Short- and Long-run Cross-border Sustainability Interdependences

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- The increasing interest in climate change risks, environmental degradation, corporate social responsibility, and ESG (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.

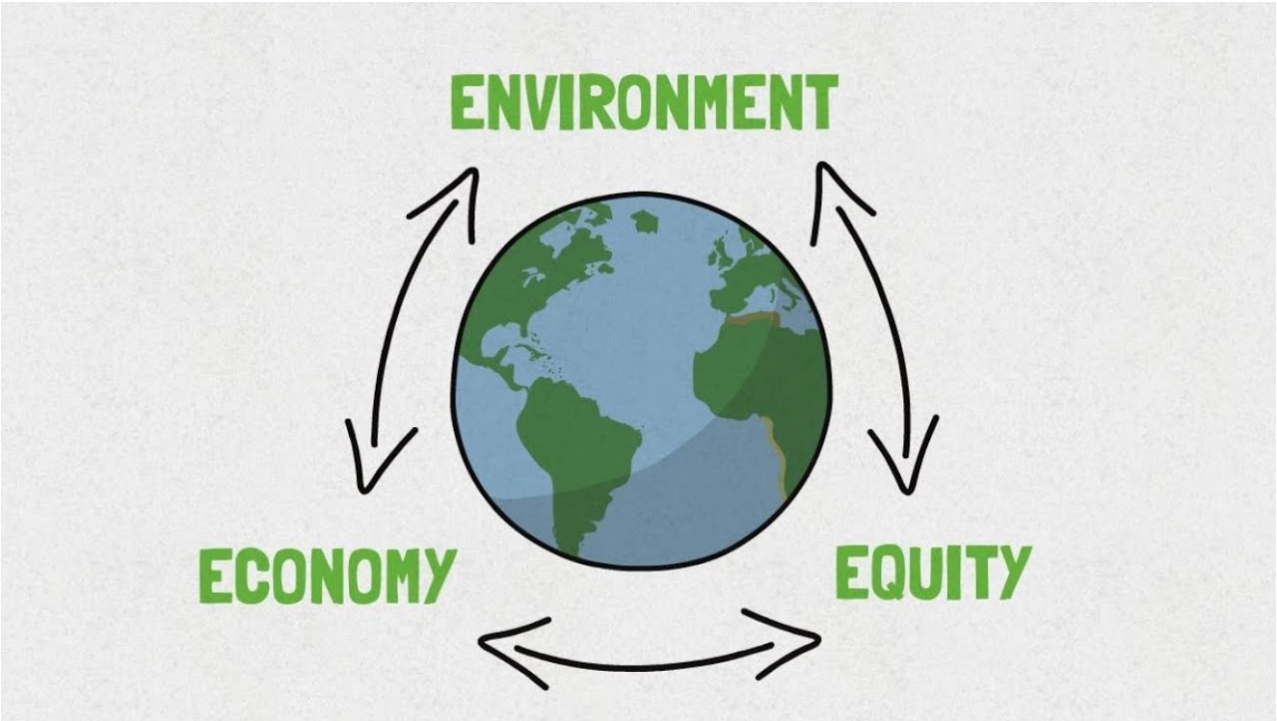
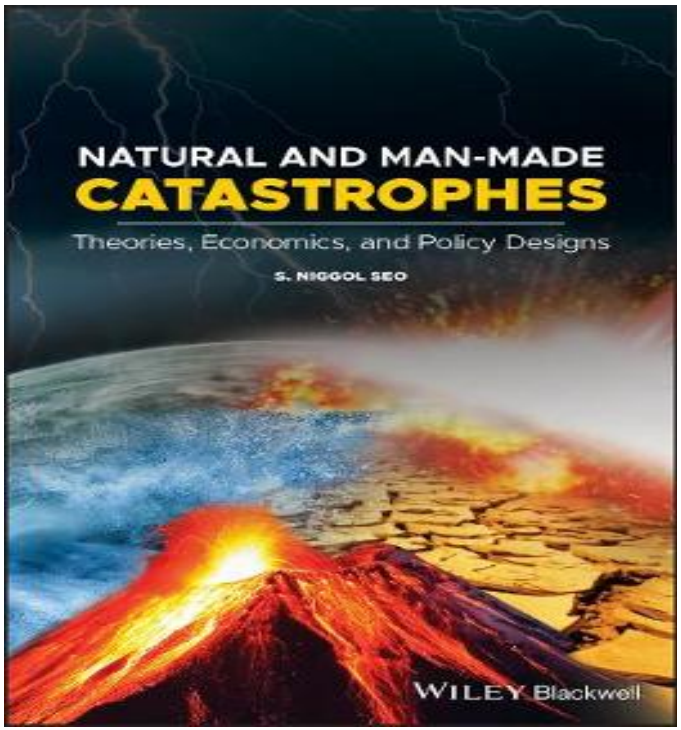


