The Short- and Long-run Cyclical Variation of the Cross-asset Nexus: MIDAS Evidence on Financial and 'Financialised' Assets.

Abstract

We study the dynamic interdependence between stocks, a risky and financial 'by definition' asset class, and the 'financialised' assets from the real estate and commodity markets. Through a trivariate corrected-DCC-MIDAS setting (a new modified version of the well-established MIDAS correlations), we analyse short- and long-run time-varying correlation dynamics among stocks, real estate, and five commodity types: energy, precious metals, industrial metals, agriculture, and livestock. The correlation analysis identifies short- and long-run hedging properties and interdependence types and concludes on strong countercyclical cross-asset interlinkages, highly dependent on the state of the economy in most cases (contagion effects) and weak procyclical connectedness for certain assets with safe-haven properties (flight-to-quality). We further investigate the macro-relevance and crisis-vulnerability of the correlations' evolution by unveiling the macro-determinants of asset co-movements. The economic environment plays a key role as a contagion or flight-to-quality transmitter, while the uncertainty channel intensifies the macro impact on the cross-asset nexus.

Keywords: contagion; corrected-DCC-MIDAS; cross-asset co-movements; economic policy uncertainty; flight-to-quality

JEL classification: C32; D80; E44; G15; Q02; R33

1 Introduction

The devastating socioeconomic impact of the recent health crisis has rekindled academic, market, and policy interest in the connectedness among different economies, industries, and asset markets. Episodes of economic turmoil can be attributed either to endogenous financial stress conditions (e.g., the credit crunch in the 2008 subprime crisis, sovereign defaults in the 2010 European sovereign debt crisis) or to exogenous factors (e.g. the recent pandemic-induced crisis, geopolitical tensions, terrorism, climate-related disasters). Notwithstanding the causes of a crisis, endogenous or exogenous to the financial system (economic or non-economic events, Iwanicz-Drozdowska et al., 2021), the shock emanating from a single asset market or country rapidly spreads to further economic facets (other markets, sectors, countries) up to the entire financial system. Such shock spillovers in the cross-border or the cross-asset dimension are often characterised as financial contagion (Allen and Gale, 2000, Baur, 2012, Londono, 2019). Tight interlinkages across markets contribute to significant systemic risk build-ups and jeopardise the whole macro-financial stability. In normal times with rising investor gains, high interdependences are mostly ignored since they are not considered threats, but as the virtues of globalisation, financial liberalisation and integration in real economic terms (Beine et al., 2010, De Nicolò and Juvenal, 2014). However, in turbulent periods, policymakers and market practitioners recognise the negative externalities of such financial co-movement dynamics with detrimental effects on diversification benefits and systemic resilience (Castiglionesi, 2007, Bratis et al., 2020).

In this vein, the objective of the present paper is to shed light on the time-varying interconnectedness among markets, focusing on financial and 'financialised' assets. The well-documented financialisation of non-financial (by definition) assets has further stimulated the risk transmission or contagion mechanism during tranquil or distress times (Adams and Glück, 2015, Basak and Pavlova, 2016, Aalbers et al., 2020). Therefore, we study the dependences between stocks, a risky financial investment vehicle, and two types of financialised assets, that is real estate and commodities. Besides the overall commodities benchmark, our analysis further delves into the major categories of commodities, that is energy, precious metals, industrial metals, agriculture, and livestock. We first propose the cDCC-GARCH-MIDAS[1] specification, a novel extension of the DCC-GARCH-MIDAS model of Colacito et al. (2011), modified by the correction of Aielli (2013) on the classic DCC of Engle (2002a). Our MIDAS correlation model is used to quantify the cross-asset nexus with short- (daily) and long-run (monthly) dynamic conditional correlations among global stock, real estate, and commodity (aggregated and disaggregated) indices. We examine all possible pairwise combinations through trivariate systems of asset returns (i.e. equities with real estate, equities with commodities, real estate with commodities, and intra-commodity co-movements) and identify the hedging or safe-haven properties and contagion or flight-to-quality phenomena (Baur and Lucey, 2009, 2010) in the short and long term. Moreover, our empirical investigation unveils the driving forces of cross-asset correlations and their crisis vulnerability. We demonstrate the daily and monthly macro fundamentals determining the short- and long-run correlations' evolution, respectively, and focus on the correlations' response to crisis shocks.

Our results show that contagion phenomena are apparent in most asset pairs and turmoil times. Flight-to-quality conditions characterise part of the real estate - commodities link but not across all crises, while precious metals frequently act as safe havens in combinations with other commodities or asset classes. The stronger cross-asset nexus can be attributed to greater attention on investments in those assets or tighter economic linkages to a lesser extent. Lower dependences with safe haven assets involved indicate investors' fear and herding to protect from imminent crises or, in some cases, a loose interconnection in the supply chain. Overall, commodities are more interconnected with stocks than with real estate. We further find significant differentiation in the cross-asset nexus across three crisis periods (the 2008 global financial crisis [GFC], the European sovereign debt crisis [ESDC], and the Covid-19 crisis [COV]) and between the short- versus long-run correlation dynamics. In the GFC, most real estate - commodities correlations decrease whereas they increase during the pandemic. The majority of intra-commodity correlations drop during the ESDC, unlike the other two crises. In some asset pairs, we further observe different responses of the co-movement pattern in their short- and long-run trajectory across crisis subsamples. During COV, the short-run correlations of three combinations with precious metals increase on average, while the long-run ones decrease slightly. This could be indicative of resilience to crisis shocks for those asset pairs. Furthermore, in most cases where we identify contagion (correlations increase and positive level in-crisis), we also conclude that the correlations are more macro-sensitive and crisis-vulnerable than the ones that decrease during crises.

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

The overall macro sensitivity in the whole sample period demonstrates the countercyclical behaviour of most co-movement patterns, while the correlations of precious metals with equities and real estate are the procyclical ones.

Given the important and novel findings of the present study, our contribution to the financial contagion literature is manifold. First, we investigate the trivariate system of global equity - real estate - commodities benchmarks with the overall commodities index disaggregated into its major types. Our analysis covers the combinations of financial with financialised assets (equities - real estate, equities - commodities), financialised assets only (real estate - commodities), and intra-commodity co-movements, as well (all pairs of energy, metals - precious and industrial, agriculture, and livestock). Inspired by Karanasos and Yfanti (2021), who were the first to include all three asset classes and identify their correlation determinants (daily and monthly aggregates of conditional correlations), we proceed with the investigation of the different commodity types and a more sophisticated correlation model, the cDCC-GARCH-MIDAS, which allows for both daily and long-run correlation computation (rather than a monthly aggregation of the daily time series). Second, we compare the cross-asset dependence response to three major crisis shocks, two financial and one health crisis, concluding on the time-varying correlation patterns that signify contagion, flight-to-quality, or safe-haven asset properties. Third, our key novelty and contribution lie in the empirical analysis, which distinguishes between short- and long-run dynamics of correlations evolution, where we find significant differences in the short- and long-run cyclical variation of correlations in response to economic fluctuations (short- vs. long-run hedging properties and contagion, flight-to-quality, higher / lower interdependence phenomena). Fourth, we conduct our macro sensitivity investigation, applying a wide variety of both high and low frequency economic fundamentals, beyond the ones used in Karanasos and Yfanti (2021) as correlation determinants. We further emphasise the key role of the uncertainty channel in amplifying the contagion dynamics and examine the crisis shocks, using the actual timelines rather than statistical identification of the structural breaks. Fifth, from an econometric perspective, we contribute to the financial econometrics literature with the modification of the DCC-GARCH-MIDAS with Aielli's correction on correlations estimation, establishing the novel cDCC-GARCH-MIDAS specification with in-sample and forecasting superiority compared to all DCC nested models .

To the best of our knowledge, our study is the first in the existing literature on asset co-movements to include a representative risky financial asset class (global stocks) and both major financialised asset types (real estate and commodities) with a detailed breakdown of commodities. Our multifaceted investigation provides novel findings on both directions of asset market linkages: their hedging properties and their interdependence type. Our correlation analysis also provides important economic insights about the cross-asset momentum, which can be interpreted by markets' financialisation, economic linkages, supply chain factors, or investor trading behaviour (see, for example, Xu and Ye, 2023). The correlation estimation with a corrected and more consistent MIDAS model, the correlation analysis in the short- and long-run horizon, the macro sensitivity with high and low frequency macro and news factors, and the inclusion of three distinct crisis shocks on the correlations' time-variation further demarcate our research from the extant bibliography. The empirical results on the cyclical variation of the cross-asset nexus (either countercyclical or procyclical correlation dynamics) are important for market practitioners and regulatory authorities. Traders, investors, and risk managers can utilise our findings in designing asset allocation and hedging strategies. Contagion erodes diversification benefits and hedging effectiveness, while flight-to-quality opportunities can act as safeguards in times of crisis. Policymakers and systemic supervisors are particularly cautious about sources of systemic risk threatening investors' welfare and financial stability. On the one hand, higher interdependence in stress times leads to massive losses in the portfolios of market participants, destabilising the whole financial system. Correlation determinants can act as early warning signals of imminent crisis episodes. On the other hand, safe-haven assets are often considered stabilisers protecting systemic resilience. The various aspects of short- and long-run cross-asset connectedness findings should be employed in designing macro- and micro-prudential policies, proactive and reactive regulatory interventions, either conventional or unconventional.

The remainder of the paper is structured as follows. In the following Section, we discuss the theoretical underpinnings of asset co-movements and develop the hypotheses to be tested in the empirical analysis of the cross-asset nexus. Section 3 describes our methodology and dataset. In Section 4, we present the cDCC-GARCH-MIDAS estimations and the dynamic correlations computed. Section 5 investigates the macro relevance and crisis vulnerability of the cross-asset nexus. Section 6 evaluates the in-sample and forecasting performance of the proposed model and presents an empirical application of portfolio hedging. Section 7 discusses our results and their implications for policymakers and market practitioners and the last Section concludes our study.

