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Short- and long-run cross-border European sustainability interdependences

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Abstract

The increasing interest in climate change risks, environmental degradation, corporate social responsibility, and environmental, social, governance principles has motivated the recent soaring focus of policymakers, market practitioners, and academics on sustainable investments. In this vein, we investigate the cross-country interconnectedness among sustainability equity indices. Using a bivariate Dynamic Conditional Correlations-Mixed Data Sampling (DCC-MIDAS) specification, we study the short- and long-run time-varying dependence dynamics between European and five international (Australia, Brazil, Japan, US, and Canada) sustainability benchmarks. Our cross-country dynamic correlation analysis identifies the interdependence types and hedging characteristics in the short- and long-run across the business cycle. The significant macro- and crisis-sensitivity of the sustainability correlation pattern unveils strong countercyclical cross-country sustainability interlinkages for most index pairs and crisis periods. We further reveal the high- and low-frequency contagion transmitters or interdependence drivers in the macro environment during the 2008 global financial turmoil, the European sovereign debt crisis, and the recent pandemic-induced crash. Finally, we demonstrate that climate change risks and policy considerations are potent catalysts for both countercyclical and procyclical cross-border sustainability spillovers.

Keywords Climate change risk · Contagion · DCC-MIDAS · Economic policy uncertainty · ESG investment · Financial/health crisis · Sustainability interdependence

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 environ-

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ment (Huang et al., 2017; Nechi et al., 2020; Tsai et al., 2023; EBA, 2022; Aloui et al., 2023). Green finance and transformation, climate change physical and transition risks are at the epicenter of corporate governance priorities (Garefalakis & Dimitras, 2020; Giannarakis et al., 2020; Kalaitzoglou et al., 2021; Behl et al., 2022). Similarly, investors have started targeting at corporate securities with high ESG (environmental, social, governance) standards to fulfill strong sustainability mandates (Jawadi et al., 2019; Benedetti et al., 2021; Liagkouras et al., 2022; Semmler et al., 2022; Boubaker et al., 2023).

Against this backdrop, we investigate the cross-border co-movement of major sustainability benchmarks through a time-varying (dynamic) correlations econometric framework. Sustainability interlinkages are still underresearched in the relevant bibliography, and our study fills this notable literature gap with significant implications. 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 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 (Naeem et al., 2021; Chai et al., 2022; Liagkouras et al., 2022; Rizvi et al., 2022; 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 (Lin et al., 2018; Zhu et al., 2018; Cerqueti et al., 2021; Miled et al., 2022; Benkraiem et al., 2022).

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 (Dynamic Conditional Correlations-Generalised Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling). The specification of Colacito et al. (2011) quantifies the stock index dependence dynamics by computing their short- and long-run dynamic conditional correlations, in contrast to the simpler one 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 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 behaviour of our time series 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 rise 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 macro-financial variables 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 and Lin (2022), Zhang et al. (2022), and the literature therein). Hence, adding to this burgeoning strand of the economics and finance bibliography, our study is the first to distinguish between short- and long-run 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 their 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 lower the hedging potential and effectiveness of cross-country sustainability investment strategies and trigger regulatory authorities to devise stabilising policies that mitigate contagion turbulence.

The remainder of the study is structured as follows. Section 2 presents the theoretical framework of our paper, reviews the related literature, and develops the hypotheses to test our research questions. In Sect. 3, we describe the methodological approach and the data used. Section 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.

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; Kumar et al., 2022; Boroumand 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 (El Ghoul & Karoui, 2017; Aouadi & Marsat, 2018; 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 (Forbes & Rigobon, 2002; Baur, 2012), 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 and Lin (2022) focus on spillovers among global ESG leaders. Such ESG interdependence studies (see also, Reboredo, 2018; Jin et al., 2020; Le et al., 2021) 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 gap in the literature 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 Forbes and Rigobon (2002) and Baur and Lucey (2009), 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 that there are higher or lower interdependence phenomena (see Table 1, Panel A, for all possible scenarios given correlation changes and levels during crises). Turning to the hedging features, we will follow Baur and 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 lowers 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 1, 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*).

