Higher Interdependence (Higher Int.), and Lower Interdependence (Lower Int.).

5.5 Macroeconomic sensitivity investigation

Motivated by our conclusions on the counter- and procyclical behaviour of cross-asset correlations, we attribute their variation to global macro and news factors. We first regress the daily and monthly Fisher-transformed correlations on high and low-frequency fundamentals (Eqs. (5.18) and (5.19)) and scrutinise the sensitivity of the macro drivers to the economic uncertainty channel (eq. (5.20)). Next, we investigate the crisis impact on the correlation determinants (eq. (5.21)) and the mediating role of uncertainty (eq. (5.22)).

5.5.1 Correlation macroeconomic regression analysis

The correlation macro drivers are traced in well-established metrics tracking the major facets of the business cycle dynamics, so we apply the macroeconomic factors to see how they influence the cross-correlation. We apply the following macroeconomic factors to the short- and long-run correlations: sentiment (uncertainty, confidence), infectious disease, credit, news, activity, and prices daily and monthly proxies, based on data availability. The macro sensitivity analysis tests the last two hypotheses (H6 and H7) through Eqs. (5.18) and (5.19), where we identify the macro effects on the short- and long-run cross-asset nexus. ADF tests reject the unit root hypothesis for both daily and monthly correlations computed by the cDCC-MIDAS model and Fisher-transformed (the test statistics are available upon request). Hence, our dependent and explanatory variables are suitable for the OLS regressions of Eqs. (5.18) and (5.19). Based on we have two frequency data in this chapter, our daily correlation can be explained by daily fundamentals, this analysis can use for studying the early warning signals of imminent crisis episodes when most financial correlations soar (contagion or higher interdependence) or other cases (flight-to-quality or lower interdependence). Therefore, it has become essential to utilise macros that illustrate day-to-day economic developments. This necessity has proved to be urgent, especially during turbulent times like the recent pandemic crisis, when macro deterioration has occurred on a daily basis and policy tools can rely on nowcasting to alleviate the crisis shocks (Berger et al. 2020, Diebold 2020).

The short-run correlations regressions

Table 5.9 reports the daily correlations regression results (eq. (5.18)). Regarding the significance of the macro regressors, we first notice that the infectious disease effect on financial volatility is significant in four cases only because this particular index increases significantly only during COV. Therefore, its effect on the full period is limited. The activity effect is insignificant in three precious metals combinations while the impact of freights is insignificant in four intra-commodity pairs. The dollar strength is estimated significant in 12 cases but is insignificant for both procyclical pairs. Finally, uncertainty, financial stress, and news proxies are always significant with a potent effect on cross-asset co-movements.

The countercyclical correlations confirm *H6*. When the cross-asset co-movements increase in economic slowdowns and are characterised by contagion during crises, we estimate a positive impact of economic and financial uncertainty, infectious disease and financial stress and a negative effect of news sentiment, activity, freights, and dollar value for the whole sample. *H6* is confirmed for most pairwise daily correlations, consistently with the crisis behaviour reported in Table 5.6. The correlations that increase and become or remain positive during most crises (at least in two of the three crises examined) in the Panel A of table 5.8 exhibit countercyclicality driven by higher uncertainty and disease effects, tighter credit conditions, negative news sentiment, lower activity, freights, and dollar strength. The only cases where the signs of the macro factors are opposite, following *H7*, are the EQU-PRM and RE-PRM. We recall that (table 5.8) EQU-PRM daily co-movement decreases significantly during GFC (lower interdependence) and increases but remains negative during COV (safe haven). RE-PRM correlations decrease and become negative during GFC (flight-to-quality and safe haven) and positive but close to zero during COV (lower interdependence and safe haven). Therefore, their procyclical behaviour dominates their whole sample's macro sensitivity. On the one hand, uncertainty, disease, and financial stress exert a negative influence on the two precious metals combinations with equities and real estate. On the other hand, news, activity, freights, and dollar price have a positive impact.

The long-run correlations regressions

Furthermore, the long-run correlations are regressed on monthly fundamentals (EPU, financial stress, confidence, activity, inflation, and freights). Table 5.9 presents the estimation results (eq. (5.19)). Regarding the overall significance of the long-run correlation determinants, EPU and credit proxies are always significant. The insignificant cases are two for the activity effect, six for inflation, and eight for freights. The confidence impact is insignificant only in the metals connectedness (PRM-INM). In general, we draw similar conclusions to the daily regression analysis. We demonstrate that the monthly co-movement of precious metals with equities and real estate is procyclical overall, confirming H7, and consistently with the daily analysis. Both long-run correlations decrease during two of the three crises, GFC and COV (table 5.7). Accordingly, uncertainty and credit coefficients are estimated as negative whereas investors' confidence, economic activity, inflation rate, and freight rate parameters are positive.

However, for the other pairs most correlations are positive and increase either across all crisis subsamples or in two crises (Table 5.8, Panel B) and, therefore, can be characterised as countercyclical, according to *H6*. That is, EPU and financial stress increase correlations while confidence, activity, and prices reduce them. In one case, we further notice mixed signs, partially confirming both *H6* and *H7*. For the two metals pair (PRM-INM), four out of six macro regressors' signs are as expected by *H6* (countercyclicality), with sentiment and activity insignificant. Inflation and freights exert a positive influence, under the context of *H7*, and the latter effect is insignificant. We recall that the long-run correlation among metals is found to decrease during ESDC and COV, but the crisis averages remain positive and not close to zero (Table 5.8, Panel B). The graphical analysis shows that the PRM-INM monthly series initially decreases in the ESDC and increases in the later ESDC times. In COV, it appears rather stable.

Overall, our baseline regressions reveal the cross-asset correlation determinants in the global macro environment for the whole sample period. The short- and long-run analyses provide quite similar conclusions despite the differences identified in the crisis breakdown among daily and monthly series (Table 5.8). Most interdependences are countercyclical *(H6)* while certain correlations of precious metals (safe havens) with financial and financialised assets exhibit procyclical behaviour. The countercyclical correlation results are in line with previous studies, which have revealed the negative business cycle impact on cross-asset interdependence Conrad et al. (2014), Karanasos & Yfanti (2021), Mobarek et al. (2016). Similarly, our findings on the procyclical cases are consistent with correlation determinant studies with safe havens involved where economic slowdown leads to flights-to-quality or a decrease in interdependences (Asgharian et al. 2016).

Table 5.9: Short-run (daily) cross-asset correlations regressions on macro fundamentals, eq. (5.18)

	ζ_0	$\rho_{SR,t-1}$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$	BIC AIC	$\overline{R}^2$ DW
EQU-NRG	0.4453*** (0.1323)	0.9602*** (0.0020)	0.0037** (0.0017)	0.0243* (0.0132)	0.0017 (0.0013)	0.0098*** (0.0026)	−0.0408** (0.0188)	−0.0066* (0.0038)	−0.0637* (0.0377)	−0.0006*** (0.0002)	−4.3779 −4.3973	0.9841 2.0442
EQU-PRM	0.0813 (0.1073)	0.9570*** (0.0024)	−0.0034*** (0.0013)	−0.0455*** (0.0201)	−0.0036* (0.0019)	−0.0017*** (0.0007)	0.0252*** (0.0112)	0.0010* (0.0005)	0.0275* (0.0149)	0.0007 (0.0005)	−4.7312 −4.7505	0.9739 1.9997
EQU-INM	0.2252** (0.1023)	0.9718*** (0.0020)	0.0027*** (0.0011)	0.0116** (0.0058)	0.0013** (0.0005)	0.0068*** (0.0015)	−0.0249** (0.0118)	−0.0030*** (0.0003)	−0.0340* (0.0194)	−0.0009** (0.0004)	−4.9665 −4.9858	0.9846 2.0629
EQU-AGR	0.2486*** (0.0876)	0.9552*** (0.0034)	0.0021** (0.0010)	0.0375** (0.0189)	0.0032** (0.0013)	0.0049*** (0.0019)	−0.0234*** (0.0064)	−0.0038** (0.0018)	−0.0397* (0.0236)	−0.0004 (0.0004)	−4.7262 −4.7455	0.9799 2.0734
EQU-LIV	0.3233*** (0.0728)	0.9648*** (0.0041)	0.0013*** (0.0003)	0.0514** (0.0193)	0.0015 (0.0015)	0.0040** (0.0018)	−0.0249** (0.0121)	−0.0052* (0.0031)	−0.0875*** (0.0213)	−0.0006* (0.0003)	−5.1170 −5.1363	0.9838 2.0017
RE-NRG	0.1564 (0.1279)	0.9786*** (0.0023)	0.0028*** (0.0009)	0.0514** (0.0262)	0.0018 (0.0015)	0.0041*** (0.0011)	−0.0270* (0.0142)	−0.0158*** (0.0059)	−0.0414*** (0.0160)	−0.0011* (0.0006)	−5.0408 −5.0601	0.9852 2.0737
RE-PRM	0.2019*** (0.0798)	0.9433*** (0.0040)	−0.0019*** (0.0002)	−0.0155*** (0.0015)	−0.0011 (0.0017)	−0.0017*** (0.0004)	0.0400*** (0.0164)	0.0050 (0.0038)	0.0453** (0.0230)	0.0009 (0.0007)	−4.6983 −4.7177	0.9721 2.0091
RE-INM	−0.0939 (0.0997)	0.9779*** (0.0026)	0.0016*** (0.0005)	0.0415** (0.0153)	0.0014 (0.0015)	0.0025** (0.0011)	−0.0250* (0.0137)	−0.0116*** (0.0046)	−0.0447* (0.0263)	−0.0007** (0.0003)	−4.9641 −4.9834	0.9861 2.0239
RE-AGR	0.1471* (0.0808)	0.9506*** (0.0037)	0.0024* (0.0013)	0.0435*** (0.0169)	0.0022 (0.0015)	0.0011*** (0.0002)	−0.0241** (0.0108)	−0.0143*** (0.0051)	−0.0456** (0.0236)	−0.0005* (0.0003)	−4.8157 −4.8350	0.9701 2.0089
RE-LIV	0.1061* (0.0610)	0.9458*** (0.0039)	0.0016*** (0.0005)	0.0358** (0.0161)	0.0018 (0.0016)	0.0020*** (0.0005)	−0.0225** (0.0115)	−0.0052*** (0.0021)	−0.0282*** (0.0102)	−0.0006* (0.0004)	−5.2452 −5.2645	0.9661 2.0271
NRG-PRM	0.1365** (0.0689)	0.9769*** (0.0023)	0.0035*** (0.0013)	0.0062*** (0.0016)	0.0013 (0.0012)	0.0022** (0.0010)	−0.0194*** (0.0066)	−0.0016*** (0.0004)	−0.0204 (0.0227)	−0.0013 (0.0023)	−4.9439 −4.9632	0.9868 2.0113
NRG-INM	0.2846** (0.0990)	0.9803*** (0.0021)	0.0079*** (0.0012)	0.0301** (0.0131)	0.0016* (0.0009)	0.0019** (0.0009)	−0.0276* (0.0149)	−0.0014*** (0.0004)	−0.0099*** (0.0028)	−0.0004* (0.0002)	−4.9460 −4.9653	0.9881 2.0380
NRG-AGR	0.2448** (0.0590)	0.9860*** (0.0013)	0.0079* (0.0047)	0.0113** (0.0045)	0.0012 (0.0017)	0.0038*** (0.0008)	−0.0129** (0.0067)	−0.0030*** (0.0011)	−0.0071*** (0.0014)	−0.0003* (0.0002)	−6.3734 −6.3927	0.9942 1.9945
NRG-LIV	0.1495*** (0.0582)	0.9718*** (0.0018)	0.0010* (0.0006)	0.0096** (0.0046)	0.0016 (0.0012)	0.0029*** (0.0010)	−0.0115* (0.0069)	−0.0013*** (0.0004)	−0.0199*** (0.0051)	−0.0002 (0.0005)	−6.4916 −6.5109	0.9874 2.0335
PRM-AGR	−0.0306 (0.0543)	0.9789*** (0.0021)	0.0025*** (0.0003)	0.0062*** (0.0018)	0.0011 (0.0007)	0.0009* (0.0006)	−0.0124* (0.0068)	−0.0010 (0.0017)	−0.0057*** (0.0016)	−0.0006** (0.0003)	−6.2525 −6.2718	0.9838 2.0828
PRM-LIV	−0.0781* (0.0424)	0.9541*** (0.0038)	0.0034*** (0.0008)	0.0096* (0.0053)	0.0012 (0.0011)	0.0012* (0.0007)	−0.0074*** (0.0026)	−0.0028* (0.0016)	−0.0024 (0.0122)	−0.0004 (0.0003)	−5.9538 −5.9731	0.9721 2.0148
INM-AGR	0.2248*** (0.0631)	0.9786*** (0.0075)	0.0026*** (0.0003)	0.0021*** (0.0004)	0.0004 (0.0004)	0.0017*** (0.0006)	−0.0047** (0.0024)	−0.0003*** (0.0001)	−0.0030 (0.0077)	−0.0001 (0.0001)	−7.6720 −7.6913	0.9879 1.9874
INM-LIV	0.1963*** (0.0406)	0.9866*** (0.0012)	0.0019*** (0.0004)	0.0035*** (0.0012)	0.0004 (0.0005)	0.0016*** (0.0006)	−0.0018*** (0.0005)	−0.0011** (0.0005)	−0.0308*** (0.0093)	−0.0001 (0.0001)	−7.5060 −7.5253	0.9942 1.9740
PRM-INM	0.2808** (0.1164)	0.9773*** (0.0023)	0.0025* (0.0013)	0.0122*** (0.0014)	0.0032 (0.0041)	0.0015* (0.0008)	−0.0095* (0.0052)	−0.0029 (0.0060)	−0.0047 (0.0034)	−0.0012* (0.0007)	−4.6356 −4.6549	0.9847 2.0342
AGR-LIV	0.1246** (0.0552)	0.9820*** (0.0020)	0.0071*** (0.0023)	0.0123* (0.0075)	0.0005 (0.0007)	0.0021** (0.0010)	−0.0097** (0.0042)	−0.0005** (0.0002)	−0.0137*** (0.0055)	−0.0003* (0.0002)	−6.2283 −6.2476	0.9914 2.0991