2 Theoretical Background

The empirical finance literature has provided ample evidence on financial markets' co-movements. In this Section, we discuss the key takeaways of the existing literature on the dependence dynamics across markets to motivate our research, develop our theoretical hypotheses, and demonstrate the contribution and implications of our study.

2.1 Literature Review

A direct outcome of the gradual liberalisation, deregulation, and globalisation over the last three decades is financial integration and tight interconnectedness (Eiling and Gerard, 2015). Markets and economies are highly interdependent during all states of the economy. Financial contagion postulates significantly heightened financial correlations due to a crisis shock (Forbes and Rigobon, 2002). Numerous studies have examined the cross-border (same-asset) dimension of financial interdependences and the cross-asset linkages (globally or regionally). Foreign trade and capital (investment and credit) flows have been catalytic on the cross-country linkages. The financial markets literature shows how stock markets in different countries co-move and how this co-movement is intensified during crises (Bae et al., 2003, Baur, 2012). Such risk spillovers result in a rapid magnifying propagation of stress conditions from one region to the neighbouring ones or globally. Several financial instruments traded in typically distinct national markets (organised or over the counter) exhibit common trends and responses to shocks. Equities, bonds, foreign exchange rates, credit defaults swaps (CDS), and real estate are among the assets widely explored for their cross-country spillovers. Such markets are found to be very closely aligned in normal times and extremely interconnected in crisis periods (see, for example, Bratis et al., 2020, Hurn et al., 2022).

Turning to the cross-asset dimension of financial interconnectedness, empirical research has demonstrated either contagion or flight-to-quality conditions during crises for several asset pairs. For example, sovereign bonds or precious metals are considered safe havens. In market stress times, they attract investors who quit or hedge positions in riskier assets such as stocks. Equities and real estate investment vehicles mostly experience common contagious shocks, while several financial assets are highly correlated with certain commodities given their financialisation in the last two decades (Henderson et al., 2015). A large number of studies have investigated the interdependence between stocks and bonds (Asgharian et al., 2016), stocks and commodities (Creti et al., 2013), stocks and real estate (Liow, 2012), intra-commodity co-movements (Alquist et al., 2020), alongside several other asset combinations at the global or regional level (Apergis et al., 2019).

Despite the vast amount of cross-asset dependence studies on equities - real estate and equities - commodities, there is still little evidence on real estate - commodities links, which are equally important. For instance, energy prices play a key role in real estate development through the cost, income, monetary policy, and financial market channels (Breitenfellner et al., 2015). Higher oil or industrial metal prices increase the building costs, induce a significant wealth effect, demand shocks, and multi-asset portfolio re-rebalancing from real estate to commodity investments. Huang and Zhong (2013) and Karanasos and Yfanti (2021) are among the relatively scarce attempts to investigate the correlations between real estate and commodities, in association with a third financial instrument, the former with bonds and the latter with equities. Both papers use aggregate commodity indices, while the present study disaggregates the index into the major commodity types and provides novel results on cross-asset interlinkages. Further research (see, for example, Nguyen et al., 2021, Kilian and Zhou, 2021) mostly relates oil with the housing market (residential properties), providing evidence on both negative and positive correlations sensitive to time (increased connectedness as financialisation progresses), regional factors (e.g., oil-producers vs. oil-importers) and market conditions (crises or other extreme events exacerbate correlations). A further strand of literature attributes cross-asset interdependences to economic linkages and trading patterns. Casassus et al. (2013) explain the intra-commodity long-run co-movements with production, substitution, or complementary relationships among commodities, while the short-run momentum is due to supply and demand imbalances driven by macro forces or inventories, among others. The commodities financialisation evidence shows supply chain effects on their correlations (see, for example, Cheng and Xiong, 2014), similar to equities dependences driven by various types of relations among firms (Acemoglu et al., 2012). More recently, Xu and Ye (2023) argue in favour of investor trading strategies rather than asset-specific fundamentals as the major determinants of the cross-asset momentum. Extrapolative beliefs, overreaction to news, higher investor attention, and speculative demand increase commodity markets' co-movement.

The time-varying interdependence among markets is quantified by the multivariate GARCH framework, which computes the conditional correlations of asset returns (see, for example, the DCC of Engle, 2002a, the Asymmetric DCC - ADCC of Cappiello et al., 2006, the DCC-GARCH-MIDAS of Colacito et al., 2011, and the Dynamic Equicorrelations - DECO of Engle and Kelly, 2012). Among the few studies that go beyond the computation of correlations and explore the drivers of their evolution are mostly the ones applying a DCC-GARCH-MIDAS type of model, where they explain the long-term component of asset co-movements with low frequency macro fundamentals (Conrad et al., 2014, Asgharian et al., 2016, Mobarek et al., 2016, Boffelli et al., 2016, Conrad and Stürmer, 2017). Moreover, Yang et al. (2012) and Karanasos and Yfanti (2021) use high frequency correlation determinants with non-MIDAS dynamic correlation models. Yang et al. (2012) investigate the stocks - bonds - real estate correlations through the ADCC model and attribute their time-varying pattern to daily macro-financial factors. Karanasos and Yfanti (2021) reveal the daily and monthly cross-asset correlation determinants with a DECO specification. The DECO model computes the daily equicorrelations and the authors proceed with monthly averaging of the daily series to achieve both high and low frequency correlation macro analyses. Motivated by Karanasos and Yfanti (2021), we choose the MIDAS framework, by improving its estimation with Aielli's correction (see Aielli, 2013, for the relative merits of the DCC correction), because it is the only specification that computes both short- and long-run correlation dynamics (see also the DCC merits for contagion testing in Chiang et al., 2007). Therefore, we further demarcate our study from existing literature with the correction of the classic DCC-GARCH-MIDAS, the analysis of the short- and the long-run dimension of the cross-asset nexus, and the macro sensitivity based on both high and low frequency correlation determinants. In line with Casassus et al. (2013), the long-run component of correlations incorporates the economic or supply chain linkages. Alongside the short-run, part they are both explained by the macro dynamics. Next, we develop the theoretical hypotheses to be tested in our investigation of markets' co-movements.

2.2 Hypotheses

Our empirical analysis of the correlation dynamics among global equities, real estate, and commodities involves two important aspects. We first scrutinise the anatomy of the pairwise correlation time series computed by the trivariate cDCC-GARCH-MIDAS system to conclude on the hedging properties of the assets (diversifier or hedge or safe haven) and the type of interdependence (contagion or flight-to-quality). Second, we proceed with the macro sensitivity exercise, which unveils the major drivers of cross-asset connectedness in the macroeconomic environment.

In the correlation time series statistical analysis, we follow Forbes and Rigobon (2002) and Baur and Lucey (2009, 2010) to identify the hedging properties of the assets and to distinguish between contagion, flight-to-quality, or simple interdependence (Table 1, Panel A). Baur and Lucey (2010) define the hedging features based on the overall average correlations, which can imply whether the assets act as diversifiers or hedges. The diversifiers are positively, but not perfectly, correlated, whereas the hedges are uncorrelated or negatively correlated. Throughout the present study, we consider uncorrelated assets the pairs with zero correlation or a positive correlation but lower than 0.100. Contrary to the safe haven property, the diversifier and hedge definitions do not require an examination of the correlation time-varying behaviour across normal and turbulent times. We can identify diversifiers and hedges based on the overall average of the dynamic correlation time series. The analysis of the correlations' response to crises can designate the safe haven asset which is uncorrelated or negatively correlated to others during market stress circumstances. Moreover, according to Forbes and Rigobon (2002), contagion means a significant increase in the correlation trajectory during a crisis compared to the pre-crisis correlation levels. The correlation increase is attributed to the crisis shock, that is the deterioration of the macro environment's fundamentals characterising the crisis period. In addition, the contagion definition requires the in-crisis correlation level to be positive. Flight-to-quality is the phenomenon where correlations significantly decrease during crises and their in-crisis level is negative (Baur and Lucey, 2009). Pre-crisis positive (negative) correlations become negative (more negative).

The crisis vulnerability of the correlation pattern connects the contagion / flight-to-quality classification, where we observe the in-crisis correlation changes (increase or decrease from the pre-crisis level) and levels, with the safe haven property, where the in-crisis level matters. Hence, the flight-to-quality, which requires correlation decrease and negative level, involves, by definition, a safe haven asset. In other words, flight-to-quality implies (it is a sufficient condition for) safe heaven, and, therefore the latter is a necessary condition for the former. If correlations increase during market stress conditions but their level remains negative, we cannot conclude that there is contagion. We characterise this case as higher interdependence and the one asset of the correlation pair (the one with the rising prices during crises) as a safe haven. If correlations decrease but remain positive during crises, it is not a flight-to-quality but lower interdependence with increased diversification benefits. In the special case of correlations increasing to positive but low levels during crises (uncorrelated assets with average dynamic correlations between 0 and 0.100) the assets are safe havens and we define the interdependence types as: i) weak contagion if the change is significant and ii) higher weak interdependence if the change is insignificant (see also Table 1, Panel C, for the in-crisis correlation change and level combinations indicative of each interdependence type and safe haven property during crises). Hence, we can observe safe haven properties when correlations are positive but very low, close to zero ($0 < \rho < 0.100$), regardless of whether we have (weak) contagion or higher interdependence. Against this backdrop, we test the following hypotheses on the dynamics of the short- and long-run cross-asset correlations extracted from the cDCC-GARCH-MIDAS estimations:

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

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

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

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

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

Turning to the macro sensitivity exercise, we intend to attribute the correlation pattern to economic fluctuations. Motivated by the well-documented rising interdependences during crises (contagion) and lower negative correlations for flight-to-quality in turbulent times (safe haven assets), we expect that weak economic conditions, indicative of market stress, lead to contagion or flight-to-quality for safe havens. Conversely, strong fundamentals drive most cross-asset correlations down, increasing the diversification benefits for investors. For safe havens, we may observe flight-from-quality movements with decreasing negative correlations (Baur and Lucey, 2009). Inspired by the studies on high (e.g., Karanasos and Yfanti, 2021) and low (e.g., Conrad et al., 2014) frequency correlation determinants, we identify key daily and monthly macro and news factors characterising most aspects of the economic environment, where the global equity, real estate, and commodity markets operate (see Section 3.2 for a detailed presentation of the variables used as daily and long-term correlation determinants).