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 Sect. 3.1 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 (Bekaert et al., 2013; Baker et al., 2016; Berger et al., 2023). News and sentiment reflected by news dissemination are equally catalytic for the economy (Buckman et al., 2020; Shapiro et al., 2020). 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 (Engle et al., 2013; Conrad et al., 2014; Mobarek et al., 2016).

In Table 1, 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 to have 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 moderating role of EPU 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 Pastor and Veronesi (2013) and Karanasos and Yfanti (2021), among others.

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

Table 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

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)	−	+

The table presents the theoretical underpinningsof the sustainability interdependences. Panel Asummarises our hypotheses on theinterdependence types (H1 & H2). Panel B recapsour hypotheses on the macro-sensitivity ofsustainability interdependences (H3 & H4).

Table 2 Data description

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

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

of the DCC-MIDAS output on global daily and monthly macro proxies, the moderating role of the uncertainty channel, and the crisis impact.

3.1 Data description

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)[1] and calculate the returns to be included as input in the bivariate 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 2, Panel A). The summary statistics (descriptive statistics and unit root tests) of the return series are reported in Table 10 of the "Appendix". Since we will focus on the dynamic correlations of the EU with the other five countries, we also compute the corresponding static correlation coefficients (EU Corr

[1] Our country selection is based on data availability. Given that we aim to explore the sustainability interlinkages of Europe with other global markets, we choose major stock markets with DJSI data series, which cover all three crisis periods and represent most continents/regions worldwide. Australia and Japan are used as representatives of the Asia-Pacific region. North America is represented by US and Canada, and South America is proxied by Brazil. Only Africa is not incorporated since the DJSI dataset does not provide enough data for African indices.

column in Table 10). 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 system of equations.

Next, we detail the macro variables used as correlation determinants in the macro-sensitivity analysis (Table 2, 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 on the world economy and for 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 (Engle et al., 2013; Conrad et al., 2014; Mobarek et al., 2016; Conrad & Stürmer, 2017; Karanasos & Yfanti, 2021; Yfanti et al., 2023). Hence, the variables used for each economic driver are as follows (see also Table 2 notes for the sources of the regressor data, and Table 11 in the "Appendix" for the regressors' summary statistics):

Variables increasing in economic worsening

1. 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 have been 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 correlation regressions and rises in weak economic periods.
2. 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 (Bloom, 2014; Bekaert et al., 2013) and soars in turbulent times.
3. 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.
4. 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.

5. Climate change risk (*CC*): The log-transformed monthly climate policy uncertainty index (CPU_τ) proxies climate change risk (Gavriilidis, 2021) in long-run correlation regressions. 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

1. 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., 2020) 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 values), apparent in recessionary periods.
2. 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.
3. 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, falling in weak economic periods.
4. 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.
5. 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. The five variables increasing in economic worsening are expected to have 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. The five variables decreasing in economic worsening will negatively affect correlations in contagion periods, given that lower news sentiment, confidence, activity, freights, and inflation will raise 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:

1. GFC: 09/08/2007–31/03/2009.

2. ESDC: 09/05/2010–31/12/2012.
3. 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 waves of the pandemic 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.

3.2 Econometric framework

3.2.1 The dynamic correlations

The conditional means

The daily index return, at time t (the high-frequency time scale), is denoted by r_{it}, $i = 1, 2$. It is assumed that the conditional (on the information at time $t-1$ set, Ω_{t-1}) distribution of r_{it} is given by $r_{it}\,|\Omega_{t-1} \sim i.i.d.\ N(\mu_i, h_{it})$, with conditional covariance: $h_{ij,t} = \mathbb{C}ov(r_{it}, r_{jt}\,|\Omega_{t-1})$. That is $\mu_i = \mathbb{E}(r_{it}\,|\Omega_{t-1})$, is the conditional mean ($\mathbb{E}$ denotes the expectation operator), and $h_{it} \overset{def}{=} h_{ii,t} = \mathbb{V}ar(r_{it}\,|\Omega_{t-1})$, $i = 1, 2$ is the conditional variance. Alternatively, r_{it} can be written as

$$r_{it} = \mu_i + \varepsilon_{it}, \tag{1}$$

where the error ε_{it} will be analysed below.

The errors

The DCC-MIDAS model can be thought of as a *double* Time-Varying Multivariate GARCH type of model. To see this explicitly, we will consider two sets of errors: $\varepsilon_{i\mathbf{t}}$ in Eq. (1) and e_{it} (see Eq. (9) below).