Notes:

The table reports the estimation results of the daily correlations regressions on daily macro factors for each pairwise cross-asset combination. Each correlation series is explained by a constant (ζ_0), the first autoregressive term ($\rho_{SR,t-1}$), and the macro regressors (eq. (5.18)). The numbers in parentheses are standard errors. ***, **, * 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. $\overline{R}^2$ is the adjusted R^2.

Table 5.10: Long-run (daily) cross-asset correlations regressions on macro fundamentals, eq. (5.19)

	δ_0	$\rho_{LR,t-1}$	$EPU_{LR,t-1}$	$FS_{LR,t-1}$	$SENT_{LR,t-1}$	$EC_{LR,t-1}$	$INFL_{LR,t-1}$	$FR_{LR,t-1}$	BIC AIC	$\overline{R}^2$ DW
EQU-NRG	0.0022	0.6235***	0.0022***	0.0019***	−0.0108**	−0.0008**	−0.0007**	−0.0128***	−6.4702	0.6463
	(0.0194)	(0.0583)	(0.0010)	(0.0005)	(0.0046)	(0.0004)	(0.0003)	(0.0054)	−6.6738	2.0580
EQU-PRM	0.0036	0.5674***	−0.0012***	−0.0017**	0.0088**	0.0009**	0.0004**	0.0322**	−6.2714	0.5767
	(0.0259)	(0.0665)	(0.0003)	(0.0008)	(0.0045)	(0.0004)	(0.0002)	(0.0134)	−6.4758	1.9675
EQU-INM	−0.0059	0.6195***	0.0052**	0.0018**	−0.0093***	−0.0008***	−0.0002***	−0.0085***	−6.9827	0.6251
	(0.0184)	(0.0619)	(0.0023)	(0.0008)	(0.0031)	(0.0001)	(0.0000)	(0.0011)	−7.1870	2.1672
EQU-AGR	0.0031	0.4715***	0.0037***	0.0028***	−0.0198***	−0.0013*	−0.0009***	−0.0154*	−6.3599	0.4826
	(0.0408)	(0.0717)	(0.0012)	(0.0011)	(0.0057)	(0.0007)	(0.0003)	(0.0079)	−6.5642	2.0517
EQU-LIV	0.0212	0.4483***	0.0041**	0.0024***	−0.0219***	−0.0016**	−0.0004**	−0.0070*	−7.0571	0.4706
	(0.0300)	(0.0668)	(0.0021)	(0.0008)	(0.0038)	(0.0008)	(0.0002)	(0.0038)	−7.2614	1.9822
RE-NRG	0.0610	0.6193***	0.0006***	0.0013*	−0.0401***	−0.0003*	−0.0002	−0.0223	−6.2308	0.6529
	(0.0569)	(0.0566)	(0.0001)	(0.0007)	(0.00126)	(0.0002)	(0.0004)	(0.0147)	−6.4352	2.1299
RE-PRM	0.0176	0.3391***	−0.0026***	−0.0012***	0.0060***	0.0007*	0.0004	0.0166	−6.4506	0.3448
	(0.0400)	(0.0886)	(0.0003)	(0.0004)	(0.0021)	(0.0004)	(0.0003)	(0.0133)	−6.6549	1.9902
RE-INM	0.0460	0.5158***	0.0045***	0.0028**	−0.0027***	−0.0006***	−0.0014***	−0.0090***	−6.5888	0.5421
	(0.0368)	(0.0596)	(0.0013)	(0.0013)	(0.0007)	(0.0002)	(0.0003)	(0.0022)	−6.7932	2.0233
RE-AGR	0.0077	0.3392***	0.0035***	0.0022**	−0.0071***	−0.0006*	−0.0002***	−0.0130*	−6.4209	0.3788
	(0.0313)	(0.0720)	(0.0011)	(0.0011)	(0.0017)	(0.0003)	(0.0000)	(0.0071)	−6.6252	1.9722
RE-LIV	0.0304	0.5250***	0.0035**	0.0006***	−0.0051**	−0.0002***	−0.0003*	−0.0071***	−6.9840	0.5433
	(0.0344)	(0.0728)	(0.0018)	(0.0002)	(0.0025)	(0.0000)	(0.0002)	(0.0021)	−7.1884	1.9758
NRG-PRM	0.4182	0.3419***	0.0026***	0.0010**	−0.0014***	−0.0008***	−0.0011	−0.0137	−6.5672	0.3973
	(0.4936)	(0.0858)	(0.0006)	(0.0005)	(0.0002)	(0.0002)	(0.0010)	(0.0214)	−6.7716	1.9442
NRG-INM	0.0030	0.5737***	0.0053**	0.0017**	−0.0109***	−0.0010***	−0.0004*	−0.0069*	−6.7763	0.6193
	(0.0438)	(0.0719)	(0.0023)	(0.0008)	(0.0031)	(0.0003)	(0.0003)	(0.0040)	−6.9806	2.0827
NRG-AGR	0.0097	0.4466***	0.0056***	0.0036**	−0.0243***	−0.0018***	−0.0005*	−0.0032	−5.1589	0.4978
	(0.0818)	(0.0719)	(0.0022)	(0.0018)	(0.0086)	(0.0006)	(0.0003)	(0.0026)	−5.3632	1.9900
NRG-LIV	0.1086	0.2380***	0.0115***	0.0028***	−0.0063***	−0.0022***	−0.0002	−0.0122***	−5.0887	0.2891
	(0.0885)	(0.0841)	(0.0037)	(0.0011)	(0.0012)	(0.0006)	(0.0005)	(0.0023)	−5.2916	1.9624
PRM-AGR	0.0145	0.3905***	0.0016**	0.0021*	−0.0110***	−0.0003	−0.0005	−0.0044***	−5.9127	0.4119
	(0.0171)	(0.0748)	(0.0008)	(0.0012)	(0.0034)	(0.0003)	(0.0004)	(0.0017)	−6.1148	1.9894
PRM-LIV	0.0005	0.1775***	0.0019***	0.0036***	−0.0044***	−0.0008***	−0.0001	−0.0041	−6.1818	0.2497
	(0.0140)	(0.0853)	(0.0004)	(0.0010)	(0.0012)	(0.0002)	(0.0002)	(0.0192)	−6.3862	1.9617
INM-AGR	−0.0080	0.4366***	0.0021***	0.0026***	−0.0256***	−0.0007*	−0.0005**	−0.0008	−6.8461	0.4656
	(0.0095)	(0.0738)	(0.0004)	(0.0006)	(0.0087)	(0.0004)	(0.0002)	(0.0010)	−7.0505	2.0556
INM-LIV	−0.0055	0.2978***	0.0037***	0.0029***	−0.0198***	−0.0011***	−0.0004**	−0.0012**	−6.9266	0.3625
	(0.0100)	(0.0656)	(0.0014)	(0.0007)	(0.0079)	(0.0002)	(0.0002)	(0.0005)	−7.1310	2.0338
PRM-INM	−0.0008	0.3478***	0.0078**	0.0003*	−0.0149	−0.0005	0.0010***	0.0025	−6.4553	0.3559
	(0.0416)	(0.0695)	(0.0033)	(0.0002)	(0.0197)	(0.0016)	(0.0003)	(0.0085)	−6.6599	2.0305
AGR-LIV	0.0068	0.2527***	0.0026**	0.0036***	−0.0126***	−0.0007**	−0.0003*	−0.0029	−6.2699	0.3453
	(0.0441)	(0.0705)	(0.0012)	(0.0013)	(0.0033)	(0.0003)	(0.0002)	(0.0041)	−6.4735	1.9695

Notes: The table reports the estimation results of the long-run correlations regressions on monthly macro factors for each pairwise cross-asset combination. Each correlation series is explained by a constant (δ_0), the first autoregressive term ($\rho_{LR,t-1}$), and the macro regressors (eq. (5.19)). The numbers in parentheses are standard errors. ***, **, * 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. $\overline{R}^2$ is the adjusted R^2.

Next, we focus on the uncertainty channel of the economy. The well-documented power of uncertainty in moving or leading the business cycle is further examined in the case of cross-asset correlations. The direct EPU effect is always significant in the short- and long-run co-movements in tables 5.9 and 5.10, which demonstrates that EPU can be considered a powerful correlation determinant and contagion or flight transmitter in contagion or flight-to-quality phenomena during crises. Meanwhile, our evidence suggests that higher EPU levels increase countercyclical correlations and reduce procyclical correlations patterns. Motived by our results and also the wider empirical evidence, we believe the EPU have significant influence to the dynamic correlations; hence, we are interested in further discover how the indirect EPU effect on the cross-assets' correlations.

The macroeconomic regression regressions in the short- and long-run correlations (Eqs. (5.18) and (5.19)) have unveiled the direct EPU influence on the correlation, and both of them show the significant uncertainty effect on countercyclical correlations Pástor & Veronesi (2013) and also on procyclical or flight-to-quality cases Costantini & Sousa (2022). Hence, the indirect influence reveals the EPU impact on the remaining macro regressors and their role in driving the correlation pattern. We estimate the eq. (5.20) for the daily correlations by including each EPU interaction term separately for each explanatory variable (estimation of restricted forms of eq. (5.20) for the EPU indirect effect on each macro).