We first test uncertainty, a major driver of the business cycle, which involves agents' aggregate sentiment, risk perceptions, and expectations (Fernández-Villaverde et al., 2015, Bloom et al., 2018, Alessandri and Mumtaz, 2019). Uncertainty is strongly related to the market players' downside risk and subsequent portfolio rebalancing or firms' investment reallocations with direct implications for financial markets co-movements. Uncertainty shocks are of both supply and demand nature, eroding the stability of the financial system and the whole economic outlook. Increased economic policy (EPU) and financial uncertainty (FU), infectious disease news effect on financial uncertainty (ID) and decreased investors' confidence - sentiment (SENT) - are expected to be associated with higher correlations in the case of contagion and lower correlations in the case of safe haven assets and flights-to-quality. Our next correlation determinant is the high frequency news effect (Albuquerque and Vega, 2009, Jiang et al., 2012), a significant indicator for nowcasting the real economy. We include an economic news sentiment (NS) index (positive sentiment means optimism/confidence). A potent disease news impact should exacerbate correlations, while higher news sentiment should eliminate contagious shocks. Moreover, the credit channel is an important feature of the macroeconomy (Gilchrist and Zakrajšek, 2012, Alessandri and Mumtaz, 2019) and is proxied by financial stress (FS). Higher values of financial stress indices denote tighter credit and liquidity conditions, which will increase (decrease) cross-asset dependence in contagion (flight-to-quality) cases. Next, activity growth proxies (EC) are also included as key correlation determinants with a negative effect on contagious shocks. Collapsing activity, the primary crisis feature, amplifies interdependences except for the safe havens or flights-to-quality (Pastor and Veronesi, 2013, Asgharian et al., 2016, Anderson et al., 2021). Another important part of economic fluctuations, we consider, is prices (Engle et al., 2013, Mobarek et al., 2016), with an inflation indicator (INFL), freights indices (FR), and foreign exchange rates (FX) proxied by the US dollar value. Descending levels of inflation, freights, and dollar strength are mostly characteristics of market slowdowns associated with higher correlation in contagion phases.

Table 1. Overview of hypotheses and expected results.

Panel A. Hedging properties & interdependence hypotheses

Correlation pattern	Hedging property Interdependence	Hypothesis
Positively, but not perfectly, correlated (whole sample average: $+, < 1$)	Diversifier	H1
Uncorrelated or negatively correlated (whole sample average: 0 or $-$)	Hedge	H2
In-crisis uncorrelated or negatively correlated (in-crisis: 0 or $-$)	Safe haven	H3
In-crisis increase & positive level (in-crisis: $\uparrow, +$)	Contagion	H4
In-crisis decrease & negative level (in-crisis: $\downarrow, -$)	Flight-to-quality	H5

Panel B. Macro sensitivity (correlation determinants)

Macro effect on correlations	Expected sign H6	 H7
Economic policy uncertainty (EPU)	$+$	$-$
Financial uncertainty (FU)	$+$	$-$
Infectious disease news impact (ID)	$+$	$-$
Financial Stress (FS)	$+$	$-$
Sentiment / Confidence (SENT)	$-$	$+$
News sentiment (NS)	$-$	$+$
Economic activity (EC)	$-$	$+$
Inflation (INFL)	$-$	$+$
Freights (FR)	$-$	$+$
Foreign Exchange rates (FX)	$-$	$+$

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

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

Notes: The table presents an overview of the hypotheses we test in the statistical and macro sensitivity correlation analysis. Panel A illustrates the correlation pattern features, characterising each hedging property and interdependence phenomenon (H1 - H5). Panel B recaps the expected signs of each macro effect on correlation evolution under H6 and H7. Panel C reports the in-crisis correlation change and level combinations that indicate the interdependence types and safe haven property during crises.

Although news and sentiment (soft data) are not pure macro metrics of real activity, prices, or financial flows (hard data), they play a crucial role in business cycle fluctuations. An economy can suffer a terrible fate due to shifts in investors' preferences (investment or spending). Shifts in perceptions and expectations can be induced by aggregate fear and massive bad news signalling, real or fake (let us call it information contagion in the case of real news, and infodemics in the case of fake news), rather than a collapse of hard data. Hence, such soft data shape the whole macro environment since they can point out behavioural externalities that are sufficiently critical and powerful to destabilise markets and economies. Taking into account both hard and soft data macro effects, we develop our last hypotheses to be tested in the macro analysis of correlations (see also Table 1, Panel B, for the expected signs of each macro effect under each type of interdependence according to our last two hypotheses):

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

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

Finally, our macro sensitivity exercise examines the crisis vulnerability of the cross-asset nexus and the important role of the uncertainty channel. Based on *H6* and *H7*, we further expect that crisis shocks and higher uncertainty intensify the macro and news effects on correlations' evolution either in contagion or flight-to-quality cases. The macro relevance of cross-asset correlations has significant implications for financial stability and systemic risk. Contagious shocks materialise as domino effects that drive a great number of major financial markets to a common turmoil, threatening the stability of the whole financial system. Contagion episodes are driven by the correlation's susceptibility to crises and the associated weak economic fundamentals. Such episodes eliminate diversification benefits and lead to massive losses in downturns. Market players from most industrial sectors (not only financials) experience capital shortfalls leading to severe systemic risk build-ups (Martínez-Jaramillo et al., 2010, Dungey et al., 2022).

3 Methodology and Data

In this Section, we detail our methodological approach and the dataset used. We propose the cDCC-GARCH-MIDAS model applied on daily asset returns using a trivariate specification for the multi-asset combinations (ten in total) of equity, real estate, and commodity indices (commodity indices are aggregated and disaggregated into five subindices). Next, we extract the daily and long-term (monthly) correlation time series (each trivariate system computes three pairwise daily and monthly correlation series) and proceed with the analysis of the time-varying pattern of the cross-asset nexus, its daily and monthly macro determinants and response to crisis shocks. Our main objective is to identify the hedging properties of the financial and financialised assets under scope, contagion or flight-to-quality phenomena during crises, the correlations' macro and news drivers, macro sensitivity and crisis vulnerability. Our dataset consists of the daily index prices, considered as global benchmarks of each asset included in the cross-asset combinations, and the macro proxies used as correlation determinants.

3.1 The Econometric Approach

3.1.1 The cDCC-GARCH-MIDAS model

The Conditional Means

The N-th dimensional vector of daily returns, at time t (the high frequency time scale) is denoted by $\mathbf{r}_t = [r_{i,t}]_{1\leq i\leq N}$, hereafter we will drop the subscript $1 \leq i \leq N$ (in our empirical results $N = 3$). It is assumed that the conditional (on the information at time $t-1$, set $\mathbf{\Omega}_{t-1}$) distribution of $\mathbf{r}_t$ is given by $\mathbf{r}_t\,|\mathbf{\Omega}_{t-1} \sim i.i.d.\ N(\boldsymbol{\mu}, \mathbf{H}_t)$, where $\boldsymbol{\mu} = \mathbb{E}(\mathbf{r}_t)$, is the vector of the unconditional means and $\mathbb{E}$ denotes the element-wise expectation operator, and $\mathbf{H}_t = [h_{ij,t}]_{i,j=1\ldots,N}$ (hereafter we will drop the subscript $i, j = 1 \ldots, N$) is the $N \times N$ conditional covariance matrix, that is $h_{ij,t} = Cov(r_{it}, r_{jt} | \Omega_{t-1})$. Alternatively, $\mathbf{r}_t$ can be written as

$$\mathbf{r}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where the vector of the errors $\boldsymbol{\varepsilon}_t = \mathbf{r}_t - \boldsymbol{\mu}$ will be analysed below. This implies that the return for each asset is given by $r_{it} = \mu_i + \varepsilon_{it}$.

The Errors

The cDCC-GARCH-MIDAS (or cDCC-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: $\boldsymbol{\varepsilon}_\mathbf{t}$ in eq. (1) and $\mathbf{e}_t = [e_{it}]$ (see eq. (9) below).

The $\boldsymbol{\varepsilon}_t$

Regarding $\boldsymbol{\varepsilon}_t$, we assume that $\boldsymbol{\varepsilon}_t | \boldsymbol{\Omega}_{t-1} \sim i.i.d.\ N(\mathbf{0}_{N\times 1}, \mathbf{H}_t)$, namely it is conditionally normally distributed with mean vector $\mathbf{0}_{N\times 1}$, and conditional covariance matrix $\mathbf{H}_t = [h_{ij,t}] = \mathbb{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' | \boldsymbol{\Omega}_{t-1})$. We will assume that the vector of the conditional variances, $\mathbf{h}_t = [h_{it}]$, $h_{it} \overset{\text{def}}{=} h_{ii,t}$, follows a GARCH-MIDAS model (see the analysis below). We will use the notation $\widetilde{\mathbf{H}}_t = diag[\mathbf{h}_t]$, that is $\widetilde{\mathbf{H}}_t$ is the $\mathbf{H}_t$ matrix with its non-diagonal entries equal to zero. The conditional correlation matrix of $\boldsymbol{\varepsilon}_t$, denoted by $\mathbf{R}_t = [\rho_{ij,t}]$, is given by:

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

or elementwise $\rho_{ij,t} = h_{ij,t} / \sqrt{h_{it}} \sqrt{h_{jt}}$.