The ε_{it}

Regarding ε_{it}, we assume that it is conditionally normally distributed with mean 0, and conditional covariance $h_{ij,t} = \mathbb{E}(\varepsilon_{it}\varepsilon_{jt}|\Omega_{t-1})$, $i, j = 1, 2$. We will also assume that the conditional variance, h_{it}, follows a GARCH-MIDAS model (see the analysis below). The conditional correlation of ε_{it}, denoted by $\rho_{ij,t}$, is given by:

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

with $\left|\rho_{ij,t}\right| \leq 1$.

Notice that ε_{it} can be expressed as $\varepsilon_{it} = \sqrt{h_{it}}\xi_{it}$. In other words, the *devolatilised* error ξ_{it} is equal to $\varepsilon_{it}/\sqrt{h_{it}}$, which implies that the conditional correlation of ξ_{it} is also $\rho_{ij,t}$.

The e_{it}

Regarding e_{it}, we assume that it is conditionally normally distributed with mean 0, and conditional covariance $q_{ij,t} = \mathbb{E}(e_{it}e_{jt}|\Omega_{t-1})$, and it is also assumed that it is equal to $e_{it} = \sqrt{q_{ii,t}}\xi_{it}$. These two assumptions entail (in view of the definition of the *devolatilised* errors) that the conditional correlation of e_{it} is also $\rho_{ij,t}$:

$$\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}. \tag{3}$$

In the second step of our estimation procedure, we will assume that $q_{ij,t}$ follows the DCC-MIDAS model [see Eq. (9)]. It follows from eqs. (2) and (3) that

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

To summarise, the model in the first step estimates the vector of the errors, ε_{it}, and the vector of the conditional variances, h_{it}, using a GARCH-MIDAS process (see, for example, Engle et al., 2013; Conrad & Loch, 2015), and thus, correspondingly the vector of the *devolatilised* errors, ξ_{it}. In the second step, it estimates the matrix of the conditional covariances of the errors e_{it}, $q_{ij,t}$. Once h_{it} and $q_{ij,t}$ are estimated, then the estimated $\rho_{ij,t}$ (the conditional correlations of the errors, either e_{it}, or ξ_{it}, or ε_{it}) are obtained using the first equality in Eq. (4), and then the estimated conditional covariances $h_{ij,t}$ are obtained using the second equality in Eq. (4).[2]

The conditional variances

We will employ a two-component specification for the modelling of volatilities. First, we will introduce another time scale, that is the low-frequency one (i.e., monthly or quarterly, or biannual) denoted by τ. σ_i and m_i will denote the short- and long-run variance components, respectively, for asset i. We assume that the latter component (the MIDAS one) is held constant across the days of the month, quarter or half-year. The number of days that m_i is held fixed (i.e., a month or a quarter) is denoted by $K_v^{(i)}$, where the superscript i indicates that this may be asset specific and the subscript v differentiates it from a similar scheme that will be introduced later for correlations.

In particular, we will assume that each conditional variance, h_{it}, follows the two-component GARCH-MIDAS model[3]:

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

where σ_{it} follows a GARCH(1, 1) process:

$$\sigma_{it} = (1 - \alpha_i - \beta_i) + \alpha_i \xi_{i,t-1}^2 \sigma_{i,t-1} + \beta_i \sigma_{i,t-1} \tag{5}$$

(notice that in view of Eq. (1), that is $\varepsilon_{it} = r_{it} - \mu_i$, and the fact that $\varepsilon_{it}^2 = m_{i\tau}\sigma_{it}\xi_{it}^2$, we have: $\xi_{it}^2\sigma_{it} = (r_{it} - \mu_i)^2/m_{i\tau}$), while the MIDAS component $m_{i\tau}$ is a weighted sum of $M_v^{(i)}$ lags of realised variances (RV) over a long horizon:

$$m_{i\tau} = m_i + \theta_i \sum_{l=1}^{M_v^{(i)}} \varphi_l(\omega_v^{(i)}) RV_{i,\tau-l} \tag{6}$$

2 As pointed out by Colacito et al. (2011), the asymptotic properties of the two-step estimator are discussed in Comte and Lieberman (2003), Ling and McAleer (2003), and McAleer et al. (2008). These papers deal with fixed-parameter DCC models. Wang and Ghysels (2015) provide a rigorous analysis of the ML (Maximum Likelihood) estimation of the GARCH-MIDAS model. The regularity conditions that guarantee the standard asymptotic results for the two-step estimation of the DCC-MIDAS (see p. 48 in Colacito et al., 2011) is an open question.