Table 5.11 reports the estimated interaction terms in the short-run correlation regression (the indirect effect of EPU). The uncertainty channel intensifies all macro effects by adding an increment to each macro parameter, our idea is similar as (Karanasos & Yfanti 2021, Pástor & Veronesi 2013). The positive/negative economic effects increase in absolute terms by higher uncertainty levels across all correlations, either countercyclical or procyclical. For the countercyclical cases, given increased EPU, the financial uncertainty, disease, and credit effects become more positive while the news, activity, freights, and dollar value effects become more negative. In the two procyclical correlation series (EQU-PRM and RE-PRM), we estimate the opposite signs for the EPU interaction terms, as expected.

The overall significance of the indirect uncertainty effects is similar to the significance of the respective macro effect in theshort-run regression (table 5.9). For the economic activity and freight rate, we estimate one more significant coefficient in RE-PRM and

NRG-PRM correlations, respectively. The EPU sensitivity analysis confirms the decisive effect of uncertainty and provides clear evidence about the potent indirect impact of uncertainty on the cross-asset nexus, beyond the direct one already estimated in the daily macro economic regression (Eq. 5.18).

Table 5.11: The EPU effect on the macro drivers of daily cross-asset correlations, Eq. (5.20)

$EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-NRG	0.0014^{***} (0.0004)	0.0005 (0.0005)	0.0012^{***} (0.0005)	-0.0087^{***} (0.0023)	-0.0010^{***} (0.0002)	-0.0100^{*} (0.0054)	-0.0004^{*} (0.0002)
EQU-PRM	-0.0032^{**} (0.0016)	-0.0012^{*} (0.0007)	-0.0008^{***} (0.0002)	0.0101^{***} (0.0041)	0.0006^{*} (0.0004)	0.0057^{*} (0.0030)	0.0004 (0.0003)
EQU-INM	0.0056^{***} (0.0010)	0.0006 (0.0006)	0.0007^{**} (0.0003)	-0.0076^{*} (0.0043)	-0.0017^{***} (0.0005)	-0.0011^{***} (0.0004)	-0.0004^{**} (0.0002)
EQU-AGR	0.0028^{**} (0.0014)	0.0012^{**} (0.0005)	0.0005^{**} (0.0002)	-0.0070^{***} (0.0021)	-0.0026^{*} (0.0014)	-0.0168^{***} (0.0044)	-0.0002 (0.0002)
EQU-LIV	0.0183^{***} (0.0073)	0.0007 (0.0006)	0.0015^{**} (0.0007)	-0.0017^{***} (0.0004)	-0.0026^{*} (0.0015)	-0.0268^{***} (0.0039)	-0.0003^{*} (0.0002)
RE-NRG	0.0164^{***} (0.0046)	0.0005 (0.0006)	0.0033^{***} (0.0008)	-0.0067^{***} (0.0014)	-0.0082^{***} (0.0029)	-0.0268^{***} (0.0055)	-0.0006^{*} (0.0003)
RE-PRM	-0.0021^{***} (0.0005)	-0.0005 (0.0007)	-0.0013^{***} (0.0005)	0.0132^{**} (0.0063)	0.0027^{**} (0.0012)	0.0023^{***} (0.0005)	0.0005 (0.0003)
RE-INM	0.0046^{***} (0.0011)	0.0007 (0.0006)	0.0021^{***} (0.0003)	-0.0065^{*} (0.0035)	-0.0061^{***} (0.0023)	-0.0014^{***} (0.0004)	-0.0003^{*} (0.0002)
RE-AGR	0.0027^{**} (0.0013)	0.0008 (0.0006)	0.0002^{***} (0.0000)	-0.0055^{***} (0.0015)	-0.0068^{***} (0.0026)	-0.0008^{**} (0.0004)	-0.0003^{*} (0.0002)
RE-LIV	0.0166^{***} (0.0065)	0.0007 (0.0007)	0.0006^{**} (0.0003)	-0.0060^{**} (0.0031)	-0.0033^{*} (0.0019)	-0.0012^{*} (0.0007)	-0.0002^{*} (0.0001)
NRG-PRM	0.0025^{*} (0.0014)	0.0006 (0.0005)	0.00018^{***} (0.0003)	-0.0052^{***} (0.0016)	-0.0010^{***} (0.0002)	-0.0009^{*} (0.0004)	-0.0007^{***} (0.0003)
NRG-INM	0.0029^{***} (0.0011)	0.0007^{*} (0.0004)	0.0004^{**} (0.0002)	-0.0099^{**} (0.0049)	-0.0006^{***} (0.0002)	-0.0033^{***} (0.0004)	-0.0002 (0.0003)
NRG-AGR	0.0032^{*} (0.0018)	0.0004^{*} (0.0002)	0.0005^{***} (0.0002)	-0.0012^{**} (0.0006)	-0.0014^{***} (0.0005)	-0.0005^{**} (0.0002)	-0.0002^{*} (0.0001)
NRG-LIV	0.0024^{**} (0.0011)	0.0007 (0.0005)	0.0004^{**} (0.0002)	-0.0033^{*} (0.0019)	-0.0007^{***} (0.0002)	-0.0116^{***} (0.0031)	-0.0001 (0.0002)
PRM-AGR	0.0026^{***} (0.0006)	0.0005^{*} (0.0003)	0.0003^{***} (0.0001)	-0.0053^{**} (0.0025)	-0.0004 (0.0009)	-0.0012^{***} (0.0002)	-0.0003^{***} (0.0001)
PRM-LIV	0.0043^{**} (0.0021)	0.0006 (0.0005)	0.0006^{***} (0.0002)	-0.0066^{**} (0.0029)	-0.0014^{*} (0.0008)	-0.0005 (0.0026)	-0.0002 (0.0002)
INM-AGR	0.0012^{***} (0.0003)	0.0002 (0.0002)	0.0011^{***} (0.0001)	-0.0010^{***} (0.0003)	-0.0002^{**} (0.0001)	-0.0004 (0.0008)	-0.0001 (0.0006)
INM-LIV	0.0015^{***} (0.0004)	0.0002 (0.0002)	0.0014^{**} (0.0007)	-0.0016^{***} (0.0003)	-0.0006^{**} (0.0003)	-0.0135^{***} (0.0030)	-0.0001 (0.0005)
PRM-INM	0.0012^{***} (0.0002)	0.0014 (0.0013)	0.0003^{*} (0.0002)	-0.0040^{***} (0.0011)	-0.0013 (0.0028)	-0.0002 (0.0004)	-0.0007^{**} (0.0003)
AGR-LIV	0.0054^{***} (0.0016)	0.0001 (0.0003)	0.0002^{*} (0.0001)	-0.0077^{***} (0.0022)	-0.0004^{***} (0.0001)	-0.0059^{***} (0.0020)	-0.0002^{*} (0.0001)

Notes:

The table reports the EPU effect on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each EPU interaction term, estimated separately, are displayed. The EPU interaction terms are calculated by the multiplication of EPU ($EPU_{SR,t-1}\times$) with each macro regressor. The numbers in parentheses are standard errors.

***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

5.5.2 Crisis correlation analysis

The EPU sensitivity analysis has clearly shown the incremental effect of uncertainty in magnifying the impact of all correlations' macro drivers. Motivated by the previous results, we continue to estimate the crisis sensitivity analysis on the correlation determinants. Consistently with the indirect effect of higher EPU levels, mostly observed during crises, we expect that the crisis shock will also add a significant increment on all macro effects.

Therefore, we estimate eq. (5.21) to test the crisis shocks on the macroeconomic factors. The crisis intercept dummies ($D_{C,t}$), estimated separately from the slope dummies, confirm our conclusions about the direct crisis shock on correlation levels (Table 5.6 and Table 5.8, Panel A). For most contagion cases, we estimate a positive and significant dummy, while for correlation decreases the dummies are estimated negative or insignificant (see Table E.4 and E.6 in the Appendix). The crisis impact on the macro drivers' effect is captured by the slope dummies. We estimate the crisis slope dummies of each macro effect separately. Table 5.12, 5.13 and 5.14 present our estimation results for daily correlations and the three crisis periods examined. The number of significant cases per crisis period and per macro effect does not vary substantially, with the exception of the infectious disease effect. The disease news effect on financial volatility is significant during COV for all correlations, while in the first two crises it is insignificant for most cases (see also Table E.6 for a recap of the significant macro coefficients estimated across all macro models).

Our initial crisis analysis in Section 5.4.2 (Table 5.6 and Table 5.8 , Panel A), has identified the correlations' response to crises, with contagion and flight-to-quality phenomena, lower or higher dependences, and safe haven asset properties. For most cases with significant correlation increases to positive levels (contagion / countercyclicality), the crisis slope dummy adds a significant increment to all macro effects, confirming Karanasos & Yfanti (2021), who show the GFC impact on correlation drivers. The economic impacts are magnified under the crisis shock: positive effects (EPU, FU, ID, FS) become more positive and negative ones (NS, EC, FR, FX) become more negative. For the procyclical correlations, we notice that the opposite-signed macro effects during the crisis subsample, where we observe procyclicality patterns (correlations decrease during crises). The crisis slope dummies demonstrate that the crisis also intensifies the procyclical macro impact. Therefore, the negative uncertainty, disease, and credit effects become more negative during crises and the positive news, activity, and price effects become more positive. Turning to the combination of precious metals, we notice the two procyclial pairs which is EQU-PRM and RE-PRM. In these two pairs, we estimate the opposite GFC and COV incremental effects to the contagion cases for most regressors (see Tables 5.12 and 5.14). If we turn to the period of ESDC, the cases of procyclical are in the intra-commodities pairs (four pairs involve PRM, see table 5.13. Overall, the slope crisis dummies expand most of the macroeconomic factors' impact on the correlation. Meanwhile, we compare in-crisis correlation increases with decreases, we notice more insignificant macro regressors in the procyclical cases, indicating a more profound macro sensitivity for the countercyclical combinations.

Table 5.12: The Crisis (GFC) effect on the macro drivers of daily cross-asset correlations, eq. (5.21)