Notice that $\boldsymbol{\varepsilon}_t$ can be expressed as: $\boldsymbol{\varepsilon}_t = \widetilde{\mathbf{H}}_t^{1/2} \boldsymbol{\xi}_t$, that is $\varepsilon_{it} = \sqrt{h_{it}} \xi_{it}$. In other words, the vector of the *devolatilised* errors $\boldsymbol{\xi}_t$ is equal to $\widetilde{\mathbf{H}}_t^{-1/2} \boldsymbol{\varepsilon}_t$, which implies that $\boldsymbol{\xi}_t | \boldsymbol{\Omega}_{t-1} \sim i.i.d.\ N(\mathbf{0}_{N\times 1}, \mathbf{R}_t)$.

The $\mathbf{e}_t$

Regarding $\mathbf{e}_t$, we assume that is conditionally normally distributed with mean vector $\mathbf{0}_{N\times 1}$, and conditional covariance matrix $\mathbf{Q}_t = [q_{ij,t}] = \mathbb{E}(\mathbf{e}_t \mathbf{e}_t' | \boldsymbol{\Omega}_{t-1})$: $\mathbf{e}_t | \boldsymbol{\Omega}_{t-1} \sim i.i.d.\ N(\mathbf{0}_{N\times 1}, \mathbf{Q}_t)$, and it is also assumed that is equal to $\widetilde{\mathbf{Q}}_t^{1/2} \boldsymbol{\xi}_t$, where $\widetilde{\mathbf{Q}}_t = diag[\mathbf{q}_t]$ with $\mathbf{q}_t = [q_{ii,t}]$. These two assumptions entail (in view of the definition of the *devolatilised* errors) that the conditional correlation matrix of $\mathbf{e}_t$ is also $\mathbf{R}_t$:

$$\mathbf{R}_t = \widetilde{\mathbf{Q}}_t^{-1/2} \mathbf{Q}_t \widetilde{\mathbf{Q}}_t^{-1/2}, \tag{3}$$

or elementwise $\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t}} \sqrt{q_{jj,t}}$.

In the second step of our estimation procedure, we will assume that $\mathbf{Q}_t$ follows the cDCC-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, $\boldsymbol{\varepsilon}_t$, the vector of the conditional variances, that is $\mathbf{h}_t$, using a GARCH-MIDAS process (Engle et al., 2013), and correspondingly the vector of the *devolatilised* errors $\boldsymbol{\xi}_t$. In the second step it estimates the matrix of the conditional covariances of the errors $\mathbf{e}_t$, that is $\mathbf{Q}_t$, using a cDDC-

MIDAS process. Once $\mathbf{h}_t$ and $\mathbf{Q}_t$ are estimated then the estimated elements of $\mathbf{R}_t$ (the conditional correlations of the errors, either $\mathbf{e}_t$ or $\boldsymbol{\xi}_t$ or $\boldsymbol{\varepsilon}_t$) are obtained using the first equality in equation (4), and then the estimated non-diagonal elements of $\mathbf{H}_t$ 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]

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

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

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

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

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

(we can also allow for different individual θ's, that is θ_i) 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 $\omega_v^{(i)}$

[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). A heuristic proof of the consistency of the cDCC estimator is provided in Aielli (2013); see the discussion in its Section 3.2. 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), as well as its corrected version, is an open question.

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

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 all series, that is $M_v^{(i)} = M_v$ and $K_v^{(i)} = K_v$ for all i. In the GARCH-MIDAS the short-run component is a GARCH component (see eq. (5)), based on daily (squared returns), that moves around a long-run component driven by realised volatilities computed over a monthly or quarterly basis (see eqs. (6), (7) and (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 (MIDAS lag) years, spanned in each MIDAS polynomial, $m_{i\tau}$, varies from one to four years. More specifically, over a monthly basis, $M_v = 12, 24, 36, 48$, whereas over a quarterly basis $M_v = 4, 8, 12, 16$.

Since the number of parameters are fixed, we can compare various GARCH-MIDAS 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 with respect to the time span covered by RV.

The Conditional Correlations

First, we will define the $N \times N$ matrices $\mathbf{\Omega}_c = [\omega_c^{(ij)}]$ and $\Phi_l(\mathbf{\Omega}_c) = [\varphi_l(\omega_c^{(ij)})]$. We will also make use of the following definition.

Definition 1 *Let* $\mathbf{Z}_\tau = [z_{ij,\tau}] = \sum_{t=(\tau-1)K_c+1}^{K_c} \boldsymbol{\xi}_t \boldsymbol{\xi}_t'$, *with* $K_c = \max_{ij} K_c^{(ij)}$, $\mathbf{z}_\tau = [z_{ii,\tau}]$ *and* $\widetilde{\mathbf{Z}}_\tau = diag[\mathbf{z}_\tau]$, *that is* $\widetilde{\mathbf{Z}}_\tau$ *is a diagonal matrix with i-th diagonal element* $\sum_{t=(\tau-1)K_c+1}^{K_c} \xi_{it}^2$. *Define* $\mathbf{C}_\tau = [c_{ij,\tau}]$ *as:* $\mathbf{C}_\tau = \widetilde{\mathbf{Z}}_\tau^{-1/2} \mathbf{Z}_\tau \widetilde{\mathbf{Z}}_\tau^{-1/2}$, *that is* $c_{ij,\tau} = \frac{\sum_{t=(\tau-1)K_c+1}^{K_c} \xi_{it}\xi_{jt}}{\sqrt{\sum_{t=(\tau-1)K_c+1}^{K_c} \xi_{it}^2}\sqrt{\sum_{t=(\tau-1)K_c+1}^{K_c} \xi_{jt}^2}}$.

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

$$\mathbf{Q}_t = (1 - a - b) R_\tau(\mathbf{\Omega}_r) + a \mathbf{e}_{t-1} \mathbf{e}_{t-1}' + b \mathbf{Q}_{t-1}, \tag{9}$$

where

$$R_\tau(\mathbf{\Omega}_c) = \sum_{l=1}^{M_c} \Phi_l(\mathbf{\Omega}_c) \odot \mathbf{C}_{\tau-l},$$

with $M_c = \max_{ij} M_c^{(ij)}$, and $\odot$ stands for the Hadamard product.[5] In other words, the ij-th element of $\mathbf{Q}_t$ is given by

$$q_{ij,t} = \rho_{ij,\tau}(1 - a - b) + a e_{i,t-1} e_{j,t-1} + b q_{ij,t-1}, \tag{10}$$

where

$$\rho_{ij,\tau} = \sum_{l=1}^{M_c^{(ij)}} \varphi_l(\omega_r^{(ij)}) c_{ij,\tau-l}. \tag{11}$$

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

$$q_{ii,t} = (1 - a - b) + a e_{ii,t-1}^2 + b q_{ii,t-1},$$

[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) mentioned that for correlations a researcher has potentially the same choice. Since the fixed span is more general, we adopt this for our formulation (instead of the rolling window one).

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

and, in view of the fact that in the cDCC $\mathbb{E}(e_{i,t}^2) = \mathbb{E}(q_{ii,t}) = q_{ii}$, it follows that $q_{ii}=1$.[6]

The specification in eq. (11) 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 relative mild set of assumptions, since it is apparent from eq. (9) that the matrix $\mathbf{Q}_t$ is a weighted average of three matrices. The matrix R_t is positive semi-definite because it is a weighted average of correlation matrices. The matrix $\mathbf{e}_t\mathbf{e}_t'$ 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 DCC-MIDAS filtering scheme).

Correlations can then be computed using eq. (4). We can express eq. (10) as

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

The daily dynamics of the correlations (covariances), $\rho_{ij,t}(q_{ij,t})$, obey a cDCC scheme, with the correlations moving around a long-run component ($\rho_{ij,\tau}$). As pointed 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".

3.1.2 Correlation Regression Analysis

After estimating the cDCC-MIDAS specification for ten trivariate asset combinations, we extract the short- and long-run cross-asset pairwise correlations (for each asset pair, ij: the short-run / daily and long-run / monthly correlation time series extracted are denoted as $\rho_{ij,t}$ and $\overline{\rho}_{ij,t}$, respectively). The first step is to examine their time series graphs where the cyclical variation of the cross-asset nexus is a common characteristic either for countercyclical (contagion) or procyclical (flight-to-quality) cases. Next, we analyse the correlations' key statistics in the whole sample and across three crisis subsamples (GFC, ESDC, COV) to identify the hedging properties and contagion or flight-to-quality phenomena. In the crisis analysis, we perform mean difference tests: the Satterthwaite-Welch t-test and the Welch F-test. For each crisis, we compare the crisis mean with the pre-crisis mean and decide whether the mean change (increase or decrease) from the pre-crisis to the crisis period is statistically significant. A significant increase (decrease) in association with a positive (negative) in-crisis level means contagion (flight-to-quality). The in-crisis correlation mean will indicate the safe haven properties of the assets involved, while the whole sample mean will signify diversifiers or hedges.