Table 1. Theoretical framework of sustainability interdependences

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



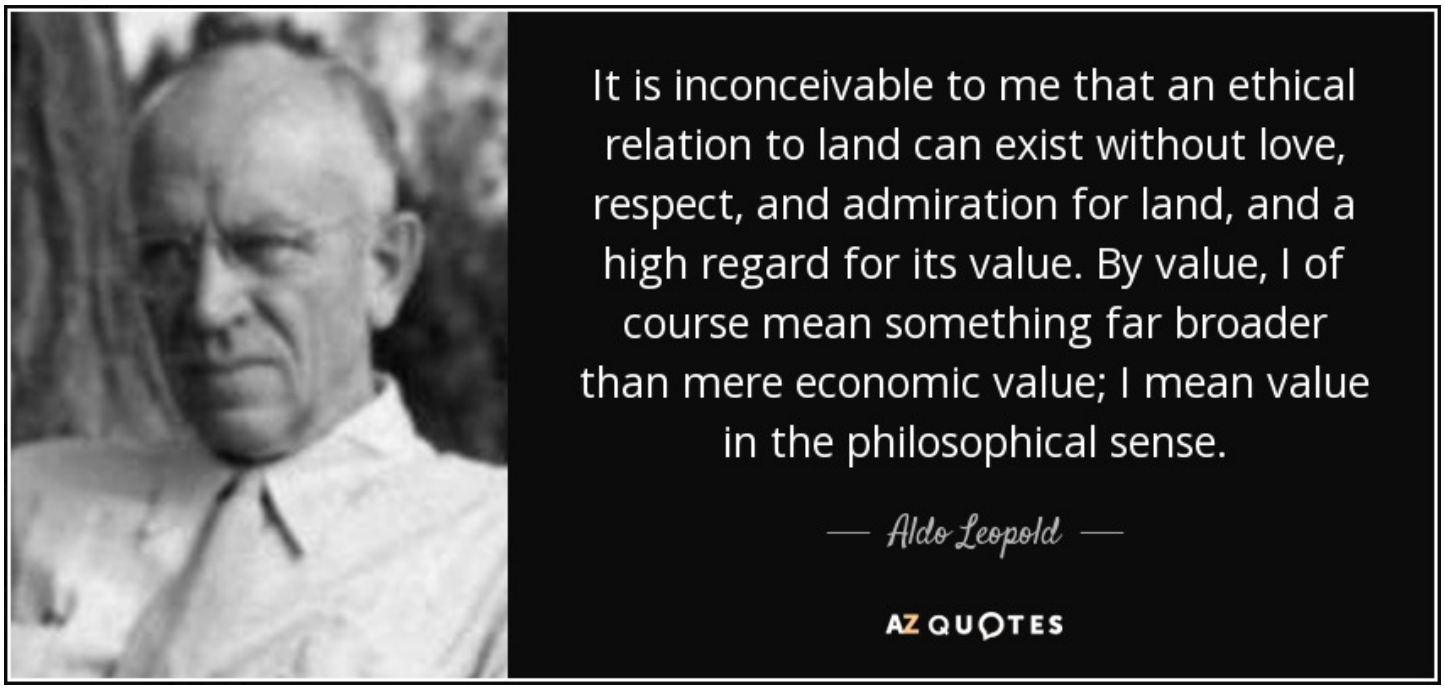
- **Contagion** and/or *Higher Interdepedence*

in-crisis correlations change $\downarrow$ / level $\longrightarrow$	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