$D_{GFC,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-NRG	0.0034*** (0.0012)	0.0030*** (0.0005)	0.0049 (0.0056)	0.0039*** (0.0014)	−0.0986*** (0.0183)	−0.0023*** (0.0005)	−0.0044** (0.0022)	−0.0015* (0.0009)
EQU-PRM	−0.0013*** (0.0003)	−0.0042*** (0.0013)	−0.0010 (0.0033)	−0.0054*** (0.0018)	0.0108*** (0.0033)	0.0045*** (0.0014)	0.0082** (0.0035)	0.0003 (0.0011)
EQU-INM	0.0054* (0.0032)	0.0036*** (0.0004)	0.0052** (0.0025)	0.0031* (0.0017)	−0.0631** (0.0327)	−0.0019*** (0.0005)	−0.0038* (0.0020)	−0.0017* (0.0010)
EQU-AGR	0.0038*** (0.0008)	0.0018*** (0.0005)	0.0018 (0.0033)	0.0011*** (0.0001)	−0.0107** (0.0048)	−0.0039*** (0.0014)	−0.0055** (0.0026)	−0.0008 (0.0011)
EQU-LIV	0.0022* (0.0014)	0.0007*** (0.0002)	0.0033 (0.0036)	0.0009*** (0.0001)	−0.0320*** (0.0125)	−0.0043*** (0.0015)	−0.0036*** (0.0011)	−0.0004*** (0.0001)
RE-NRG	0.0033*** (0.0005)	0.0107*** (0.0039)	0.0009 (0.0028)	0.0024 (0.0018)	−0.0193*** (0.0065)	−0.0178 (0.0123)	−0.0018 (0.0019)	−0.0012 (0.0018)
RE-PRM	−0.0022*** (0.0004)	−0.0026* (0.0014)	−0.0028 (0.0052)	−0.0007 (0.0020)	0.1138** (0.0574)	0.0192 (0.0105)	0.0051 (0.0044)	0.0011 (0.0016)
RE-INM	0.0080*** (0.0027)	0.0113* (0.0060)	0.0028 (0.0027)	0.0008** (0.0003)	−0.0096*** (0.0040)	−0.0026*** (0.0007)	−0.0018 (0.0013)	−0.0014 (0.0011)
RE-AGR	0.0092** (0.0038)	0.0058*** (0.0017)	0.0037 (0.0026)	−0.0033 (0.0028)	−0.0720*** (0.0227)	−0.0099 (0.0097)	−0.0056 (0.0039)	−0.0009 (0.0013)
RE-LIV	0.0012*** (0.0004)	0.0161** (0.0076)	0.0006 (0.0024)	0.0017** (0.0008)	−0.0787*** (0.0300)	−0.0172** (0.0074)	−0.0040* (0.0023)	−0.0004* (0.0002)
NRG-PRM	0.0091* (0.0049)	0.0173** (0.0081)	0.0017 (0.0035)	0.0016* (0.0009)	−0.0428* (0.0251)	−0.0071*** (0.0024)	−0.0015 (0.0015)	−0.0023* (0.0012)
NRG-INM	0.0011** (0.0004)	0.0068*** (0.0028)	0.0069** (0.0033)	0.0014* (0.0008)	−0.0256* (0.0148)	−0.0051*** (0.0012)	−0.0016*** (0.0006)	−0.0010** (0.0004)
NRG-AGR	0.0017*** (0.0005)	0.0029*** (0.0011)	0.0016 (0.0010)	0.0018* (0.0010)	−0.0221** (0.0102)	−0.0032*** (0.0010)	−0.0016*** (0.0005)	−0.0002 (0.0005)
NRG-LIV	0.0038* (0.0021)	0.0013*** (0.0005)	0.0029 (0.0022)	0.0041*** (0.0016)	−0.0036** (0.0016)	−0.0010*** (0.0003)	−0.0033** (0.0017)	−0.0002 (0.0004)
PRM-AGR	0.0011* (0.0006)	0.0060* (0.0031)	0.0003 (0.0016)	0.0014** (0.0006)	−0.0225*** (0.0033)	−0.0005* (0.0003)	−0.0018*** (0.0006)	−0.0009* (0.0006)
PRM-LIV	0.0030*** (0.0008)	0.0088* (0.0047)	0.0008 (0.0024)	0.0004* (0.0002)	−0.0099*** (0.0027)	−0.0049* (0.0025)	−0.0035** (0.0015)	−0.0002 (0.0007)
INM-AGR	0.0010* (0.0006)	0.0007*** (0.0002)	0.0015 (0.0010)	0.0006* (0.0003)	−0.0038*** (0.0010)	−0.0010** (0.0005)	−0.0005* (0.0003)	−0.0005 (0.0004)
INM-LIV	0.0030*** (0.0012)	0.0021** (0.0010)	0.0020 (0.0014)	0.0005*** (0.0001)	−0.0052*** (0.0021)	−0.0007 (0.0018)	−0.0009** (0.0004)	−0.0003 (0.0003)
PRM-INM	0.0042*** (0.0011)	0.0138*** (0.0040)	0.0011 (0.0028)	0.0018** (0.0008)	−0.1189** (0.0617)	−0.0040*** (0.0011)	−0.0008** (0.0004)	−0.0004** (0.0002)
AGR-LIV	0.0012*** (0.0004)	0.0020*** (0.0006)	0.0004 (0.0010)	0.0045*** (0.0007)	−0.0264*** (0.0105)	−0.0012* (0.0007)	−0.0005 (0.0006)	−0.0002 (0.0006)

Notes: The table reports the crisis effect on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each crisis slope dummy, estimated separately, are displayed. The crisis slope dummies are calculated by the multiplication of the respective dummy for each crisis period (GFC dummy: $D_{GFC,t-1}\times$, ESDC dummy: $D_{ESDC,t-1}\times$, COV dummy: $D_{COV,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table 5.13: The Crisis (ESDC)effect on the macro drivers of daily cross-asset correlations, eq. (5.21)

$D_{ESDC,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-NRG	0.0106^{**} (0.0047)	0.0089^{*} (0.0051)	0.0572 (0.0610)	0.0101^{***} (0.0033)	-0.0634^{***} (0.0325)	-0.0150^{***} (0.0060)	-0.0041^{**} (0.0021)	-0.0072^{***} (0.0029)
EQU-PRM	0.0017^{*} (0.0009)	0.0157^{*} (0.0094)	0.0119 (0.0153)	0.0019^{***} (0.0004)	-0.0347^{***} (0.0077)	-0.0020^{***} (0.0007)	-0.0025^{***} (0.0004)	-0.0016^{***} (0.0002)
EQU-INM	0.0018^{***} (0.0003)	0.0127^{***} (0.0031)	0.0046 (0.0123)	0.0085^{**} (0.0042)	-0.0182^{***} (0.0053)	-0.0083^{***} (0.0009)	-0.0052^{*} (0.0029)	-0.0009^{***} (0.0002)
EQU-AGR	0.0031^{***} (0.0009)	0.0078^{***} (0.0016)	0.0227 (0.0181)	0.0063^{**} (0.0032)	-0.0277^{***} (0.0036)	-0.0154^{**} (0.0070)	-0.0104^{*} (0.0056)	-0.0014 (0.0014)
EQU-LIV	0.0069^{*} (0.0038)	0.0301^{***} (0.0104)	0.0189 (0.0119)	0.0069^{***} (0.0032)	-0.0615^{***} (0.0227)	-0.0136^{*} (0.0081)	-0.0059^{*} (0.0035)	-0.0011^{**} (0.0005)
RE-NRG	0.0057^{***} (0.0018)	0.0141^{***} (0.0014)	0.0463^{***} (0.0179)	0.0010^{**} (0.0005)	-0.0124^{***} (0.0036)	-0.0058^{***} (0.0014)	-0.0053^{*} (0.0029)	-0.0031^{*} (0.0018)
RE-PRM	0.0029^{***} (0.0010)	0.0037^{***} (0.0012)	0.0098 (0.0170)	0.0009^{***} (0.0002)	-0.0667^{*} (0.0359)	-0.0116^{***} (0.0034)	-0.0049^{***} (0.0016)	-0.0007 (0.0015)
RE-INM	0.0057^{*} (0.0028)	0.0171^{*} (0.0094)	0.0233^{**} (0.0116)	0.0024^{***} (0.0009)	-0.0396^{***} (0.0133)	-0.0107^{***} (0.0037)	-0.0093^{**} (0.0042)	-0.0013^{*} (0.0007)
RE-AGR	0.0083^{**} (0.0038)	0.0184^{**} (0.0092)	0.0022 (0.0021)	0.0053^{**} (0.0026)	-0.0736^{**} (0.0315)	-0.0099^{***} (0.0011)	-0.0043^{***} (0.0017)	-0.0008 (0.0011)
RE-LIV	0.0056^{*} (0.0032)	0.0271^{***} (0.0092)	0.0013 (0.0012)	0.0040^{*} (0.0023)	-0.0509^{*} (0.0290)	-0.0124^{**} (0.0056)	-0.0103^{***} (0.0034)	-0.0002^{***} (0.0000)
NRG-PRM	0.0022^{*} (0.0013)	0.0098^{*} (0.0057)	0.0038 (0.0181)	0.0014 (0.0024)	-0.0126 (0.0314)	-0.0052 (0.0139)	0.0008 (0.0025)	0.0001 (0.0015)
NRG-INM	0.0067^{*} (0.0036)	0.0079^{***} (0.0021)	0.0263^{**} (0.0123)	0.0053^{**} (0.0024)	-0.0197^{***} (0.0044)	-0.0014^{***} (0.0003)	-0.0026^{**} (0.0011)	-0.0008^{*} (0.0005)
NRG-AGR	-0.0010^{***} (0.0003)	-0.0031^{*} (0.0017)	-0.0043 (0.0072)	-0.0053^{*} (0.0031)	0.0013^{**} (0.0006)	0.0033 (0.0061)	0.0009 (0.0006)	0.0004 (0.0006)
NRG-LIV	-0.0026^{*} (0.0015)	-0.0035^{*} (0.0020)	-0.0056 (0.0048)	-0.0047^{**} (0.0024)	0.0019^{**} (0.0009)	0.0038 (0.0037)	0.0030^{**} (0.0013)	0.0001 (0.0004)
PRM-AGR	-0.0014^{*} (0.0008)	-0.0021^{***} (0.0007)	-0.0026 (0.0031)	-0.0024^{*} (0.0013)	0.0079^{***} (0.0014)	0.0054 (0.0048)	0.0034^{*} (0.0019)	0.0002 (0.0007)
PRM-LIV	-0.0008^{***} (0.0003)	-0.0023^{*} (0.0013)	-0.0039 (0.0093)	-0.0034^{*} (0.0018)	0.0030^{***} (0.0011)	0.0021 (0.0055)	0.0010 (0.0018)	0.0004 (0.0007)
INM-AGR	0.0033^{***} (0.0014)	0.0076^{***} (0.0017)	0.0056^{**} (0.0027)	0.0026^{**} (0.0013)	-0.0069^{**} (0.0032)	-0.0033^{**} (0.0017)	-0.0041^{***} (0.0013)	-0.0002 (0.0003)
INM-LIV	0.0015^{**} (0.0007)	0.0042^{**} (0.0022)	0.0047 (0.0038)	0.0023^{*} (0.0013)	-0.0075^{***} (0.0028)	-0.0039^{*} (0.0022)	-0.0040^{**} (0.0018)	-0.0002 (0.0003)
PRM-INM	-0.0007^{*} (0.0004)	-0.0057^{**} (0.0024)	-0.0289 (0.0301)	-0.0029^{**} (0.0015)	0.0019 (0.0036)	0.0060^{***} (0.0015)	0.0025 (0.0017)	0.0003 (0.0014)
AGR-LIV	0.0019^{***} (0.0008)	0.0055^{**} (0.0028)	0.0152^{*} (0.0084)	0.0038^{*} (0.0023)	-0.0108^{**} (0.0051)	-0.0024^{***} (0.0005)	-0.0033^{*} (0.0018)	-0.0004 (0.0007)

Notes: The table reports the crisis effect on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each crisis slope dummy, estimated separately, are displayed. The crisis slope dummies are calculated by the multiplication of the respective dummy for each crisis period (GFC dummy: $D_{GFC,t-1}\times$, ESDC dummy: $D_{ESDC,t-1}\times$, COV dummy: $D_{COV,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table 5.14: The Crisis (COV) effect on the macro drivers of daily cross-asset correlations, eq. (5.21)