Following the statistical tests, we investigate the correlations' macro relevance, by identifying their determinants in the global macro environment through regression analysis. Daily ($\rho_{ij,t}$) and monthly ($\overline{\rho}_{ij,t}$) correlations are the dependent variables explained by macro and news proxies (see Section 2.2). We first apply the Fisher Z transformation of the

[6] Following Aielli (2013) one could employ a correction in the long-run correlations, $\overline{R}_t(\mathbf{\Omega}_r)$, by using the vector of the residuals, $\mathbf{e}_t$, that is using: $\mathbf{Z}_t = [z_{ij,t}] = \sum_{k=t-M_c}^{t} \mathbf{e}_k\mathbf{e}_k'$.
Note that in the DCC estimator the estimator of the long-run correlations is computed only once in the first step, whereas, with the cDCC estimator, it will be recomputed at each evaluation of the objective function of the second step (see Definition 3.4 in Aielli, 2013). We leave this for future work.

correlation time series to overcome the $[-1, 1]$ bounds. $\rho_{SR,t}$ and $\rho_{LR,t}$ are the Fisher-transformed daily and monthly correlations (we drop the subscript ij for notational simplicity). This transformation makes our dependent variables suitable for the OLS regression estimation. The explanatory variables include all major aspects of macroeconomic fluctuations as described in the Hypothesis development (*H6* and *H7*). We expect higher (lower) correlations when the regressors show an economic deterioration for contagion (flight-to-quality) cases. The daily and monthly regressors are not the same due to data availability in the high and low frequency macro domain (see the data description, with the indices proxying each economic effect in Section 3.2). The short-run (daily) correlations are regressed on the following daily macro factors: economic policy uncertainty ($EPU_{SR,t}$), financial uncertainty ($FU_{SR,t}$), infectious disease news impact on financial volatility ($ID_{SR,t}$), financial stress ($FS_{SR,t}$), news sentiment ($NS_{SR,t}$), economic activity ($EC_{SR,t}$), freights ($FR_{SR,t}$), and foreign exchange rates ($FX_{SR,t}$). The long-run (monthly) correlations are explained by monthly proxies of economic policy uncertainty ($EPU_{LR,t}$), financial stress ($FS_{LR,t}$), sentiment / confidence ($SENT_{LR,t}$), economic activity ($EC_{LR,t}$), inflation ($INFL_{LR,t}$), and freights ($FR_{LR,t}$). The regressors are included in their first lag and the macro models for each correlation time series are selected according to the parameters' significance, the information criteria (AIC: Akaike and BIC: Schwartz Information Criteria), and the goodness of fit (adjusted R^2 $[\overline{R}^2]$).

To sum up, the structure of the short-run correlation regressions is as follows:

$$\begin{aligned}\rho_{SR,t} \quad = \quad & \zeta_0 + \zeta_1 \rho_{SR,t-1} + \zeta_2 EPU_{SR,t-1} + \zeta_3 FU_{SR,t-1} + \zeta_4 ID_{SR,t-1} + \zeta_5 FS_{SR,t-1} \\ & + \zeta_6 NS_{SR,t-1} + \zeta_7 EC_{SR,t-1} + \zeta_8 FR_{SR,t-1} + \zeta_9 FX_{SR,t-1} + u_{SR,t}\end{aligned} \tag{12}$$

and the long-run correlation regression specification takes the following form:

$$\begin{aligned}\rho_{LR,t} \quad = \quad & \delta_0 + \delta_1 \rho_{LR,t-1} + \delta_2 EPU_{LR,t-1} + \delta_3 FS_{LR,t-1} + \delta_4 SENT_{LR,t-1} \\ & + \delta_5 EC_{LR,t-1} + \delta_6 INFL_{LR,t-1} + \delta_7 FR_{LR,t-1} + u_{LR,t},\end{aligned} \tag{13}$$

where ζ_0 and δ_0 are the constant terms and $u_{SR/LR,t}$ the standard stochastic error terms.

After identifying the correlation determinants, we continue the macro sensitivity analysis with the role of the uncertainty channel in the short-run correlations (similar results for the long-run correlations are available upon request). Motivated by the catalytic uncertainty effect on the business cycle, we further explore the sensitivity of the macro effects on correlations to the economic policy uncertainty fluctuations. From an economic perspective, we expect that higher EPU magnifies the macro impact on correlations (see Pastor and Veronesi, 2013, Karanasos and Yfanti, 2021). The indirect EPU effect on the macro regressors is measured by the EPU interaction terms. The interaction terms are constructed by the multiplication of the EPU variable with each macro and news factor and added to eq. (12) as follows:

$$\begin{aligned}\rho_{SR,t} &= \zeta_0+\zeta_1\rho_{SR,t-1}+\zeta_2 EPU_{SR,t-1}+(\zeta_3+\zeta_3^{EPU}EPU_{SR,t-1})FU_{SR,t-1} \\ &+(\zeta_4+\zeta_4^{EPU}EPU_{SR,t-1})ID_{SR,t-1}+(\zeta_5+\zeta_5^{EPU}EPU_{SR,t-1})FS_{SR,t-1} \\ &+(\zeta_6+\zeta_6^{EPU}EPU_{SR,t-1})NS_{SR,t-1}+(\zeta_7+\zeta_7^{EPU}EPU_{SR,t-1})EC_{SR,t-1} \\ &+(\zeta_8+\zeta_8^{EPU}EPU_{SR,t-1})FR_{SR,t-1}+(\zeta_9+\zeta_9^{EPU}EPU_{SR,t-1})FX_{SR,t-1}+u_{SR,t},\end{aligned} \tag{14}$$

where the coefficients of the interaction terms are denoted with the superscript ^{EPU}.

Next, we complement the macro sensitivity analysis with the correlations' crisis vulnerability. We explore the response of correlations to crisis shocks on their macro regressors. Making use of crisis intercept and slope dummies, we demonstrate and compare the effects of three different crises (GFC, ESDC, COV) on correlation levels (intercept dummies) and on the macro factor's influence on correlations (slope dummies). First, the three crisis dummies are denoted by $D_{C,t}$, where $C = GFC$, $ESDC$, COV. Their zero/one time series (intercept dummies) are constructed based on the respective crisis timeline (see the following Section for detailed timelines) as follows: $D_{C,t} = 1$ if t is included in the crisis period else $D_{C,t} = 0$. The slope dummies are calculated by the crisis dummy multiplication with each macro regressor. Both intercept and slope dummies are incorporated in eq. (12):

$$\begin{aligned}\rho_{SR,t} &= \zeta_0+\zeta_0^{C}D_{C,t}+\zeta_1\rho_{SR,t-1}+(\zeta_2+\zeta_2^{C}D_{C,t-1})EPU_{SR,t-1}+(\zeta_3+\zeta_3^{C}D_{C,t-1})FU_{SR,t-1} \\ &+(\zeta_4+\zeta_4^{C}D_{C,t-1})ID_{SR,t-1}+(\zeta_5+\zeta_5^{C}D_{C,t-1})FS_{SR,t-1}+(\zeta_6+\zeta_6^{C}D_{C,t-1})NS_{SR,t-1} \\ &+(\zeta_7+\zeta_7^{C}D_{C,t-1})EC_{SR,t-1}+(\zeta_8+\zeta_8^{C}D_{C,t-1})FR_{SR,t-1}+(\zeta_9+\zeta_9^{C}D_{C,t-1})FX_{SR,t-1}+u_{SR,t},\end{aligned} \tag{15}$$

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

Lastly, we test the indirect EPU effect during crises by multiplying the EPU interaction terms with the crisis slope dummies:

$$\begin{aligned}\rho_{SR,t} &= \zeta_0+\zeta_1\rho_{SR,t-1}+\zeta_2 EPU_{SR,t-1}+(\zeta_3+\zeta_3^{EPU\_C}D_{C,t-1}EPU_{SR,t-1})FU_{SR,t-1} \\ &+(\zeta_4+\zeta_4^{EPU\_C}D_{C,t-1}EPU_{SR,t-1})ID_{SR,t-1}+(\zeta_5+\zeta_5^{EPU\_C}D_{C,t-1}EPU_{SR,t-1})FS_{SR,t-1} \\ &+(\zeta_6+\zeta_6^{EPU\_C}D_{C,t-1}EPU_{SR,t-1})NS_{SR,t-1}+(\zeta_7+\zeta_7^{EPU\_C}D_{C,t-1}EPU_{SR,t-1})EC_{SR,t-1} \\ &+(\zeta_8+\zeta_8^{EPU\_C}D_{C,t-1}EPU_{SR,t-1})FR_{SR,t-1}+(\zeta_9+\zeta_9^{EPU\_C}D_{C,t-1}EPU_{SR,t-1})FX_{SR,t-1}+u_{SR,t},\end{aligned} \tag{16}$$

where the EPU under crisis coefficients are denoted by the superscript $^{EPU\_C}$. Based on the macro sensitivity of markets' interdependence (*H6* and *H7*), for both crisis regressions (eqs. (15) and (16)), we expect that the estimated coefficients will demonstrate that the crisis shock amplifies (crisis coefficients increase in absolute terms) the correlation level change (crisis intercept dummies), the direct macro effect on correlations (crisis slope dummies), and the indirect EPU impact on the macro drivers of the cross-asset nexus (EPU interaction multiplied by crisis slope dummies).

3.2 Data Description

After detailing our methodological approach, we describe the asset and macro data used in our cross-asset interdependence analysis (definitions of variables and sources reported in Table A.1 of the Appendix). Our daily data sample starts on 01/01/2001 and ends on 27/07/2020, with a total of 5,106 observations (daily asset returns and daily macro regressors). The sample of the monthly macro variables (used in the long-run correlation regression analysis, eq. (13)) spans from January 2001 until July 2020, which is 235 monthly observations.

Following the financial correlations literature (Section 2.1), we first use widely applied global benchmarks for the asset markets under scope. Equities (EQU) are proxied by a global equity index, the MSCI World Equities index (MXWO), which contains large- and mid-cap equities of twenty-three developed stock markets. For Real Estate markets (RE), we consider the Dow Jones (DJ) Real Estate Investment Trusts index (REIT) as a global real estate market performance benchmark. It represents the securitised real estate investments, consisting of all publicly US REITs in the Dow Jones stock index. Global commodity prices are tracked by the Standard & Poor's Global Commodity indices (GSCI), which comprises twenty-four commodities from five broad categories. We use the aggregate commodity GSCI index (COM) and the five subindices corresponding to each category: Energy (NRG), Precious Metals (PRM), Industrial Metals (INM), Agriculture (AGR), and Livestock (LIV).