- **Flight-to-Quality** and /or *Lower Interdepedence*

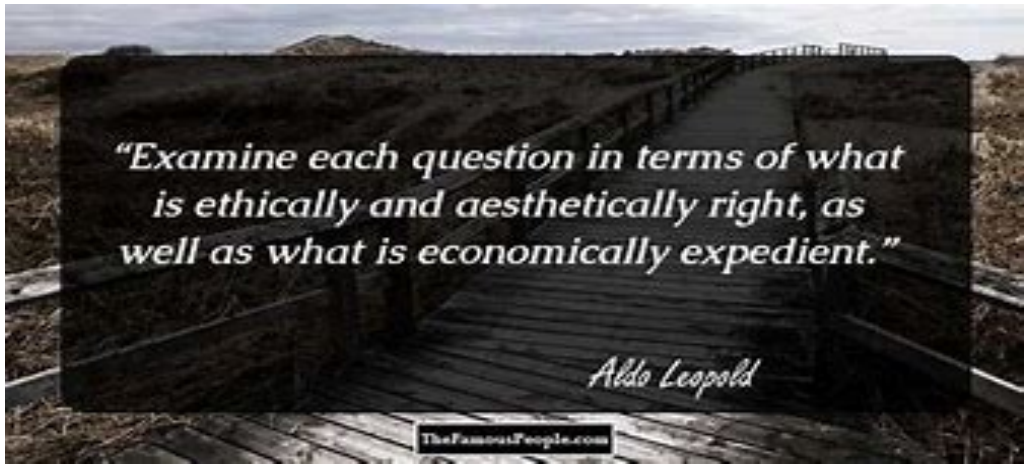
- Turning to the hedging features, we will follow Baur and Lucey (2010) theory.
- Regarding the first two hedging properties, we will define **diversifiers and hedges** based on the whole sample average of the correlation time series.
- *Diversifiers* are the (not perfectly) positively correlated assets,
- while *hedges* are negatively correlated or uncorrelated.

Aldo Leopold (January 11, 1887 – April 21, 1948) was an American writer, philosopher, naturalist, scientist, ecologist, forester, conservationist, and environmentalist. He was a professor at the University of Wisconsin



- 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*).

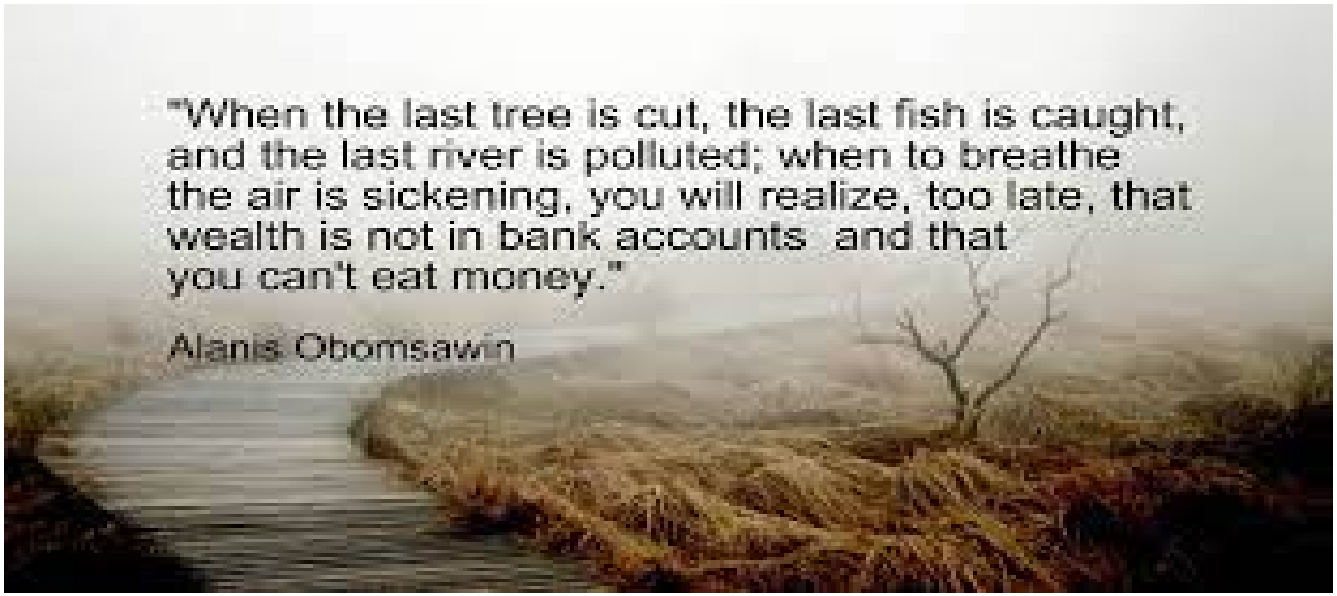
- Motivated by recent studies on *correlation macro determinants* (Karanasos and Yfanti, 2021, **JIFMIM** Yfanti et al., 2023, **EJOR**),
- we will include global proxies that capture the various aspects of the macro environment where financial markets operate