3 We should use the notation $h_{it,\tau}$, but we drop the subscript τ for notational simplicity.

where the so-called Beta weights are defined as

$$\varphi_l(\omega_v^{(i)}) = \frac{\left(1 - \frac{l}{M_v^{(i)}}\right)^{\omega_v^{(i)}-1}}{\sum_{j=1}^{M_v^{(i)}} \left(1 - \frac{j}{M_v^{(i)}}\right)^{\omega_v^{(j)}-1}}, \tag{7}$$

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

$$RV_{i\tau} = \sum_{t=(\tau-1)K_v^{(i)}+1}^{\tau K_v^{(i)}} r_{it}^2. \tag{8}$$

The rate of decay of the beta weights in Eq. (7) is determined by the size of $\omega_v^{(i)}$, that is large (small) values of $\omega_v^{(i)}$ generate a rapidly (slowly) decaying pattern. We will consider the case where the parameters $M_v^{(i)}$ and $K_v^{(i)}$ are the same across both series, that is $M_v^{(i)} = M_v$ and $K_v^{(i)} = K_v$ for $i = 1, 2$. The short-run component [see Eq. (5)] is based on daily (squared returns), which moves around a long-run component driven by realised volatilities computed over a monthly or quarterly basis [(see Eqs. (6)–(8)].[4] In the former case $K_v = 22$, whereas in the latter $K_v = 66$. As τ varies, the time span that $m_{i\tau}$ is fixed (that is M_v) also changes. In particular, the number of (lag) years, spanned in each MIDAS polynomial, $m_{i\tau}$, varies from one to four years. More specifically, in a monthly basis, $M_v = 12, 24, 36, 48$, whereas in a quarterly basis $M_v = 4, 8, 12, 16$.

Since the number of parameters is fixed, we can compare various models with different time spans. More specifically, following Colacito et al. (2011) and Engle et al. (2013), we profile the log-likelihood function in order to maximise it with respect to the time span covered by RV.

The conditional correlations
First, we will make use of the following definition.

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

Using the vector of the *devolatilised* residuals, ξ_{it}, we employ the DCC-MIDAS (the MIDAS version of the DCC model) to obtain $q_{ij,t}$ as follows:

$$q_{ij,t} = \rho_{ij,\tau}(1 - a - b) + a\xi_{i,t-1}\xi_{j,t-1} + bq_{ij,t-1}, \tag{9}$$

where

$$\rho_{ij,\tau} = \sum_{l=1}^{M_c^{(ij)}} \varphi_l(\omega_r^{(ij)})c_{ij,\tau-l}. \tag{10}$$

Notice that $q_{ii,t}$ is given by

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

[4] Note that in the case of volatility, Engle et al. (2013) found that although $m_{i,\tau}$ can be formulated either via keeping it locally constant or else based on a local moving window, the difference between the two appears to be negligible. Colacito et al. (2011) noted that for correlations, a researcher potentially has the same choice. Since the fixed span is more general, we adopt this for our formulation (instead of the rolling window one).

The specification in Eq. (10) can accommodate weights $\omega_c^{(ij)}$, lag lengths $M_c^{(ij)}$, and span lengths of historical correlations $K_c^{(ij)}$ to differ across any pair of series. Typically, and following Colacito et al. (2011), we will use a single setting common to all pairs of series, similar to the choice of a common MIDAS filter in the univariate models. In the case of a common decay parameter ω_c independent of the pair of returns series selected, the covariance matrices are positive definite under a relatively mild set of assumptions since it is apparent from Eq. (9) that the matrix $\mathbf{Q}_t = [q_{ij,t}]$ is a weighted average of three matrices. The matrix $\mathbf{R}_\tau = [\rho_{ij,\tau}]$ is positive semi-definite because it is a weighted average of correlation matrices. The matrix $\boldsymbol{\xi}_t\boldsymbol{\xi}_t'$, where $\boldsymbol{\xi}_t = [\xi_{it}]$, is always positive semi-definite by construction. Therefore, if the matrix $\mathbf{Q}_0$ is initialised to be a positive semi-definite matrix, it follows that $\mathbf{Q}_t$ must be positive semi-definite at each point in time (see Colacito et al. (2011), for the implication of a single versus multiple parameter choices for the filtering scheme).