The asset variables are included in the cDCC-MIDAS in their return form. Daily asset returns (r_{it}) are calculated on each asset index price series as follows: $r_{i,t} = [\ln(P_{i,t}^{Close}) - \ln(P_{i,t-1}^{Close})] \times 100$, with $P_{i,t}^{Close}$ the daily closing price on day t. Table A.2 of the Appendix reports the summary statistics of the asset returns. The unit root test rejects the null hypothesis allowing the input of the asset returns in the MIDAS model estimation[7]. The descriptive statistics figures show that energy price returns are the most volatile among all assets while the livestock series exhibits the lowest standard deviation. Interestingly, the pairwise correlation coefficients indicate the highest connectedness among equities and real estate (0.66). Equities-commodities are more connected than the real estate-commodities pair ($0.45 > 0.21$). Beyond the aggregate commodities, in the commodity subtypes, we observe lower correlations in association with real estate than with equities, consistently with the aggregate results. intra-commodity correlations are all below 0.40, with the lowest figure in the PRM-LIV combination (0.05). Overall, the returns correlation coefficients are all positive and in some cases close to zero for precious metals pairs.

Moreover, we describe the high and low frequency macro fundamentals that explain the short- and long-run dynamic correlations, respectively. The economic effects on the cross-asset nexus cover most facets of the macro environment driving the global asset markets' performance and connectedness (see also Eiling and Gerard, 2015). As discussed in the Hypotheses section (Section 2.2), we account for investors' sentiment (EPU, FU, ID, SENT), news (NS), credit conditions (FS), economic activity (EC), and prices (INFL, FR, FX). Not all effects are incorporated in both the short- and long-run correlation macro regressions (eq. (12) and (13)). We rely on the data availability of daily and monthly macro-financial and news proxies for each effect. Hence, for each daily and monthly correlation determinant, the following indices are

[7] We perform various unit root tests beyond the Augmented Dickey-Fuller test with the same conclusions (e.g. the Phillips-Perron test, the Kwiatkowski, Phillips, Schmidt, and Shin test, the results are available upon request).

used:

1. *EPU* (daily [d] and monthly [m]): For the economic policy uncertainty impact, we apply the daily and monthly newspaper-based US EPU indices ($EPU_{d,t}$ and $EPU_{m,t}$) of Baker et al. (2016). The US uncertainty is incorporated in our analysis as a global uncertainty proxy available at both high and low frequencies. EPU indices based on news analytics are considered the most inclusive metrics of agents' uncertainty feelings since they take into account economic and policy-related sentiments. There is ample empirical evidence on the EPU acting as a potent catalyst of the macro environment and on its explanatory power in financial markets' performance (see, for example, Pastor and Veronesi, 2013). 2. *FU* (daily): For financial uncertainty, we make use of the daily S&P500 implied volatility index, VIX (VIX_t). VIX is well-documented as a reliable proxy of financial uncertainty and risk aversion globally, with destabilising and recessionary local and cross-border effects (Bekaert et al., 2013). 3. *ID* (daily): The infectious disease news impact on financial markets is captured by the daily Infectious Disease Equity Market Volatility Tracker (ID_EMV_t) created by Baker et al. (2020). The ID_EMV index is a news-based index that measures the disease news effect on US stock market volatility (financial uncertainty). Since the Covid-19 pandemic has recently dominated the whole socioeconomic context, we expect that ID_EMV will be highly significant in explaining the evolution of cross-asset correlations. 4. *FS* (daily and monthly): The credit channel, a major contributor to the cyclical economic fluctuations (Gilchrist and Zakrajšek, 2012), is further proxied by daily and monthly financial stress indices, indicative of the prevailing credit and liquidity conditions. We use the daily global OFR (Office for Financial Research) Financial Stress Index (FSI_t) in the short-run correlation regressions. In the long-run macro analysis, we apply the monthly Kansas City Fed Financial Stress Index ($KCFSI_t$) for the US. Higher FS indices mean tighter credit and liquidity terms during weak economic periods.

5. *SENT* (monthly): In the long-run correlations' macro sensitivity, we include a monthly global survey-based confidence indicator. The G7 Business Confidence Index growth ($gBCI_t$) captures the aggregate positive sentiment effects on long-run correlations (see, for example, the crucial role of sentiment/emotions for systemic risk and crises in Breaban and Noussair, 2018). 6. *NS* (daily): The high frequency news influence on short-run cross-asset correlations is critical. Good economic news decisively triggers agents' confidence or optimism and bad news can lead to massive herding behaviour and co-movements across markets (Albuquerque and Vega, 2009). Hence, we use the daily US News Sentiment Index (NSI_t) from the San Francisco Fed. NSI is constructed by Shapiro et al. (2020), who distinguish between negative and positive economic news through a sentiment scoring lexical analysis in US newspapers. 7. *EC* (daily and monthly): The economic activity effect on financial correlations is included in both short- and long-run dependence dynamics. The daily activity proxy used is the US yield curve slope (or term spread) calculated by the difference of ten-year minus three-month US treasury yields ($YCsl_t$). The term spread is widely acknowledged by the literature for its predictive power of the real variables (Estrella and Hardouvelis, 1991). An increase in the treasury term structure slope predicts higher GDP growth and a decrease in the slope predicts activity contraction. Our monthly activity proxy is the G7 Industrial Production growth (gIP_t), explaining the long-run correlations. 8. *INFL* (monthly): The global inflation effect is captured by the monthly G7 Producer Price Index growth ($gPPI_t$). Daily inflation data are not available and, therefore, are absent from daily correlation analysis. 9. *FR* (daily and monthly): The freights effect on cross-asset dependences is proxied by daily and monthly indices. The daily Baltic Dry Index (BDI_t) is a global overall freights indicator. The monthly Cass Freight

Index (CFI_t) tracks the North American freights market, considered a universal proxy in our macro analysis. 10. FX (daily): Currency values are proxied by the daily DXY index growth ($gDXY_t$), a measure of the US dollar strength relative to a wide variety of currencies.

The daily and monthly macro regressors cover all economic facets and are expected to exert a significant influence on the evolution of cross-asset correlations. We consider the US indices as global proxies for the respective macro effect. The indices are incorporated in the short- and long-run correlation regressions in their level form (ID_EMV_t, FSI_t, $KCFSI_t$, NSI_t, CFI_t) or transformed to log-level ($EPU_{d,t}$, $EPU_{m,t}$, VIX_t, BDI_t), daily level change ($\Delta YCsl_t$), and daily growth ($gBCI_t$, gIP_t, $gPPI_t$, $gDXY_t$). The regressors' transformation is based on multicollinearity and unit root considerations, as well as their best fit in correlation regressions (significance, information criteria, and $\overline{R}^2$). Table A.3 in the Appendix reports the summary statistics of the variables used as correlation drivers. The rejection of the null unit root hypothesis (ADF - Augmented Dickey-Fuller tests) ensures the suitability of the macro-financial time series for the correlation regressions. We further perform the Variance Inflation Factors (VIF) multicollinearity test, which rejects any multicollinearity bias (the results are available upon request).

The economic and news variables are classified into ten economic effects (EPU, FU, ID, FS (+ *H6*, − *H7*), SENT, NS, EC, INFL, FR, FX (− *H6*, + *H7*), see also Table A.1, Panel B). The indices pattern characterising economic worsening or crises (higher uncertainty, disease impact on financial volatility, and financial stress, lower confidence, news sentiment, activity, inflation, freights, and dollar strength) will exacerbate cross-asset interdependence under *H6* or lead to flight-to-quality decreasing correlations under *H7* (see also the expected signs of the macro effects in Table 1, Panel B). Conversely, economic expansion (lower uncertainty, disease impact on financial volatility, and financial stress, higher confidence, news sentiment, activity, inflation, freights, and dollar strength) will reduce (increase) correlations under *H6* (*H7*). Hence, the uncertainty, disease, and financial stress effects on the cross-asset nexus should be positive (negative), the confidence, news, activity, and prices impact should be negative (positive) based on *H6* (*H7*). Consequently, according to the contagion (flight-to-quality) hypothesis, financial correlations are countercyclical (procyclical) since rising (falling) interdependences are associated with economic slowdowns.

Lastly, we close our data section with the crisis timelines. For the GFC, we follow the Bank for International Settlements (BIS) and the Federal Reserve Bank of St. Louis timelines. For the other two crises, we use the European Central Bank ESDC timeline and the World Health Organisation (WHO) COV pandemic chronology. The three crisis subsamples are the following: 1. GFC subsample: 9/8/07 - 31/3/09. The GFC starting point was the suspension of certain BNP Paribas investment funds in August 2007 and it lasted until the first quarter of 2009. 2. ESDC subsample: 9/5/10 - 31/12/12. The Greek default in May 2010 established the beginning of ESDC, which lasted until the end of 2012. 3. COV subsample: 11/3/20 - 27/7/20. The COV started in March 2020, when the WHO characterised the Covid-19 outbreak as a pandemic and is still in place until the end of the whole sample.

The crisis timelines are used in the breakdown of the whole sample to the three crisis subsamples, where we investigate the correlations' crisis vulnerability. We prefer the actual crisis dates to a structural breaks procedure because we intend to explain the response of the cross-asset dependence to the whole crisis period as it is depicted in the macro aggregates. The structural breaks analysis of correlation dynamics (see Karanasos and Yfanti, 2021) does not illustrate the full picture of the influence that the actual crisis episode, as a whole, exerts on correlations. For example, the break dates statistically identified are close to the start of a crisis but they are not the actual starting points according to the official timelines. The break dates may be either before or after the official dates. During most crisis subsamples, we observe the deterioration of economic fundamentals included as correlation determinants. Uncertainty increases, confidence decreases, disease news impact on financial volatilities is stronger during COV mostly, bad news prevails, credit conditions become tighter, economic activity and prices drop. Accordingly, during crises, we expect higher countercyclical (contagion) and lower procyclical (flight-to-quality) cross-asset correlations.