- Moving to the correlation drivers and macro-sensitivity, we develop the last two hypotheses as follows

- 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*).

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 Conditional Means**

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

- **The Errors**
- The DCC-GARCH-MIDAS model can be thought of as a *double* TV-MGARCH (Time Varying Multivariate GARCH) type of model.
- To see this explicitly, we will consider two sets of errors:

- 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, $h_{it} \overset{def}{=} h_{ii,t} = \mathbb{V}ar(r_{it}|\Omega_{t-1})$, follows a **GARCH-MIDAS** model (see the analysis below).

- The conditional correlation of ε_{it}, denoted by $\rho_{ij,t}$, is given by:

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

  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 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 is equal to $e_{it} = \sqrt{q_{ii,t}}\zeta_{it}$.
- These two assumptions entail (in view of the definition of the *devolatilised* errors) that the conditional correlation of e_{it} is also $\rho_{ij,t}$:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t}}\sqrt{q_{jj,t}}. \tag{2}$$

- In the second step of our estimation procedure, we will assume that $q_{ij,t}$ follows the **DCC-MIDAS** model.
- It follows from eqs. (1) and (2) that

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} = \frac{h_{ij,t}}{\sqrt{h_{it}}\sqrt{h_{jt}}}. \tag{3}$$

We shall never achieve harmony with land, any more than we shall achieve absolute justice or liberty for people. In these higher aspirations, the important thing is not to achieve but to strive.

- Aldo Leopold

- 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 (Engle et al., 2013), and thus, correspondingly the vector of the *devolatilised* errors, $\tilde{\xi}_{it}$.
- In the second step it estimates the matrix of the conditional covariances of the errors e_{it}, $q_{ij,t}$, using a DCC-MIDAS process.

- 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 equation (3),
- and then the estimated conditional covariances $h_{ij,t}$ are obtained using the second equality in eq. (3).

- **The Conditional Variances**
- In particular, we will assume that each conditional variance, h_{it}, follows the two component GARCH-MIDAS model.

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

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

$$\sigma_{it} = (1 - \alpha_i - \beta_i) + \alpha_i \xi_{i,t-1}^2 \sigma_{i,t-1} + \beta_i \sigma_{i,t-1} \tag{4}$$

- (notice that in view of the mean equation, 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: $\xi_{i,t-1}^2 \sigma_{i,t-1} = (r_{it} - \mu_i)^2 / m_{i\tau})$,

- while the **MIDAS component** $m_{i\tau}$ is a weighted sum of $M_v^{(i)}$ lags of realised variances (RV) over a long horizon:

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

- where the so-called Beta weights are defined as

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

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

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

- **The Conditional Correlations**

Definition

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

- 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:

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

- where

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

- **DATA**
- 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 in 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)