Correlations can then be computed using Eq. (4). We can express Eq. (9) as

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

The daily dynamics of the correlations (covariances), $\rho_{ij,t}(q_{ij,t})$, obey a DCC scheme, with the correlations moving around a long-run component ($\rho_{ij,\tau}$). As pointed out by Colacito et al. (2011): "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".

3.2.2 Macro-sensitivity

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 Sect. 3.1. According to *H3* and *H4* (see Sect. 2), we expect weak fundamentals to increase countercyclical correlations or lower 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:

$$\begin{aligned}\rho^*_{ij,t} &= \delta_0 + \delta_1\rho^*_{ij,t-1} + \delta_2 EPU_{t-1} + \delta_3 FU_{t-1} + \delta_4 DIS_{t-1} \\ &\quad + \delta_5 CR_{t-1} + \delta_6 NW_{t-1} + \delta_7 EA_{t-1} + \delta_8 FT_{t-1} + u_t,\end{aligned} \tag{11}$$

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:

$$\rho^*_{ij,\tau} = \zeta_0 + \zeta_1 \rho^*_{ij,\tau-1} + \zeta_2 EPU_{\tau-1} + \zeta_3 CR_{\tau-1} + \zeta_4 CC_{\tau-1} + \zeta_5 CONF_{\tau-1} + \zeta_6 EA_{\tau-1} + \zeta_7 FT_{\tau-1} + \zeta_8 PR_{\tau-1} + u_\tau. \quad (12)$$

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

The correlation regressors are included in their level, log-level, first difference, or growth form (see Sect. 3.1). We choose the most appropriate form of the data series, which ensures the significance and robustness of each regressor's impact on correlations and rejects the unit root and multicollinearity hypotheses among the macro-financial variables. The unit root is rejected from the ADF tests (see the ADF test statistics in Table 11 of the "Appendix"). Multicollinearity bias is also ruled out through the Variance Inflation Factors (VIF) test. We run VIF tests for each daily and monthly regressor and result with no or low correlations among the independent variables, which do not distort the estimation of the OLS regression coefficients (VIF test statistics available upon request).

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 Pastor & Veronesi, 2013). The uncertainty increment is captured by the EPU interaction terms in the following regression:

$$\begin{aligned}\rho^*_{ij,t} &= \delta_0 + \delta_1 \rho^*_{ij,t-1} + \delta_2 EPU_{t-1} + (\delta_3 + \delta_3^{EPU} EPU_{t-1}) FU_{t-1} \\ &\quad + (\delta_4 + \delta_4^{EPU} EPU_{t-1}) DIS_{t-1} + (\delta_5 + \delta_5^{EPU} EPU_{t-1}) CR_{t-1} \\ &\quad + (\delta_6 + \delta_6^{EPU} EPU_{t-1}) NW_{t-1} + (\delta_7 + \delta_7^{EPU} EPU_{t-1}) EA_{t-1} \\ &\quad + (\delta_8 + \delta_8^{EPU} EPU_{t-1}) FT_{t-1} + u_t, \end{aligned} \quad (13)$$

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. (11) to capture the crisis-vulnerability of sustainability interdependences. Intercept dummies measure the influence of the crisis on correlation levels, and slope dummies measure the impact of the crisis on the macro determinants' effects on correlations. The three crisis intercept dummies, $DUM_{C,t}$, are constructed based on the crisis timelines (see Sect. 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:

$$\begin{aligned}\rho^*_{ij,t} &= \delta_0 + \delta_0^C DUM_{C,t} + \delta_1 \rho^*_{ij,t-1} + (\delta_2 + \delta_2^C DUM_{C,t-1}) EPU_{t-1} \\ &\quad + (\delta_3 + \delta_3^C DUM_{C,t-1}) FU_{t-1} \\ &\quad + (\delta_4 + \delta_4^C DUM_{C,t-1}) DIS_{t-1} + (\delta_5 + \delta_5^C DUM_{C,t-1}) CR_{t-1} \\ &\quad + (\delta_6 + \delta_6^C DUM_{C,t-1}) NW_{t-1} \\ &\quad + (\delta_7 + \delta_7^C DUM_{C,t-1}) EA_{t-1} + (\delta_8 + \delta_8^C DUM_{C,t-1}) FT_{t-1} + u_t, \end{aligned} \quad (14)$$