4 cDCC-MIDAS Estimation Results

In this Section, we discuss the cDCC-MIDAS estimation results. We run ten trivariate models. The first six combinations are the financial with the other two financialised asset classes, EQU with RE and COM (one aggregate and five disaggregated commodity indices). The remaining models are the four trivariate intra-commodity combinations. From each trivariate system, three short- and three long-run pairwise dynamic correlation series are computed. In the present study, we analyse twenty-three daily and twenty-three monthly unique pairwise cross-asset correlations in total. We do not need all thirty daily plus all thirty monthly series computed because some correlation pairs are repeated as components of a trivariate model. For example, the EQU-RE daily correlation is computed six times in the first six combinations of EQU-RE-COM with almost identical results, since the variance equations are identical for each asset series. In what follows, we first present the estimation of the cDCC-MIDAS variance and correlation equations, and then we extract and analyse the pairwise daily and monthly cross-asset correlations.

4.1 Trivariate cDCC-MIDAS Estimation

The cDCC-MIDAS model consists of the variance and correlation parts. The estimation results of each asset's GARCH-MIDAS variance equation are identical for all trivariate models where the asset return series is included. Table 2, Panel A reports the parameters of the eight variance equations. In all cases, the arch (α_i) and garch (β_i) coefficients of the short-run variance dynamics are significant, stable, and with a sum lower than the unity ($\alpha_i + \beta_i < 1$), meaning that the short-term component is mean-reverting to the long-term trajectory (Conrad et al., 2014). In the MIDAS long-run variance part, all three coefficients are significant in most cases: the long-term variance intercept (m_i), the parameter of the monthly $RV_{i\tau}$ (θ_i) which drives the long-term component, and the respective MIDAS variance weight parameter (ω_v^i). The realised variance long-run effects are always positive with similar magnitude (θ_i between 0.10 and 0.19). The degree of smoothing (ω_v^i) varies substantially from close to unity (suggesting a flatter optimal weighting scheme) to 6.44 and is estimated insignificant only for one asset (RE). The choice of the polynomial characteristics M_v and K_v in eqs. (6) and (8), as pointed out by Colacito et al. (2011) and Engle et al. (2013), amounts to model selection with a fixed parameter space, and therefore is achieved via profiling the likelihood function for various combinations of M_v and K_v. The model with monthly RV ($K_v = 22$) offers the best fit (dominates in terms of the likelihood profile, and the Akaike and Schwartz information criteria as well), which is also in line with the results in Colacito et al. (2011) and Conrad et al. (2014). It is also enough to take four MIDAS lag years, that is $M_v = 12 \times 4 = 48$, to capture the dynamics of $m_{i\tau}$ (the optimal value of the log likelihood is obtained when we use four lag years).[8]

Table 2. cDCC-MIDAS Variance and Correlation equation results.

Panel A. Variance equation

	EQU	RE	COM	NRG	PRM	INM	AGR	LIV
μ_i	0.0622***	0.0577***	0.0027	0.0126	0.0296*	0.0128	−0.0221	−0.0125
	(0.0103)	(0.0146)	(0.0187)	(0.0247)	(0.0154)	(0.0179)	(0.0163)	(0.0134)
α_i	0.1417***	0.1242***	0.0585***	0.0690***	0.0466***	0.0525***	0.0530***	0.0551***
	(0.0094)	(0.0073)	(0.0035)	(0.0034)	(0.0026)	(0.0058)	(0.0051)	(0.0073)
β_i	0.8187***	0.8619***	0.9353***	0.9241***	0.9398***	0.9220***	0.9364***	0.9090***
	(0.0120)	(0.0082)	(0.0041)	(0.0041)	(0.0040)	(0.0105)	(0.0062)	(0.0166)
m_i	0.5472***	1.2705***	1.3472***	1.9665***	0.6848***	0.5568***	0.7275***	0.4525***
	(0.0505)	(0.1705)	(0.2369)	(0.3459)	(0.1151)	(0.1192)	(0.1797)	(0.1269)
θ_i	0.1703***	0.0996***	0.1113**	0.1027*	0.1696***	0.1833***	0.1749***	0.1866***
	(0.0122)	(0.0262)	(0.0495)	(0.0555)	(0.0161)	(0.0115)	(0.0262)	(0.0189)
ω_v^i	6.3906***	3.6994	1.0010***	1.0010***	1.0010***	3.4415***	1.0557**	6.4361**
	(1.3439)	(2.6989)	(0.2384)	(0.2684)	(0.0749)	(1.2688)	(0.4108)	(3.2203)
$logL$	−4720.40	−6443.62	−6786.03	−8029.00	−6085.85	−6685.83	−6317.16	−5243.70
AIC	9452.8	12899.2	13584.1	16070.0	12183.7	13383.7	12646.3	10499.4
BIC	9492.0	12938.5	13623.3	16109.2	12222.9	13422.9	12685.6	10538.6

Panel B. Correlation equation

	a	b	ω_r^{ij}	$logL$	AIC	BIC
EQU-RE-COM	0.0326***	0.9475***	4.4071***	−15833.9	31673.8	31693.4
	(0.0029)	(0.0067)	(1.0097)			
EQU-RE-NRG	0.0325***	0.9481***	4.0318***	−15915.5	31837.1	31856.7
	(0.0028)	(0.0062)	(0.9449)			
EQU-RE-PRM	0.0381***	0.9344***	1.9895***	−16160.8	32327.5	32347.1
	(0.0029)	(0.0068)	(0.5139)			
EQU-RE-INM	0.0300***	0.9491***	3.5806***	−15834.5	31674.9	31694.5
	(0.0030)	(0.0072)	(0.9749)			
EQU-RE-AGR	0.0284***	0.9447***	2.5484***	−16179.1	32364.1	32383.8
	(0.0032)	(0.0086)	(0.7143)			
EQU-RE-LIV	0.0237***	0.9522***	1.8690***	−16255.6	32517.3	32536.9
	(0.0024)	(0.0081)	(0.5957)			
NRG-PRM-INM	0.0270***	0.9390***	3.5009***	−16544.2	33094.4	33114.0
	(0.0028)	(0.0092)	(0.6345)			
NRG-AGR-LIV	0.0089***	0.9867***	2.2551*	−16982.6	33971.2	33990.9
	(0.0015)	(0.0043)	(1.2470)			
PRM-AGR-LIV	0.0162***	0.9359***	3.1362***	−17093.2	34192.5	34212.1
	(0.0039)	(0.0246)	(0.8177)			
INM-AGR-LIV	0.0088***	0.9813***	3.3497**	−17009.8	34025.6	34045.2
	(0.0020)	(0.0102)	(1.3690)			

Notes: The table reports the cDCC-MIDAS variance and correlation equation results of the ten trivariate cross-asset combinations. The estimation of the variance equation for each asset series is the same for all trivariate models where the series is included (Panel A). The correlation equation is estimated for ten trivariate combinations (Panel B) and computes three pairwise dynamic correlation series for each trivariate system. Numbers in parentheses are standard errors. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively. $logL$ denotes the log likelihood. AIC and BIC are the Akaike and the Schwartz Information Criteria, respectively. The time span that $m_{i\tau}$ is fixed is a month, that is $K_v = 22$. The number of lag years spanned in each MIDAS polynomial is 4, that is $M_v = 12 \times 4 = 48$.

We further estimate the correlation equations of the ten trivariate combinations (Table 2, Panel B). To determine the long-run component of conditional correlations, $\overline{R}_t$ we proceed in exactly the same way, namely we select the number of lags M_c for historical correlations and the time span over which to compute the historical correlations K_c in eq. (9).[9] As in the case of the long-term volatilities, we choose $K_c = 22$ (a monthly time span) and $M_c = 36$ (three MIDAS lag years).

Short-run correlation dynamics are determined by the parameters a and b. They are highly significant with their sum, $a + b$, stable and close to but always lower than the unity, denoting the short-term correlation mean-reversion to the long-term correlation trend. The long-term correlation component is driven by the lagged monthly realised correlations

[8] Engle et al. (2013) used a quarterly time span. Although we choose a monthly one, the results in our paper appear to be robust to the way we compute the RV. In addition, as in Conrad et al. (2014) the results (available upon request) are robust to moderate changes in M_v.

[9] As pointed out by Colacito et al. (2011), the similarity between the two procedures is not surprising, given the fact that DCC models build extensively on the ideas of GARCH and in both cases we have a MIDAS filter extracting a component which behaves like a time-varying intercept.

with a weight parameter, ω_r^{ij}, which is significant in all cases.[10] There is ample empirical evidence on the superiority of the component models with short- and long-term volatility and correlation dynamics compared to the simpler DCC specifications. For robustness purposes, we also test various macro regressors in the short- and long-term variance specification (a specification similar to the GARCH-MIDAS-X of Engle et al., 2013, for the long-term variance, combined with the GARCH-X of Engle, 2002b, where macro effects are incorporated in the short-run dynamics). The cDCC-MIDAS results produce similar daily and monthly correlations with and without the variance macro regressors. Consequently, since our main objective is not the investigation of the volatility dynamics but the analysis of the daily and monthly cross-asset correlation evolution with the corrected DCC-MIDAS estimation, we prefer the simple GARCH-MIDAS variance specification with monthly $RV_{i\tau}$ used as the main driving force of the long-term volatility component (the results of the robustness checks with the macro-augmented variance equations are available upon request).