- **Economic uncertainty** (EPU) of Baker et al. (2016); *daily and monthly*
- **Financial uncertainty** (FU): implied volatility (VIX) index (IV_t); *daily*
- **Disease risk** (DIS): It is proxied by the *daily* **infectious disease** equity market volatility tracker (ID_t) of Baker et al. (2020)
- **Credit conditions** (CR): 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 ($KCFSI_t$) in the long run
- **Climate change risk** (CC): The log-transformed *monthly* climate policy uncertainty index (CPU_t) proxies climate change risk (Gavriilidis, 2021)

- **News sentiment** (*NW*): The sentiment reflected in economic news is measured by the *daily* US news sentiment index (NSI_t) of San Francisco Fed (Buckman et al., 2020, Shapiro et al., 2020)
- **Confidence** (*CONF*): The log-transformed *monthly* US business confidence index (BCI_t) is the economic confidence proxy in long-run interdependences.
- **Economic activity** (*EA*): The *daily* Aruoba-Diebold-Scotti (Aruoba et al., 2009) US business conditions index (ADS_t) and the *monthly* US Chicago Fed national activity index ($CFNAI_t$)
- **Freights** (*FT*): We use the log-transformed *daily* Baltic dry index (BDI_t) and the *monthly* Cass freight index (CFI_t).
- **Prices** (*PR*): The *monthly* US producer price index (PPI) growth (INF_t)

- **Three Crisis Periods**
- Finally, we list the three crisis periods. The crisis subsamples are as follows:

1. **GFC**: 09/08/2007 - 31/03/2009. 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**: 09/05/2010 - 31/12/2012. The *Greek default* in May 2010 established the beginning of ESDC, which lasted until the end of 2012.
3. **COV**: 11/03/2020 - 30/09/2020. 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.

- **Dynamic Correlations**
- The short- (daily) and long-run (monthly) correlation time series are the output of the DCC-MIDAS variance-covariance matrix estimated.
- Figures 1-5 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 cycle dynamics since correlations increase in most crisis intervals (red circles).