$D_{COV,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-NRG	0.0048^{***} (0.0009)	0.0146^{***} (0.0015)	0.0019^{***} (0.0005)	0.0136^{**} (0.0061)	-0.0294^{***} (0.0064)	-0.0314^{*} (0.0180)	-0.0067^{***} (0.0018)	-0.0072^{***} (0.0029)
EQU-PRM	-0.0028^{***} (0.0004)	-0.0171^{***} (0.0050)	-0.0036^{***} (0.0007)	0.0007 (0.0023)	0.0419^{***} (0.0109)	-0.0130 (0.0119)	-0.0067^{***} (0.0017)	-0.0016 (0.0033)
EQU-INM	0.0015^{***} (0.0005)	0.0039^{***} (0.0008)	0.0078^{***} (0.0019)	0.0064^{**} (0.0029)	-0.0716^{***} (0.0184)	-0.0224^{**} (0.0102)	-0.0008^{*} (0.0004)	-0.0017^{***} (0.0004)
EQU-AGR	0.0121^{***} (0.0019)	0.0441^{**} (0.0222)	0.0044^{***} (0.0015)	0.0060^{*} (0.0035)	-0.0494^{***} (0.0088)	-0.0261^{**} (0.0134)	-0.0007^{***} (0.0002)	-0.0027^{**} (0.0013)
EQU-LIV	0.0055^{***} (0.0011)	0.0318^{***} (0.0041)	0.0034^{***} (0.0004)	0.0102^{***} (0.0032)	-0.0263^{***} (0.0079)	-0.0114^{***} (0.0023)	-0.0003^{*} (0.0002)	-0.0048^{*} (0.0028)
RE-NRG	0.0118^{***} (0.0032)	0.0366^{***} (0.0037)	0.0063^{*} (0.0034)	0.0121^{*} (0.0071)	-0.1516^{***} (0.0154)	-0.0084^{***} (0.0037)	-0.0020^{**} (0.0009)	-0.0031^{*} (0.0018)
RE-PRM	-0.0012^{***} (0.0003)	-0.0127^{***} (0.0036)	-0.0012^{***} (0.0001)	-0.0020^{***} (0.0004)	0.0906^{***} (0.0257)	0.0014 (0.0032)	0.0001 (0.0026)	0.0039 (0.0030)
RE-INM	0.0032^{**} (0.0014)	0.0220^{**} (0.0109)	0.0186^{***} (0.0021)	0.0039^{*} (0.0022)	-0.0874^{***} (0.0305)	-0.0095^{***} (0.0027)	-0.0004^{*} (0.0002)	-0.0027^{*} (0.0014)
RE-AGR	0.0153^{***} (0.0045)	0.0353^{***} (0.0133)	0.0013^{***} (0.0003)	0.0040^{*} (0.0021)	-0.0888^{***} (0.0214)	-0.0020^{*} (0.0011)	-0.0008^{**} (0.0003)	-0.0010^{**} (0.0004)
RE-LIV	0.0043^{***} (0.0013)	0.0278^{**} (0.0131)	0.0031^{***} (0.0008)	0.0085^{***} (0.0034)	-0.1117^{***} (0.0325)	-0.0070^{***} (0.0026)	-0.0073^{***} (0.0027)	-0.0013^{***} (0.0003)
NRG-PRM	0.0051^{*} (0.0028)	0.0043^{*} (0.0024)	0.0010^{***} (0.0003)	0.0041^{**} (0.0022)	-0.0184^{*} (0.0098)	-0.0093^{***} (0.0034)	-0.0039^{*} (0.0022)	-0.0029 (0.0023)
NRG-INM	0.0032^{***} (0.0008)	0.0118^{***} (0.0032)	0.0014^{***} (0.0003)	0.0031^{*} (0.0018)	-0.0261^{*} (0.0148)	-0.0099^{***} (0.0036)	-0.0015^{*} (0.0008)	-0.0059^{**} (0.0027)
NRG-AGR	0.0033^{***} (0.0012)	0.0081^{***} (0.0023)	0.0007^{***} (0.0002)	0.0023^{***} (0.0005)	-0.0469^{*} (0.0279)	-0.0151^{*} (0.0085)	-0.0012^{**} (0.0005)	-0.0025^{***} (0.0010)
NRG-LIV	0.0027^{**} (0.0014)	0.0138^{**} (0.0063)	0.0024^{***} (0.0008)	0.0020^{*} (0.0011)	-0.0819^{*} (0.0468)	-0.0094^{***} (0.0035)	-0.0005 (0.0005)	-0.0030^{**} (0.0014)
PRM-AGR	0.0053^{***} (0.0018)	0.0022^{*} (0.0013)	0.0018^{**} (0.0008)	0.0009^{***} (0.0002)	-0.0059^{***} (0.0014)	-0.0172 (0.0170)	-0.0019^{***} (0.0006)	-0.0007 (0.0017)
PRM-LIV	0.0062^{***} (0.0019)	0.0224^{***} (0.0053)	0.0020^{***} (0.0005)	0.0038^{*} (0.0022)	-0.0860^{***} (0.0292)	-0.0048 (0.0102)	-0.0029 (0.0036)	-0.0035 (0.0023)
INM-AGR	0.0025^{***} (0.0005)	0.0052^{***} (0.0019)	0.0016^{***} (0.0006)	0.0024^{**} (0.0010)	-0.0146^{***} (0.0051)	-0.0034 (0.0030)	-0.0003 (0.0003)	-0.0002^{*} (0.0001)
INM-LIV	0.0014^{*} (0.0008)	0.0087^{***} (0.0025)	0.0043^{***} (0.0015)	0.0031^{***} (0.0011)	-0.0271^{***} (0.0083)	-0.0063^{*} (0.0038)	-0.0064^{*} (0.0035)	-0.0011^{*} (0.0006)
PRM-INM	0.0195^{***} (0.0037)	0.0018^{***} (0.0006)	0.0039^{**} (0.0016)	0.0014^{***} (0.0003)	-0.2493^{**} (0.0148)	-0.0233^{*} (0.0135)	-0.0096^{***} (0.0016)	-0.0037^{**} (0.0018)
AGR-LIV	0.0048^{***} (0.0016)	0.0039^{***} (0.0013)	0.0013^{***} (0.0002)	0.0047^{***} (0.0011)	-0.0339^{***} (0.0114)	-0.0077^{*} (0.0042)	-0.0003 (0.0009)	-0.0002 (0.0010)

Notes: The table reports the crisis effect on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each crisis slope dummy, estimated separately, are displayed. The crisis slope dummies are calculated by the multiplication of the respective dummy for each crisis period (GFC dummy: $D_{GFC,t-1}\times$, ESDC dummy: $D_{ESDC,t-1}\times$, COV dummy: $D_{COV,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

we can conclude the cross-correlation are sensitivity to the corresponding crises and the macroeconomic determinants act the important role to the cross-asset correlation in the non-crisis period and in-crisis period. During the crisis period, most of macroeconomic factors are significantly amplifies which to increase the contagion or flight-to-quality episodes; this result has similar finding as Mobarek et al. (2016), they focused on the low frequency correlation determinants during crises for contagion cases only (stock markets cross-border correlations). Meanwhile, we are based on the Eq. (5.22) to analyse the indirect EPU effect with crisis shock, which presents the countercyclical and procyclical correlations are stronger during the market stress conditions. In addition, the following table 5.15, table 5.16 and table 5.17, these three tables report the EPU interaction terms for each crisis subsample. The results from three table presents the similar results as the crisis shocks, the uncertainty increase the macroeconomic factors on the dynamic correlation during three crises period, as expected from the macro and crisis sensitivity analyses so far.

All signs of the crisis interaction terms are the same as the signs of the respective crisis slope dummies (Table 5.12, 5.13 and 5.14), with the exception of some insignificant effects. The significant cases of the indirect EPU under crisis effects are similar to the significant cases of the crisis impact on the macro regressors (table E.6,Panels C and D). In the second crisis (ESDC), the ID effect is significant in more cases under the EPU moderation. Although financial uncertainty under the ESDC shock is always significant, it becomes insignificant with the EPU interaction for two procyclical cases (NRG-AGR and NRG-LIV). All in all, for most crisis-EPU interaction terms, we estimate slightly more significant coefficients than in the crisis slope dummies of the respective macro effect.

Table 5.15: The EPU effect on the macro drivers of daily cross-asset correlations during crises (GFC), eq. (5.22).

$D_{GFC,t-1}EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-NRG	0.0016*** (0.0003)	0.0002 (0.0014)	0.0012** (0.0005)	−0.0081*** (0.0017)	−0.0014*** (0.0004)	−0.0019*** (0.0007)	−0.0007* (0.0004)
EQU-PRM	−0.0036** (0.0018)	−0.0002 (0.0015)	−0.0019*** (0.0004)	0.0076*** (0.0024)	0.0038* (0.0020)	0.0041*** (0.0013)	0.0001 (0.0005)
EQU-INM	0.0037* (0.0022)	0.0021* (0.0012)	0.0006* (0.0003)	−0.0216** (0.0108)	−0.0007*** (0.0001)	−0.0005*** (0.0002)	−0.0007* (0.0004)
EQU-AGR	0.0011*** (0.0003)	0.0003 (0.0013)	0.0006* (0.0003)	−0.0098*** (0.0013)	−0.0024** (0.0012)	−0.0010*** (0.0002)	−0.0003 (0.0005)
EQU-LIV	0.0006*** (0.0002)	0.0015 (0.0015)	0.0003*** (0.0001)	−0.0079*** (0.0011)	−0.0020* (0.0012)	−0.0003* (0.0002)	−0.0003*** (0.0001)
RE-NRG	0.0036*** (0.0010)	0.0004 (0.0014)	0.0004 (0.0005)	−0.0039*** (0.0008)	−0.0091* (0.0051)	−0.0017 (0.0014)	−0.0011 (0.0009)
RE-PRM	−0.0021* (0.0011)	−0.0013 (0.0022)	−0.0005*** (0.0001)	0.0288* (0.0157)	0.0068* (0.0041)	0.0013 (0.0012)	0.0005 (0.0008)
RE-INM	0.0034** (0.0018)	0.0010 (0.0011)	0.0003*** (0.0001)	−0.0169*** (0.0021)	−0.0016*** (0.0003)	−0.0013* (0.0007)	−0.0007* (0.0004)
RE-AGR	0.0035* (0.0021)	0.0004 (0.0011)	0.0002* (0.0001)	−0.0218*** (0.0071)	−0.0053** (0.0026)	−0.0005* (0.0002)	−0.0004 (0.0006)
RE-LIV	0.0010** (0.0004)	0.0003 (0.0010)	0.0013*** (0.0003)	−0.0117*** (0.0048)	−0.0077** (0.0035)	−0.0018* (0.0010)	−0.0002* (0.0001)
NRG-PRM	0.0060* (0.0034)	0.0008 (0.0016)	0.0002*** (0.0000)	−0.0078*** (0.0013)	−0.0034* (0.0021)	−0.0008 (0.0009)	−0.0010* (0.0006)
NRG-INM	0.0025** (0.0013)	0.0030** (0.0014)	0.0005* (0.0003)	−0.0068*** (0.0023)	−0.0022*** (0.0009)	−0.0007*** (0.0001)	−0.0004* (0.0002)
NRG-AGR	0.0015*** (0.0002)	0.0007 (0.0005)	0.0004* (0.0002)	−0.0018*** (0.0007)	−0.0017*** (0.0006)	−0.0003*** (0.0001)	−0.0002 (0.0002)
NRG-LIV	0.0009*** (0.0002)	0.0013 (0.0009)	0.0014*** (0.0005)	−0.0019*** (0.0007)	−0.0004*** (0.0001)	−0.0009* (0.0005)	−0.0002 (0.0003)
PRM-AGR	0.0014*** (0.0003)	0.0002 (0.0007)	0.0002* (0.0001)	−0.0108*** (0.0027)	−0.0002* (0.0001)	−0.0010* (0.0006)	−0.0004* (0.0002)
PRM-LIV	0.0022** (0.0010)	0.0003 (0.0010)	0.0003* (0.0002)	−0.0067*** (0.0010)	−0.0024* (0.0015)	−0.0011* (0.0006)	−0.0001 (0.0003)
INM-AGR	0.0006** (0.0003)	0.0006 (0.0005)	0.0002*** (0.0000)	−0.0018** (0.0009)	−0.0004*** (0.0001)	−0.0003* (0.0002)	−0.0001 (0.0006)
INM-LIV	0.0019*** (0.0008)	0.0009* (0.0006)	0.0002* (0.0001)	−0.0039*** (0.0009)	−0.0003 (0.0009)	−0.0002** (0.0001)	−0.0002 (0.0002)
PRM-INM	0.0011*** (0.0003)	0.0006 (0.0012)	0.0004** (0.0002)	−0.0097** (0.0040)	−0.0018*** (0.0004)	−0.0007*** (0.0002)	−0.0002** (0.0001)
AGR-LIV	0.0012*** (0.0003)	0.0001 (0.0005)	0.0025*** (0.0008)	−0.0089** (0.0041)	−0.0006*** (0.0002)	−0.0005 (0.0008)	−0.0001* (0.0000)

Notes: The table reports the EPU effect during crises on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each EPU interaction term under crisis, estimated separately, are displayed. The EPU interaction terms under crisis are calculated by the multiplication of the respective dummy for each crisis period and EPU (GFC dummy: $D_{GFC,t-1} \times EPU_{SR,t-1}\times$, ESDC dummy: $D_{ESDC,t-1} \times EPU_{SR,t-1}\times$, COV dummy: $D_{COV,t-1} \times EPU_{SR,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table 5.16: The EPU effect on the macro drivers of daily cross-asset correlations during crises (ESDC), eq. (5.22).