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:

$$\begin{aligned}\rho^*_{ij,t} &= \delta_0 + \delta_1 \rho^*_{ij,t-1} + \delta_2 EPU_{t-1} \\ &+(\delta_3 + \delta_3^{EPU\_C} DUM_{C,t-1} EPU_{t-1}) FU_{t-1} \\ &+(\delta_4 + \delta_4^{EPU\_C} DUM_{C,t-1} EPU_{t-1}) DIS_{t-1} + (\delta_5 \\ &+\delta_5^{EPU\_C} DUM_{C,t-1} EPU_{t-1}) CR_{t-1} \\ &+(\delta_6 + \delta_6^{EPU\_C} DUM_{C,t-1} EPU_{t-1}) NW_{t-1} + (\delta_7 \\ &+\delta_7^{EPU\_C} DUM_{C,t-1} EPU_{t-1}) EA_{t-1} \\ &+(\delta_8 + \delta_8^{EPU\_C} DUM_{C,t-1} EPU_{t-1}) FT_{t-1} + u_t. \end{aligned} \tag{15}$$

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

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.

4.1 Dynamic correlations (estimation)

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 reports the variance (Panel A) and 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. 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 unity. In the MIDAS variance part, 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).

Moreover, in the five $\boldsymbol{\theta}$, a and b drive the daily (short-term) correlations, and they are significant in most cases with a sum lower than the unity to ensure the mean-reversion of the daily process to the long-term average. Only in the EU-US pair, we estimate a much smaller (compared with the other pairs) and insignificant b. The long-run correlations are driven by monthly realised correlations with the weight coefficient (ω_r^{ij}) always significant, with values from 1.00 to 6.56.

The short- (daily) and long-run (monthly) correlation time series are the output of the DCC-MIDAS variance-covariance matrix estimated. Figures 1a-1e show the time-varying interdependence of the European sustainability benchmark with Australia, Brazil, Japan,

Table 3 DCC-MIDAS estimation results

	EU	AUS	BRA	JP	US	CA
Panel A. Variance equation						
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

	a	b	$\omega_r^{(ij)}$	$logL$	AIC	BIC
Panel B. Correlation equation						
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

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

United States, and Canada. In most cases, the cyclical pattern follows the business 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 4) show that all correlation mean values in the short and long term are positive but significantly lower than 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 (the correlation mean values between 0.42 and 0.57 are higher than in the other three pairs), 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 10