Figure 1. EUROPE – AUSTRALIA

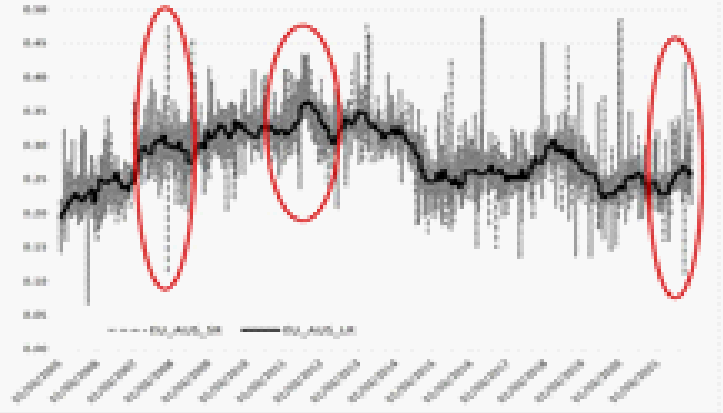


Figure 2. EUROPE – BRAZIL

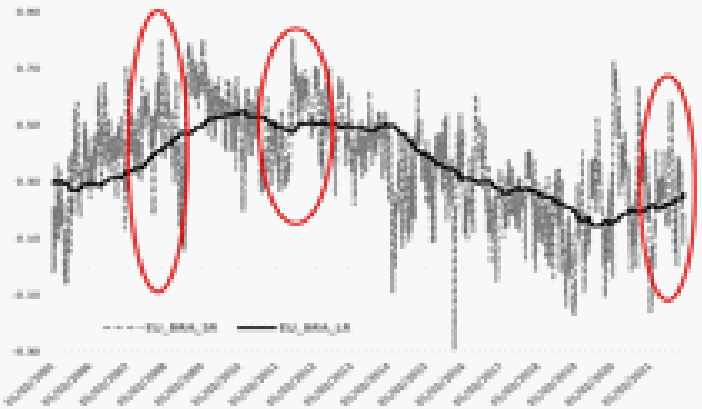


Figure 3. EUROPE – JAPAN

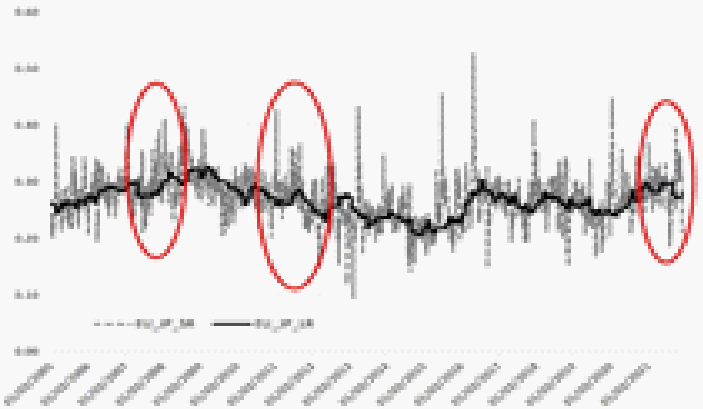
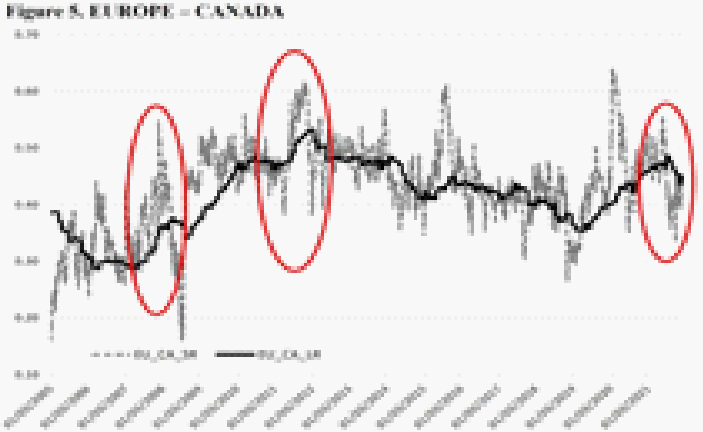


Figure 4. EUROPE – UNITED STATES OF AMERICA

Figure 5. EUROPE – CANADA



- 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).

- **Sustainability Interdependence Types**

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

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

- **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.

- 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

- **Macro-sensitivity Results**
- 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 the case of **procyclical correlations** (*H4*), we expect higher correlations in good times and lower correlations in turbulent times.
- In **countercyclical** (*H3*) patterns, correlations increase in economic worsening.

- 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*, contrary to *H4*.
- Similarly, the long-run correlations explained by low-frequency macros, are countercyclical in the whole sample (*H3*).

- **The Uncertainty Channel**
- Uncertainty is a major contributor to the business cycle dynamics with a potent *devastating impact* on the real economy and the financial markets. Increased EPU levels exert a positive influence on correlations.
- After estimating the direct EPU impact, we focus on the **indirect EPU effect** on the macro drivers of sustainability co-movements.
- That is, our macro-sensitivity analysis continues with the uncertainty channel.

- Our results show that the positive macro impacts become more positive and the negative ones more negative.
- EPU adds a significant increment in the economic influence of correlation determinants. Their economic influence **is magnified by or partially attributed** to higher uncertainty levels.
- This confirms previous studies on the indirect powerful effect of the uncertainty channel on correlations (Pastor and Veronesi, 2013, Karanasos and Yfanti, 2021, 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.

- **The Crisis Impact**
- Our macro-sensitivity regression analysis continues with the crisis impact on the macro determinants of daily correlations.
- The crisis effect on correlation levels is captured by the intercept dummies. They are *significant and positive* in all but two cases.
- In the first crisis period the GFC shock amplifies the macro impacts in line with our **contagion or countercyclicality** diagnosis for the GFC period.
- Similarly, the COV slope dummies are also estimated with the same sign as the effect in the whole sample since all pairs are **countercyclical** during the pandemic.

- **Conclusions**
- 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 effectiveness* of cross-country sustainability investment strategies and alarm regulatory authorities to devise stabilising policies that mitigate contagion turbulence.