$D_{ESDC,t-1}EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-NRG	0.0064^{**} (0.0030)	0.0254^{***} (0.0095)	0.0026^{***} (0.0010)	-0.0081^{***} (0.0022)	-0.0077^{***} (0.0031)	-0.0009^{**} (0.0004)	-0.0008^{*} (0.0005)
EQU-PRM	0.0077^{**} (0.0032)	0.0053 (0.0072)	0.0015^{***} (0.0006)	-0.0270^{***} (0.0064)	-0.0014^{***} (0.0005)	-0.0023^{**} (0.0011)	-0.0007^{***} (0.0001)
EQU-INM	0.0014^{***} (0.0003)	0.0031 (0.0054)	0.0019^{***} (0.0004)	-0.0037^{***} (0.0011)	-0.0039^{***} (0.0004)	-0.0009^{*} (0.0004)	-0.0004^{*} (0.0002)
EQU-AGR	0.0073^{**} (0.0033)	0.0117 (0.0081)	0.0018^{**} (0.0008)	-0.0113^{***} (0.0016)	-0.0075^{*} (0.0046)	-0.0079^{***} (0.0012)	-0.0008 (0.0006)
EQU-LIV	0.0053^{*} (0.0029)	0.0089^{*} (0.0052)	0.0018^{**} (0.0008)	-0.0198^{***} (0.0080)	-0.0057^{*} (0.0034)	-0.0015^{*} (0.0008)	-0.0009^{***} (0.0003)
RE-NRG	0.0018^{***} (0.0004)	0.0214^{***} (0.0084)	0.0003^{*} (0.0002)	-0.0248^{***} (0.0092)	-0.0030^{***} (0.0007)	-0.0012^{**} (0.0005)	-0.0015^{*} (0.0008)
RE-PRM	0.0026^{**} (0.0012)	0.0042 (0.0064)	0.0004^{***} (0.0001)	-0.0208^{*} (0.0119)	-0.0051^{***} (0.0015)	-0.0022^{*} (0.0012)	-0.0002 (0.0007)
RE-INM	0.0041^{*} (0.0021)	0.0112^{**} (0.0053)	0.0009^{***} (0.0003)	-0.0104^{***} (0.0029)	-0.0051^{***} (0.0018)	-0.0019^{*} (0.0010)	-0.0007^{*} (0.0004)
RE-AGR	0.0010^{***} (0.0003)	0.0019^{*} (0.0010)	0.0016^{*} (0.0009)	-0.0211^{**} (0.0102)	-0.0046^{***} (0.0014)	-0.0002^{*} (0.0001)	-0.0004 (0.0005)
RE-LIV	0.0047^{*} (0.0025)	0.0008 (0.0007)	0.0012^{**} (0.0005)	-0.0295^{***} (0.0080)	-0.0057^{**} (0.0026)	-0.0016^{*} (0.0009)	-0.0001^{*} (0.0000)
NRG-PRM	0.0003^{*} (0.0002)	0.0020 (0.0031)	0.0006^{*} (0.0003)	-0.0051^{**} (0.0025)	-0.0017^{**} (0.0008)	-0.0003 (0.0011)	-0.0001 (0.0007)
NRG-INM	0.0044^{**} (0.0022)	0.0119^{**} (0.0055)	0.0017^{**} (0.0008)	-0.0082^{**} (0.0031)	-0.0009^{*} (0.0005)	-0.0011^{**} (0.0005)	-0.0002^{*} (0.0001)
NRG-AGR	-0.0001 (0.0011)	-0.0017 (0.0032)	-0.0002^{**} (0.0001)	0.0007^{*} (0.0004)	0.0015 (0.0028)	0.0002 (0.0005)	0.0001 (0.0003)
NRG-LIV	-0.0002 (0.0008)	-0.0027 (0.0022)	-0.0004 (0.0005)	0.0014^{***} (0.0004)	0.0015^{**} (0.0007)	0.0001 (0.0005)	0.0000 (0.0002)
PRM-AGR	-0.0011^{*} (0.0007)	-0.0057^{**} (0.0028)	-0.0014^{***} (0.0005)	0.0070^{***} (0.0028)	0.0023 (0.0021)	0.0018^{***} (0.0005)	0.0001 (0.0003)
PRM-LIV	-0.0004^{***} (0.0001)	-0.0017 (0.0042)	-0.0016^{*} (0.0010)	0.0021^{***} (0.0006)	0.0010 (0.0026)	0.0003 (0.0006)	0.0002 (0.0003)
INM-AGR	0.0012^{**} (0.0006)	0.0027^{**} (0.0012)	0.0007^{**} (0.0003)	-0.0060^{*} (0.0035)	-0.0014^{**} (0.0006)	-0.0005^{***} (0.0002)	-0.0001 (0.0002)
INM-LIV	0.0018^{*} (0.0010)	0.0023 (0.0017)	0.0005^{**} (0.0002)	-0.0064^{*} (0.0038)	-0.0017^{*} (0.0009)	-0.0035^{***} (0.0014)	-0.0002^{**} (0.0001)
PRM-INM	-0.0031^{***} (0.0008)	-0.0129^{**} (0.0057)	-0.0012^{*} (0.0007)	0.0012 (0.0013)	0.0020^{*} (0.0012)	0.0008 (0.0012)	0.0003 (0.0007)
AGR-LIV	0.0050^{***} (0.0012)	0.0071^{**} (0.0035)	0.0012^{*} (0.0007)	-0.0122^{*} (0.0071)	-0.0023^{***} (0.0008)	-0.0016^{***} (0.0005)	-0.0003 (0.0005)

Notes: The table reports the EPU effect during crises on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each EPU interaction term under crisis, estimated separately, are displayed. The EPU interaction terms under crisis are calculated by the multiplication of the respective dummy for each crisis period and EPU (GFC dummy: $D_{GFC,t-1} \times EPU_{SR,t-1}\times$, ESDC dummy: $D_{ESDC,t-1} \times EPU_{SR,t-1}\times$, COV dummy: $D_{COV,t-1} \times EPU_{SR,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table 5.17: The EPU effect on the macro drivers of daily cross-asset correlations during crises (COV), eq. (5.22).

Table 11c. The EPU effect on the macro drivers of daily cross-asset correlations during crises (COV), eq. (??). (continued)

$D_{COV,t-1}EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-NRG	0.0055^{***} (0.0018)	0.0004^{***} (0.0001)	0.0062^{***} (0.0024)	-0.0272^{***} (0.0028)	-0.0111^{*} (0.0066)	-0.0048^{*} (0.0030)	-0.0026^{**} (0.0011)
EQU-PRM	-0.0060^{*} (0.0033)	-0.0012^{***} (0.0002)	0.0003 (0.0008)	0.0307^{***} (0.0087)	-0.0052 (0.0046)	-0.0031^{**} (0.0016)	-0.0006 (0.0012)
EQU-INM	0.0013^{***} (0.0003)	0.0038^{***} (0.0007)	0.0030^{**} (0.0013)	-0.0364^{***} (0.0142)	-0.0054^{***} (0.0014)	-0.0005^{*} (0.0003)	-0.0003^{*} (0.0002)
EQU-AGR	0.0094^{*} (0.0056)	0.0015^{***} (0.0006)	0.0026^{**} (0.0013)	-0.0056^{**} (0.0024)	-0.0091^{*} (0.0051)	-0.0002^{*} (0.0001)	-0.0009^{***} (0.0001)
EQU-LIV	0.0191^{***} (0.0076)	0.0012^{***} (0.0002)	0.0040^{***} (0.0015)	-0.0039^{*} (0.0022)	-0.0038^{***} (0.0004)	-0.0002^{***} (0.0000)	-0.0027^{***} (0.0010)
RE-NRG	0.0217^{***} (0.0051)	0.0024^{*} (0.0013)	0.0053^{*} (0.0029)	-0.0950^{***} (0.0348)	-0.0027^{***} (0.0005)	-0.0006^{*} (0.0004)	-0.0011^{*} (0.0007)
RE-PRM	-0.0028^{***} (0.0004)	-0.0006^{***} (0.0002)	-0.0019^{***} (0.0006)	0.0402^{***} (0.0128)	0.0012^{***} (0.0004)	0.0001 (0.0019)	0.0017 (0.0012)
RE-INM	0.0085^{***} (0.0032)	0.0079^{***} (0.0024)	0.0020^{**} (0.0009)	-0.0436^{*} (0.0270)	-0.0039^{***} (0.0014)	-0.0003^{*} (0.0002)	-0.0012^{**} (0.0006)
RE-AGR	0.0085^{***} (0.0035)	0.0010^{***} (0.0002)	0.0024^{*} (0.0012)	-0.0429^{*} (0.0235)	-0.0018^{***} (0.0006)	-0.0002 (0.0002)	-0.0005^{***} (0.0001)
RE-LIV	0.0070^{***} (0.0022)	0.0018^{***} (0.0005)	0.0033^{***} (0.0012)	-0.0172^{***} (0.0061)	-0.0055^{*} (0.0032)	-0.0016^{**} (0.0007)	-0.0006 (0.0011)
NRG-PRM	0.0038^{***} (0.0018)	0.0005^{***} (0.0002)	0.0013^{*} (0.0008)	-0.0132^{*} (0.0071)	-0.0034^{*} (0.0016)	-0.0012 (0.0020)	-0.0012^{**} (0.0005)
NRG-INM	0.0043^{***} (0.0016)	0.0005^{***} (0.0001)	0.0011^{*} (0.0006)	-0.0135^{*} (0.0075)	-0.0046^{***} (0.0019)	-0.0025^{*} (0.0015)	-0.0023^{**} (0.0011)
NRG-AGR	0.0068^{***} (0.0021)	0.0005^{***} (0.0001)	0.0009^{*} (0.0005)	-0.0176^{*} (0.0095)	-0.0042^{***} (0.0012)	-0.0002 (0.0006)	-0.0003 (0.0004)
NRG-LIV	0.0076^{***} (0.0013)	0.0009^{***} (0.0003)	0.0012^{**} (0.0005)	-0.0258^{**} (0.0128)	-0.0031^{*} (0.0018)	-0.0003 (0.0008)	-0.0002^{**} (0.0004)
PRM-AGR	0.0010^{*} (0.0006)	0.0014^{***} (0.0003)	0.0003^{***} (0.0001)	-0.0081^{***} (0.0025)	-0.0012 (0.0055)	-0.0010^{**} (0.0005)	-0.0003 (0.0006)
PRM-LIV	0.0059^{*} (0.0032)	0.0017^{***} (0.0006)	0.0014^{**} (0.0007)	-0.0169^{***} (0.0056)	-0.0020 (0.0038)	-0.0002 (0.0014)	-0.0013 (0.0009)
INM-AGR	0.0019^{***} (0.0007)	0.0012^{***} (0.0002)	0.0010^{***} (0.0004)	-0.0078^{***} (0.0024)	-0.0012^{*} (0.0007)	-0.0003 (0.0005)	-0.0001^{*} (0.0000)
INM-LIV	0.0027^{***} (0.0010)	0.0020^{***} (0.0007)	0.0012^{***} (0.0005)	-0.0072^{***} (0.0024)	-0.0037^{**} (0.0023)	-0.0021^{*} (0.0013)	-0.0005^{*} (0.0003)
PRM-INM	0.0009^{***} (0.0003)	0.0015^{**} (0.0007)	0.0002^{***} (0.0000)	-0.0398^{***} (0.0048)	-0.0107^{*} (0.0059)	-0.0024^{**} (0.0011)	-0.0013 (0.0011)
AGR-LIV	0.0017^{***} (0.0004)	0.0015^{***} (0.0004)	0.0019^{***} (0.0005)	-0.0143^{***} (0.0038)	-0.0028^{***} (0.0007)	-0.0003 (0.0013)	-0.0002 (0.0005)

Notes: The table reports the EPU effect during crises on the macro factors' impact on daily cross-asset dynamic correlations. The coefficients of each EPU interaction term under crisis, estimated separately, are displayed. The EPU interaction terms under crisis are calculated by the multiplication of the respective dummy for each crisis period and EPU (GFC dummy: $D_{GFC,t-1} \times EPU_{SR,t-1}\times$, ESDC dummy: $D_{ESDC,t-1} \times EPU_{SR,t-1}\times$, COV dummy: $D_{COV,t-1} \times EPU_{SR,t-1}\times$) with the macro regressors. The numbers in parentheses are standard errors. ***, **, * denote significance at the $0.01, 0.05, 0.10$ level, respectively.