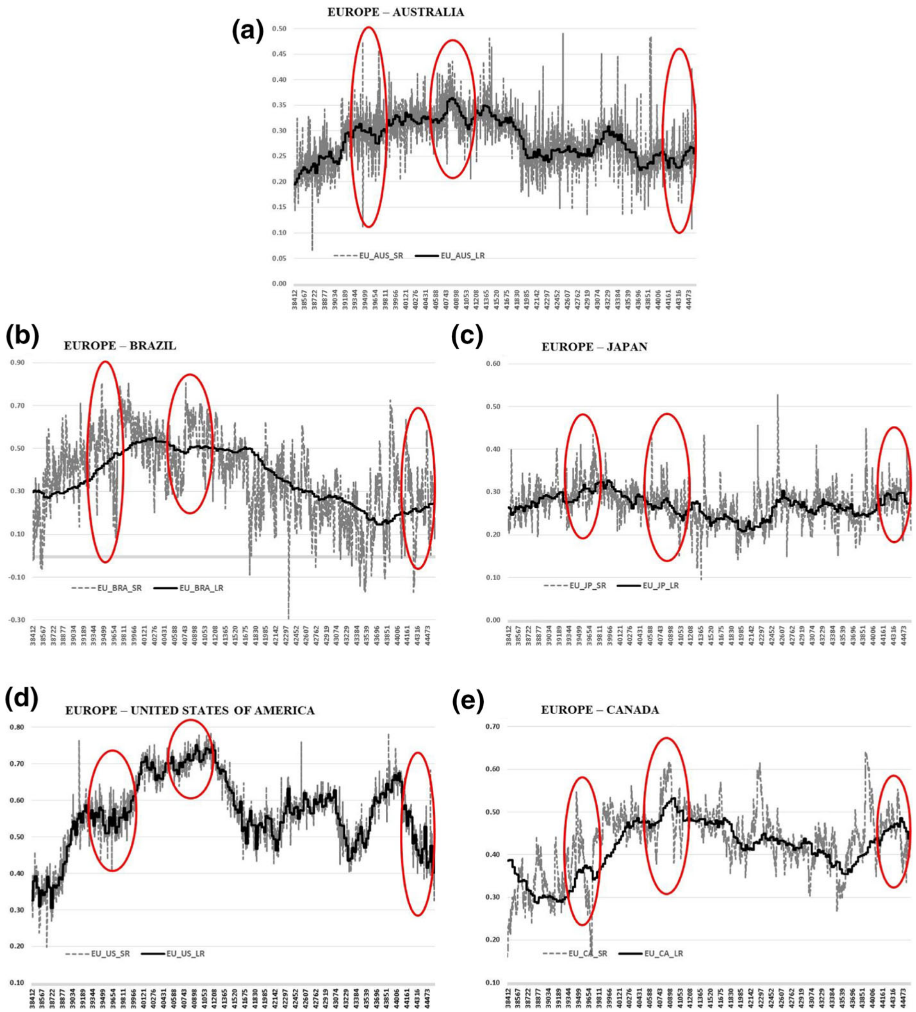

Fig. 1 Dynamic Cross-country Sustainability Correlations [grey dotted series: short-run correlation, solid black series: long-run correlation, red circle: crisis subsample]

(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 4, columns: Std.Dev.). Overall, the whole period statistics do not show any striking difference between short- and long-run patterns (similar mean, median, and minimum values) with the exception of daily EU-BRA correlations' 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

Table 4 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

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)

pre-crisis subsamples cover an equally long period with the crisis interval before the start of the crisis. We further test alternative pre-crisis subsample lengths for robustness purposes and result in similar conclusions for the interdependence types.

Table 5 (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 5, 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 do not 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.

4.2 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

Table 5 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

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

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 (uncertainty/confidence), 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. Similarly, 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 6 reports the baseline daily (Panel A) and monthly (Panel B) 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. (11)]. 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 and 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. (12)] 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 could 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 (Sect. 3.2.1), the countercyclical pattern prevails in the macro-sensitivity of the whole sample.

Our macro-sensitivity analysis continues with the uncertainty channel [Eq. (13)]. 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 impact, which is highly significant in all cases of short- and long-run correlations (Table 6), we focus on the indirect EPU effect on the macro drivers of sustainability co-movements. Table 7 reports the parameters of the EPU interaction terms in the daily correlations regression analysis (similar results for long-term correlations available upon request).

We run Eq. (13) 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. The freights and economic activity coefficients are insignificant in two cases and one case, respectively, but with the negative sign as expected and consistently with the FT and EA direct impact on daily correlations estimated in Table 6 [insignificant cases also in Eq. (11)]. The EPU impact is stronger on the financial uncertainty, credit conditions, and news sentiment regressors (higher significance levels for FU, CR, and NW EPU interaction terms). Interestingly, we observe that the credit channel and two behavioural proxies (FU and NW) are more affected by the loss of economic confidence across all pairwise cross-border sustainability interdependences. The indirect EPU effect on the economic forces behind the sustainability correlations is potent and should give an important alert to policymakers globally. Authorities' decisions that create confidence and decrease EPU levels will alleviate contagion and improve portfolios' diversification benefits