5.6 Discussion and implications

Overall, a broader lesson is that policymakers and market practitioners should pay much attention to the cross-asset interdependences, which mostly increase in times of financial and health crises and soaring EPU levels. The crisis slope dummies and the EPU interaction terms show that the macroeconomic and news cause the correlations increase due to the weak economic fundamentals.Such fundamentals serve as contagion transmitters that tighten the cross-asset nexus, giving rise to systemic risk and jeopardising financial stability. On the other hand, the lower short- and long-run correlation with safe-haven properties assets and flight-to-quality episodes offer protection during turbulent times for investors and market participants, these assets can eliminate massive losses such as the precious metals during the first crisis (GFC) and third crisis (COV). Similarly, in the GFC shock, real estate investments guarantee safety when combined with commodities (flights-to-quality and safe-haven), while in the ESDC and COV cases, contagion becomes more apparent. Financial integration and financialisation progress at an accelerating pace, eroding the diversification benefits from investing in multiple financial and financialised asset classes. In the European crisis, only intra-commodity correlations drop and the recent pandemic-induced turmoil drives most correlations higher. In the COV sub-sample, precious metals act as safe havens in the short- and long-run correlations.

Financial market regulators, investors, portfolio and risk managers should consider equally important the daily correlations and their long-term component, which in many cases leads the daily trend. However, we demonstrate that in various asset pairs the long-term component contributes to financial resilience as monthly correlations decrease, stay stable or close to zero when their daily dynamics erupt, hit by a crisis shock. Long-run correlation are less volatile compare to the short-run correlation, it is indicating a lower correlation risk, which is crucial for risk assessments, macro-prudential policies and surveillance in longer horizons. Short-run correlation dynamics influence trading and regulatory decisions such as asset allocation, hedging strategies, and devising drastic policies to withstand crisis ramifications.

The insights we glean from the short- and long-term correlation determinants, defining the counter- or procyclical behaviour of asset markets' interdependences, project important policy implications. Systemic supervisors should recognise as early warning signals of imminent disruptions the high and low frequency fundamentals which drive the time-varying co-movement of global equities, real estate, and commodities. Weaker economic conditions trigger crisis dominos effect, where countercyclical correlations explode and procyclical combinations with safe havens provide insurance against extreme losses. In the meantime, such signals should warn traders and risk managers, as well, to redesign investment tactics for an imminent collapse of diversification benefits due to financial contagion. When the economic outlook gradually deteriorates and agents‘ expectations become gloomier, a flight to safe haven assets can be a solution for market practitioners profit and loss forward-looking considerations and a stabilising factor for policymakers' oversight of the whole financial system. Our results further show more contagion and fewer flights or safe haven cases as we pass from the first to the second and the third crisis. Therefore, market and policy experts should also account for the fact that financial integration has dramatically increased interconnectedness, and as we go forward to future crises, the asset markets' synchronicity will be undermining hedging effectiveness and stabilising forces.

Hence, one safeguard to endure crisis repercussions is to build financial resilience so that the system rapidly 'bounces back' to normal after a crisis shock. In other words, to prevent countercyclical correlations from escalating too far from their pre-crisis average and rapidly mean-revert after the crisis advent, we need a mindset of resilience by building safety buffers that absorb shocks Brunnermeier (2021). Both policymakers and market players should act proactively. Regulators should promptly intervene in financial market turmoil to alleviate the damage and not induce cross-asset correlation increase. Most importantly, they could impose forward-looking stabilising measures for future market downturns in order to avert price distortions far from fundamentals due to aggregate fear and herding in times of crisis. Covered positions in risky assets hedged by almost riskless financial instruments at all times is a prudential approach for investments rather than 'flying' to safe havens when the shock occurs. Flight-to-quality episodes are not necessarily the stabilisers that we could rely on. They often pave the way for contagion in riskier financial markets (Baur & Lucey 2009). Rational investors fly massively from riskier assets (sales) to safe havens (purchases), leading to contagious shocks for the stock markets, for example, which all fall synchronously following the homogeneous stock sell preferences. Consequently, contagion associated with countercyclical correlations is not the only vice of financial integration. The financial system should also weather the flights to safety associated with procyclical correlations.

5.7 Conclusion

Our empirical analysis has examined the cyclical variation of the cross-asset nexus. We investigated the short- and long-run correlations among equities, real estate, and disaggregated into five broad categories: energy, precious and industrial metals, agriculture, and livestock. Commodity markets are more closely interconnected with equities than with real estate excluding the pair of PRM-LIV. Meanwhile, we detect the difference between the short- and long-run correlations. Short- and long-run contagion phenomena identified for most asset pairs imperil the whole financial stability, while we find that the long-term correlation components remain more resilient to crisis shocks for certain asset pairs and turbulent periods. The precious metals correlations with equities and real estate are involved in flight-to-quality episodes during the 2008 turmoil and the recent pandemic. Such safe-havens assets can stabilise the markets through increased diversification benefits, reducing the systemic risk build-ups induced by enormous losses across multiple economic sectors. However, the massive case of flight-to-quality and safe havens induce contagion among riskier assets and propagate the domino effects of the crisis further.

This chapter makes an important contribution with a broad investigation of the short- and long-run co-movements of financial assets (equities markets) and financialised instruments (real estate markets and disaggregated commodities markets) and concludes on their hedging properties and interdependence types, establishing and implementing an improved econometric correlations specification. The novel results on countercyclical and procyclical correlation dynamics should alert market practitioners and policymakers to account for cross-asset correlations in their risk assessments and proactive policy interventions. The correlations' macro and news drivers can serve a critical signalling role for imminent crises, while both higher and lower interdependences can threaten financial stability. Reinforcing macro- financial resilience backstops can encounter the negative externalities of financial integration and globalisation. For both regulatory authorities and markets, they should consider to re-build the financial system's resilience on a global and local basis. Therefore, a further research path in the cross-asset nexus study could involve the regional perspective, by investigating the cross-border dependences alongside the cross-asset dimension.

5.8 Appendix

Table E.1: Variable definitions

Panel A. Assets		Panel B. Macro-financial and news variables		
Variable	Definition	Variable	Definition	Macro effect description
EQU	Equities	$EPU_{d/m,t}$	US Economic policy uncertainty index (d/m)	EPU: Economic policy uncertainty
RE	Real estate	VIX_t	S&P 500 Implied Volatility index (d)	FU: Financial uncertainty
COM	Commodities	ID_EMV_t	Infectious Disease Equity Market Volatility tracker (d)	ID: Infectious disease news impact
NRG	Energy	FSI_t	Global Financial Stress index (d)	FS: Financial Stress
PRM	Precious Metals	$KCFSI_t$	US Financial Stress index of the Kansas City Fed (m)	FS: Financial Stress
INM	Industrial Metals	$\Delta YCsl_t$	US Yield Curve slope (or term spread) daily change (d)	EC: Economic activity
AGR	Agriculture	gIP_t	G7 Industrial Production index growth (m)	EC: Economic activity
LIV	Livestock	$gBCI_t$	G7 Business Confidence Index growth (m)	SENT: Sentiment / Confidence
		NSI_t	News sentiment index (d)	NS: News sentiment
		$gPPI_t$	G7 inflation rate (m)	INFL: Inflation
		BDI_t	Baltic Dry Index (d)	FR: Freights
		CFI_t	Cass Freight Index (m)	FR: Freights
		$gDXY_t$	DXY US Dollar index growth (d)	FX: Foreign Exchange rates

Notes:

The table reports the definitions of the data variables (assets & macro data). The asset series (Panel A) are downloaded from Refinitiv Eikon Datastream. The sample is common for daily assets and macro variables (1/3/2004 - 27/7/2020). The sample of the monthly macro variables spans from 01/2007 until 07/2020. Daily / monthly macro variables are denoted by (d) and (m), respectively. The macro data (Panel B) sources are as follows: EPU and ID_EMV indices are sourced from www.policyuncertainty.com. Implied Volatility indices, Yield Curve slope, BDI, and DXY are downloaded from Refinitiv Eikon Datastream. KCFSI is retrieved from the FRED database and NSI from San Francisco Fed. IP, PPI, and BCI are sourced from the OECD database. CFI and FSI are downloaded from Cass Information Systems Inc. and the Office of Financial Research, respectively.

Table E.2: Summary statistics of asset returns

Panel A. Asset returns statistics.						
	Mean	Median	Max	Min	Std.Dev.	ADF
EQU	0.0180	0.0596	9.0967	−10.4412	1.0350	-61.5468^{***}
RE	0.0137	0.0377	16.8063	−21.4858	1.9653	-79.4611^{***}
NRG	−0.0375	0.0000	15.9825	−30.1689	2.1155	-67.6088^{***}
PRM	0.0329	0.0178	8.7625	−10.1047	1.1941	-65.1875^{***}
INM	0.0100	0.0000	7.5884	−9.0151	1.4442	-69.4674^{***}
AGR	−0.0214	−0.0094	7.1568	−7.4753	1.2621	-64.3508^{***}
LIV	−0.0214	0.0000	5.3018	−6.2366	0.9552	-63.4380^{***}

Panel B. Cross-asset correlation coefficients.							
	EQU	RE	NRG	PRM	INM	AGR	LIV
EQU	1.000						
RE	0.656	1.000					
NRG	0.402	0.197	1.000				
PRM	0.155	0.035	0.234	1.000			
INM	0.437	0.181	0.368	0.363	1.000		
AGR	0.278	0.137	0.321	0.247	0.320	1.000	
LIV	0.194	0.112	0.143	0.045	0.135	0.158	1.000

Notes:

The table reports the summary statistics of each asset returns series: Mean, Median, Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.), the Augmented Dickey-Fuller (ADF) test statistic (Panel A), and the pairwise cross-asset correlation coefficients (Panel B). The asset series notation is as follows: Equities (EQU), Real estate (RE), Commodities (COM), Energy (NRG), Precious metals (PRM), Industrial metals (INM), Agriculture (AGR), and Livestock (LIV). ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table E.3: Summary statistics of the correlation determinants