Table 6 Dynamic sustainability correlations macro regressions

	EU-AUS	EU-BRA	EU-JP	EU-US	EU-CA
Panel A. Short-run sustainability correlations [Eq. (11)]					
δ_0	0.1293*** (0.0375)	−0.1730 (0.1237)	0.1965*** (0.0395)	0.1546* (0.0915)	0.2710*** (0.0366)
$\rho^*_{ij,t-1}$	0.8974*** (0.0205)	0.9499*** (0.0049)	0.9197*** (0.0072)	0.9648*** (0.0044)	0.9877*** (0.0026)
EPU_{t-1}	0.0073*** (0.0026)	0.0071** (0.0036)	0.0084*** (0.0011)	0.0038* (0.0022)	0.0012*** (0.0004)
FU_{t-1}	0.0262*** (0.0085)	0.0159*** (0.0048)	0.0422** (0.0175)	0.0228*** (0.0041)	0.0835*** (0.0119)
DIS_{t-1}	0.0134*** (0.0023)	0.0041** (0.0020)	0.0016* (0.0009)	0.0033* (0.0020)	0.0008* (0.0005)
CR_{t-1}	0.0953*** (0.0169)	0.0562*** (0.0109)	0.0720*** (0.0294)	0.0415*** (0.0074)	0.0187*** (0.0033)
NW_{t-1}	−0.0674*** (0.0103)	−0.0115** (0.0051)	−0.0316** (0.0136)	−0.0231*** (0.0076)	−0.0229* (0.0121)
EA_{t-1}	−0.0110** (0.0047)	−0.0089*** (0.0016)	−0.0034** (0.0016)	−0.0013** (0.0006)	−0.0013 (0.0015)
FT_{t-1}	−0.0002* (0.0001)	−0.0005 (0.0005)	−0.0006* (0.0004)	−0.0011*** (0.0003)	−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	0.9379	0.9658	0.9751	0.9781
Panel B. Long-run sustainability correlations [Eq. (12)]					
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	−6.7680	−6.6714	−6.9415	−3.8374	−6.5582
BIC	−6.5521	−6.4563	−6.7256	−3.6215	−6.3408
DW	2.0140	2.0725	2.0757	2.0966	2.0313
$\overline{R}^2$	0.9834	0.9867	0.9742	0.9451	0.9853

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 and monthly macro regressors [Eqs. (11) and (12)]. 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 7 The economic uncertainty impact on the macro determinants of short-run sustainability correlations, Eq. (13)

$EPU_{t-1}\times$	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)

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

and hedging effectiveness in responsible investment strategies. On the other hand, regulatory uncertainty distorts the investment environment and contributes to contagion risks.

To sum up, 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 (Pastor & Veronesi, 2013; Karanasos & Yfanti, 2021; Yfanti et al., 2023) and warns macro-informed traders and policymakers in investing and regulating the financial system by promoting sustainable investments and green transition.

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. (14). The estimated parameters of the crisis intercept dummies are reported in Table 12 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 5, Panel A).

Next, we run Eq. (14) to estimate the crisis slope dummies, reported in Table 8. 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 EU countercyclical pairs (AUS, US, CA). For BRA and JP, the two EU procyclical pairs in the European crisis, the crisis slope dummies have the opposite sign to 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).

Table 8 The crisis impact on the macro determinants of short-run sustainability correlations, Eq. (14)

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)

Table 8 continued

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-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)

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

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. (15). In Table 9, 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 8. The EPU moderation makes more slope dummies significant for the freights proxy compared with the crisis impact (Table 8). Overall, the uncertainty channel's magnifying impact on the macro determinants is aggravated by the crisis shocks in most cases, confirming the increased macro-sensitivity during turbulent times.

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 that there are 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 lower 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 to adopt 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 transi-

Table 9 The economic uncertainty impact on the macro determinants of short-run sustainability correlations in crisis periods, Eq. (15)

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)

Table 9 continued

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-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)

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 tion to the greener. Lastly, ESG risk regulatory frameworks should incorporate possible risk concentrations driven by increased sustainability interdependences.

5 Conclusions

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.

A Appendix

See Tables 10, 11 and 12.

Table 10 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

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 11 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*

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 12 The crisis impact on the level of daily sustainability correlations, Eq. (14)

	$DUM_{GFC,t}$	$DUM_{ESDC,t}$	$DUM_{COV,t}$
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)

The table reports the crisis impact on daily correlations [Eq. (14)]. The crisis intercept dummies are estimated separately from the crisis slope dummies. The inter- cept 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

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