Macro effect	Macro variable	Mean	Median	Max	Min	Std.Dev.	ADF
Panel A. Daily determinants.							
EPU	$EPU_{d,t}$	1.9258	1.9244	2.9072	0.5211	0.2902	-6.4871^{***}
FU	VIX_t	1.2352	1.1973	1.9175	0.9609	0.1655	-5.4444^{***}
ID	ID_EMV_t	0.1164	0.0000	6.8370	0.0000	0.5011	-3.1580^{**}
FS	FSI_t	-0.2388	-1.7460	29.320	-5.3340	4.7711	-2.9235^{**}
NS	NSI_t	0.0106	0.0307	0.4886	-0.7258	0.2252	-4.2380^{***}
EC	$\Delta YCsl_t$	-0.0006	-0.0015	1.1980	-0.6260	0.0705	-66.579^{***}
FR	BDI_t	3.2372	3.1741	4.0716	2.4624	0.3443	-2.6522^{*}
FX	$gDXY_t$	0.0016	0.0000	-2.5237	-3.0646	0.4847	-64.679^{***}
Panel B. Monthly determinants.							
EPU	$EPU_{m,t}$	1.9503	1.9253	2.7016	1.5713	0.1984	-3.9532^{***}
FS	$KCFSI_t$	0.0028	-0.4294	5.4128	-1.0397	1.1908	-2.5681^{*}
$SENT$	$gBCI_t$	-0.0132	-0.0030	0.8178	-1.0677	0.2361	-4.3833^{***}
EC	gIP_t	0.7782	2.1553	9.5047	-22.378	5.2441	-3.5847^{***}
$INFL$	$gPPI_t$	2.1531	2.7618	10.321	-7.6907	3.2531	-3.5205^{***}
FR	CFI_t	1.1326	1.1390	1.3470	0.8510	0.1044	-3.1211^{**}

Notes:

The table reports the summary statistics of the daily (Panel A) and monthly (Panel B) macro proxies (proxy of each macro effect) used as regressors in the short- and long-run correlations regressions: Mean, Median, Maximum (Max), Minimum (Min), Standard Deviation (Std.Dev.), and the Augmented Dickey-Fuller (ADF) test statistic. The macro variables reported are the following: the US EPU index (daily: $EPU_{d,t}$ and monthly: $EPU_{m,t}$), the S&P500 IV log-transformed index (VIX_t), the Infectious Disease Equity Market Volatility Tracker (ID_EMV_t), the global Financial Stress index (FSI_t), the US Financial Stress index of the Kansas City Fed ($KCFSI_t$), the G7 Business Confidence Index growth ($gBCI_t$), the News Sentiment Index (NSI_t), the daily change of the US Yield Curve slope ($\Delta YCsl_t$), the G7 Industrial Production index growth (gIP_t), the G7 inflation rate ($gPPI_t$), the Baltic Dry Index (BDI_t), the Cass Freight Index (CFI_t), and the DXY US Dollar index growth ($gDXY_t$).

***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

Table E.4: The Crisis effect on daily cross-asset correlations, eq. (5.21)

	$D_{GFC,t}$	$D_{ESDC,t}$	$D_{COV,t}$
EQU-NRG	0.0070^{**} (0.0034)	0.0115^{***} (0.0045)	0.0030^{*} (0.0017)
EQU-PRM	-0.0061 (0.0077)	0.0260^{***} (0.0085)	0.0048 (0.0046)
EQU-INM	0.0111^{**} (0.0056)	0.0318^{***} (0.0041)	0.0126^{***} (0.0055)
EQU-AGR	0.0207^{***} (0.0031)	0.0127^{***} (0.0052)	0.0041^{*} (0.0023)
EQU-LIV	0.0095^{**} (0.0046)	0.0324^{***} (0.0138)	0.0033^{***} (0.0007)
RE-COM	-0.0017 (0.0020)	0.0055^{***} (0.0020)	0.0026^{*} (0.0014)
RE-NRG	-0.0101 (0.0079)	0.0054^{***} (0.0011)	0.0057^{***} (0.0025)
RE-PRM	-0.0127^{***} (0.0042)	0.0075^{***} (0.0019)	-0.0071^{*} (0.0044)
RE-INM	-0.0035 (0.0047)	0.0124^{***} (0.0032)	0.0023^{***} (0.0007)
RE-AGR	0.0024 (0.0035)	0.0272^{***} (0.0020)	0.0159^{***} (0.0061)
RE-LIV	0.0168^{*} (0.0090)	0.0320^{**} (0.0176)	0.0119^{**} (0.0059)

Notes: The table reports the crisis effect on daily cross-asset dynamic correlations (eq. (5.21)). The coefficients of the crisis intercept dummies, estimated separately from the crisis slope dummies, are displayed. The three dummies corresponding to each crisis subsample are the GFC dummy: $D_{GFC,t}$, the ESDC dummy: $D_{ESDC,t}$, and the COV dummy: $D_{COV,t}$. The numbers in parentheses are standard errors. ***, **, *denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table E.5: The Crisis effect on daily cross-asset correlations, eq. (5.21)

	$D_{GFC,t}$	$D_{ESDC,t}$	$D_{COV,t}$
NRG-PRM	0.0165^{*} (0.0079)	-0.0015 (0.0054)	0.0034 (0.0032)
NRG-INM	0.0081^{***} (0.0022)	0.0196^{***} (0.0069)	0.0011^{*} (0.0006)
NRG-AGR	0.0134^{***} (0.0036)	-0.0039^{***} (0.0008)	0.0025^{***} (0.0002)
NRG-LIV	0.0016^{***} (0.0005)	-0.0014^{**} (0.0006)	0.0014^{***} (0.0004)
PRM-AGR	0.0047^{*} (0.0028)	-0.0048^{**} (0.0024)	0.0076 (0.0063)
PRM-LIV	0.0018^{*} (0.0010)	-0.0037^{*} (0.0016)	0.0015^{**} (0.0007)
INM-AGR	0.0057^{***} (0.0020)	0.0022^{**} (0.0012)	0.0020^{***} (0.0002)
INM-LIV	0.0015^{***} (0.0004)	0.0026^{*} (0.0016)	0.0014^{***} (0.0003)
PRM-INM	0.0125^{*} (0.0069)	-0.0012^{*} (0.0005)	0.0049^{*} (0.0030)
AGR-LIV	0.0248^{***} (0.0047)	0.0023^{***} (0.0007)	0.0063^{***} (0.0005)

Notes: The table reports the crisis effect on daily cross-asset dynamic correlations (eq. (5.21)). The coefficients of the crisis intercept dummies, estimated separately from the crisis slope dummies, are displayed. The three dummies corresponding to each crisis subsample are the GFC dummy: $D_{GFC,t}$, the ESDC dummy: $D_{ESDC,t}$, and the COV dummy: $D_{COV,t}$. The numbers in parentheses are standard errors. ***, **, *denote significance at the $0.01, 0.05, 0.10$ level, respectively.

Table E.6: Significant cases

Macro effects	EPU	FU	ID	FS	NS	EC	FR	FX
Panel A. The macro effect (macro parameters).								
total sample	20	20	4	20	20	20	16	12
Panel B. The indirect EPU effect (interaction terms).								
total sample		20	5	20	20	18	17	12
Panel C. The Crisis effect (crisis slope dummies).								
GFC	20	20	2	17	20	16	13	8
ESDC	20	20	5	19	18	15	16	8
COV	20	20	20	19	20	15	15	14
Panel D. The in-crisis indirect EPU effect (crisis-EPU terms).								
GFC		20	3	19	20	19	16	10
ESDC		18	10	19	19	17	15	9
COV		20	20	19	20	17	12	12

Note:

All 23 correlation series in total of the macro effects, the indirect EPU effect, the crisis effect, and the in- crisis indirect EPU effect on the daily cross-asset correlations' macro drivers. (sum up of significant estimates in tables 5.9, table 5.11, table 5.12 to table 5.14, and tables 5.15 to table 5.17)

6 Conclusion

This thesis aims to study the multivariate GARCH framework in the dynamic correlation of cross-assets in the economic and financial markets. In addition, we use three types of multivariate GARCH models: GJR-MGARCH-DECO, DCC-MIDAS and corrected DCC-MIDAS. After the estimation of multivariate GARCH models, we progress to the correlation analysis to conclude the cross-assets hedging properties; meanwhile, we study the corresponding crisis shock to define the cross-assets safe-haven property and their independent types. Motived by the outcome of correlation analysis, we consider that macroeconomic factors have a significant influence on the dynamic correlations and the crisis shocks can expand macroeconomic factors' impact on the correlations as well. In the end, our conclusion provides our empirical evidence to suggest the investors and policy markers to re-consider their investment strategies and policies.

In the first chapter, we examine the tourism dynamic correlations in the recent crises; we also identify the macro determinants of the time-varying correlations among 11 Travel & Leisure sectoral stock indices. Through the GJR-MGARCH-DECO estimation, our results suggest that cross-border tourism interlinkages are related to a couple of macroeconomic determinants (economic policy, financial uncertainty, credit and liquidity conditions, geopolitical risk, and economic and real estate activity). Additionally, our correlation analysis provides the contractive economic environments (increase uncertainty, tight credit, shallow liquidity, and geopolitical turbulence) happen which increase the tourism sector correlations; or the opposite situation, if some economic fundamentals (economic and real estate activity) are strong, the correlations go up. Therefore, our results match the previous literature. The last part of the macro sensitivity analysis indicates that uncertainty and crisis have an impact on tourism integration. Therefore, investors should notice the tourism sector have serious contagion problem during the uncertainty period, they should include other sectors' indexes such as commodities, real estate indexes.

In the second chapter, we progress to study the dynamic correlation between cross-countries stock indexes. We apply the daily stock market indexes to the DCC-MIDAS model, this model allows us to study the short- and long-run correlation together. We further examine the difference between two different frequency data among the major sustainability benchmarks, then we notice these correlations have the countercyclicality and contagion prevail in our sample periods. In addition, our results suggest a few DJSI procyclical cases during the ESDC. Through our macroeconomic sensitivity investigation, we notice that macroeconomic factors have a significant impact on the short- and long-run correlations and our empirical analysis suggests these macroeconomic determinants expand their influence under the uncertainty channel and crisis shocks. Hence, the second chapter suggests that DJSI investors should consider their investment strategies regarding the dynamic correlations to reduce the portfolio's risk. Especially, DJSI investors can consider the pair of EU-JP, it is less correlated compared to other pair in the ESDC period; this evidence indicates that DJSI investors can consider this pair to reduce their investment risk for DJSI. However, we discover most of the pairs are contagions during the three crisis periods; in other words, the pair of DJSI cannot reduce investors' investment risk. Hence, if DJSI investors want to reduce their investment portfolio risk, they can consider other financial assets such as real estate or commodities markets.

For the last two chapters, we investigate the relationship between financial assets and two 'financisisation' assets via a new modification of the DCC-MIDAS model; the third chapter focus on the three benchmark indexes (global equities, real estate and aggregated commodities), the last chapter focus on the connection between two benchmark markets (global equities and real estate) and disaggregated commodities categories (energy commodities, precious metals, industrial metals, agriculture and livestock). Our results show the highest correlation in the third chapter is the pair of equities and real estate, and the highest correlation in the fourth chapter is the pair of equities and industrial metals; the last chapter also indicates the intra-commodities' connections are the strongest compared to the other two groups (equities - commodities and real estate - commodities). Meanwhile, both chapters present the difference between the short- and long-run correlations, and we indicate the hedging properties and interdependence of each pair and also the corresponding crisis. In addition, our correlation analysis covers the macroeconomic factors of the correlations. These two chapters suggest the crisis shocks expand the macroeconomic factors on the correlation. Based on these two chapters' empirical evidence, we can suggest that investors should consider the pair of Real estate and intra-commodities and the pair of intra-commodities to reduce systems' risk. In the meantime, investors should pay attention to the macroeconomic variable such as economic policy uncertainty most likely increases their investment portfolio risk. Therefore, we can conclude these two chapters summarise investors are not only focusing on the financial market itself but also need to consider the macroeconomic environment.

The further research about the dynamic correlation, we can include cross-sectors and cross-countries together to analyse their dependencies. Meanwhile, we can continue our work in the cDCC-GARCH-MIDAS model to modify the long-run component (MIDAS) part.

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