4.2 Short- and Long-run Correlations

After estimating the cDCC-MIDAS model for the ten trivariate combinations, we extract the daily and long-run (monthly) correlation time series computed for each asset pair included in the trivariate system. The twenty-three unique asset pairs (for each pair one daily and one monthly correlation series is extracted) can be classified into the following groups: i) equities with real estate (one pair), ii) equities with commodities (six pairs), iii) real estate with commodities (six pairs), and iv) intra-commodity (ten pairs). The correlation graphs (Figures A.1 - A.23 in the Appendix) show a cyclical variation of the cross-asset nexus. We mainly observe two different types of interdependence dynamics. On the one hand, countercyclical correlations and the real economy move in opposite directions (see equities with real estate and most commodities). On the other hand, when the time-varying pattern of correlations follows the business cycle, the cross-asset dependence is procyclical (certain precious metals pairs). Countercyclical correlations increase during crises and procyclicals decrease (red cycles indicate the crisis periods examined). The cyclical property of each correlation series can differ across time. There are dependences rising (countercyclical) in response to COV while they fall (procyclical) in the GFC (combinations of real estate with most commodity indices). The graphical analysis further demonstrates differences between the daily (grey dotted line) and the long-term (black solid line) component of correlations. For example, for several precious metals co-movements with other commodities or equities and real estate, the charts display slightly or fairly different patterns of the short- and long-run correlations in some crisis subsamples.

The correlations' summary statistics (see Table A.4 in the Appendix) give an overview of the average levels and dispersion measures of the time-varying daily and monthly correlations for the whole seventeen-year period under investigation. For most combinations, the mean values of the short- and long-run times series are quite close, while the long-term component is less volatile. Minimums show that most correlations go through the negative territory. Mean values demonstrate that the equity market is more correlated to commodities (aggregated and disaggregated) than the real estate market. This is indicative of the financialisation hypothesis of Cheng and Xiong (2014), among others (equities with commodities), and contrary to expectations about the closer economic linkages of real estate with commodities due to direct supply chain

[10] Since we consider three assets we have the possibility that several long-run MIDAS filters as well as multiple DCC parameters apply. We have estimated models with two sets of DCC parameters and/or two MIDAs filters, and the results (available upon request) were robust to these changes.

effects (Breitenfellner et al., 2015). The intra-commodity co-movements are stronger than the real estate - commodities combinations, confirming their tight production, substitution, or complementary relations (Casassus et al., 2013). The highest average connectedness is observed for the EQU-RE pair (financialisation). In the equities (real estate) - commodities group, the highest correlation mean value is recorded in EQU-INM (RE-INM) and the lowest in EQU-LIV (RE-PRM). Among commodities, the two metals (PRM-INM) are the most interdependent and the PRM-LIV pair is the least interconnected, with an average correlation close to zero. Metals' economic linkages are stronger, while precious metals with livestock are the least connected through supply chain effects. Apart from the economic significance of correlations, from the investor's perspective, the whole sample mean values further allow us to consider the two hedging properties under *H1* and *H2*. All correlations are positive and not close to unity (on average), confirming the first hypothesis (*H1*), that the assets involved can serve as diversifiers when included in pairs in multi-asset portfolios. The only exceptions are the asset combinations which are characterised as hedges (*H2*) because, although their correlations are not negative, they are close to zero (lower than 0.100). The uncorrelated pairs, operating as hedges, are RE-PRM, RE-AGR, RE-LIV, and PRM-LIV. All other asset combinations involve diversifiers. The whole sample statistics of both short- and long-run correlations give identical conclusions for diversifiers and hedges. In sharp contrast, the crisis subsample statistics will reveal differences among daily and monthly patterns, further asset properties, the correlations' time-varying behaviour, and its economic significance.

Our initial crisis analysis relies on correlation subsample averages and the mean difference tests (Satterthwaite-Welch t-test and Welch F-test, reported in Tables A.5 and A.6 of the Appendix). We compare the pre-crisis and crisis correlation mean values and conclude whether the mean differences are statistically significant. The crisis subsamples are defined by the respective timelines. The pre-crisis periods, which we consider for the mean difference tests, are of equal length to the in-crisis time interval. Alternative pre-crisis periods are tested for robustness purposes and give similar results (the results are available upon request). Based on the in-crisis levels and the signs of the change in levels, we test the next three hypotheses: *H3*, *H4*, and *H5*. Table 3 presents the interdependence types and safe haven properties identified in the correlation statistical analysis across the crisis subsamples (Tables A.5 and A.6). In the first asset pair, EQU-RE, both daily and monthly correlations increase significantly during all three crises, except for the COV subsample (see the first row of Table 3). In the pandemic, the long-term component's increase is not statistically significant (higher interdependence). However, in Figure A.1, we observe a considerable monthly correlation increase during the last crisis. Hence, for our first combination of a financial with a financialised asset, we can conclude that the overall positive and increasing in-crisis (countercyclical) correlations demonstrate contagion, according to *H4* and the related empirical evidence, which mainly focuses on the GFC-induced short-run contagion effects (Liow, 2012, Heaney and Sriananthakumar, 2012, Yang et al., 2012, Huang and Zhong, 2013, Karanasos and Yfanti, 2021).

Turning to the pairs of equities with commodities (aggregate index and subindices), the tests mostly show contagion across all crises for both short- and long-run correlations apart from the precious metals case (see the top part of Table 3). EQU-AGR monthly correlations exhibit an insignificant increase (higher interdependence) in the GFC subsample but the graphical analysis shows a stable pattern in the early GFC period and a significant upturn in late-GFC. The GFC contagion in the EQU-LIV pair is associated with a low in-crisis correlation average, which is 0.06 for the long-term component, mostly indicative of long-run safe haven properties. During COV, precious metals can be considered safe havens (*H3*) since they are negatively correlated or uncorrelated with equities. Flight-to-quality is observed only in the COV long-run pattern of EQU-PRM, where both level and change conditions are satisfied under *H5*. The COV short-run close-to-zero correlations increase slightly on average. In the GFC, correlations remain positive and decrease (increase) in the short (long) run indicating lower interdependence (contagion). In the ESDC, the statistics signify contagion (*H4*), with a moderate short- and long-run positive rise in correlations. Hence, most equities-commodities correlations demonstrate contagion, with the exception of precious metals, confirming Creti et al. (2013), among many others. The stronger in-crisis co-movement of equities with real estate and commodities further confirms the financialisation trend which is intensified due to investor trading behaviour (possible overreaction or extrapolative beliefs) rather than firms'/assets' fundamentals or tighter economic linkages. The flight-to-quality reaction to crises is also indicative of investors' recessionary fears and herding rather than looser economic relations.

Regarding the co-movement of the real estate market with commodities (see the middle part of Table 3), during the first crisis, all pairs are uncorrelated or negatively correlated (all GFC correlation averages lower than 0.100) denoting safe haven properties (*H3*). The only combinations with correlation increases but still close to zero (weak contagion) are RE-LIV (daily and monthly series) and RE-INM (monthly series). The GFC shock gives rise to flight-to-quality conditions (*H5*) for three out of six asset pairs in the short run (RE-COM, RE-NRG, RE-PRM) and the long run (RE-COM, RE-NRG, RE-AGR). In sharp contrast, Nguyen et al. (2021) diagnose contagion among oil and housing markets during GFC, while Huang and Zhong (2013) demonstrate a large increase of REITs and aggregate commodities correlations in the same period. In the ESDC, all real estate correlations are positive and increase significantly, satisfying the contagion hypothesis (*H4*). In the recent pandemic crisis, short-run contagion (*H4*) occurs since correlations increase significantly, except for the RE-PRM case. In the monthly patterns, correlations increase (except for RE-LIV) but the change is not significant in most cases and all correlations remain below 0.100 (long-run higher weak interdependence or weak contagion and safe havens during COV). The RE-LIV monthly interdependence exhibits an insignificant slight fall in the long run which denotes a rather stable pattern. The RE-PRM correlations decrease in the short term and increase in the long term but remain positive and close to zero, indicating safe haven asset behaviour (*H3*). Therefore, with the exception of PRM, we can conclude that real estate markets are less connected with most commodities in the first decade of the financialisation process, allowing for flight-to-quality (or lower interdependence) episodes and safe haven features. Starting from late-GFC times (Figures A.8-A.13 in the Appendix), the correlations have increased significantly with clear evidence of contagion or higher interdependence phenomena thereafter, demonstrating investors' increasing attention to financialised assets (Xu and Ye, 2023).

Compared with Karanasos and Yfanti (2021), who find that, following the GFC structural break, all correlations increase, we hereby conclude that this is not the case when the actual crisis timeline is considered and the commodity index is disaggregated. For EQU-PRM and most of the real estate-commodities combinations, correlations decrease during GFC. A further feature in the short- and long-run patterns is the stable or decreasing interdependences in the initial GFC stage followed by a remarkable increase in the late GFC phase (see, for example, EQU-AGR, RE-COM, RE-NRG, RE-INM, RE-AGR graphs). This could indicate that the propagation of the crisis shock across assets is not swift and concurrent for all markets to drive their co-movement higher from the initial phases of a crisis episode. Investors gradually incorporate bad news at a pace that is different among markets. They could be, at first, reluctant to admit the crisis advent or perceive the incoming news as asset or regionally focused. Hence, returns move more independently at first as in tranquil times and when deep-in-crisis, they start to tightly co-move with soaring correlations.

Table 3. Short- and Long-run interdependences and safe haven property.

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

Notes: The table recaps the interdependence phenomena and safe haven property identified in the short- and long-run correlations statistical analysis (Tables A.5 and A.6) across the three crisis subsamples (GFC, ESDC, COV). The in-crisis interdependence types are as follows: Contagion, Weak contagion, Flight-to-quality, Higher interdependence (Higher int.), Higher weak interdependence (Higher weak int.) and Lower interdependence (Lower int.).

The last part of this crisis analysis focuses on intra-commodity co-movements (see the bottom part of Table 3). The GFC shock induces daily and monthly contagion across most commodity pairs ($H4$), in line with Le Pen and Sévi (2018), among others, who estimate higher excess co-movement or interconnectedness across all commodity types after 2007. However, in two PRM pairs with LIV and INM in the short run, there is lower interdependence and weak contagion, respectively. In the long run, three LIV pairs (with NRG, PRM, and AGR) exhibit weak contagion, that is correlations less than 0.100, and therefore safe haven asset behaviour. During ESDC, short-run correlations decrease but remain positive (lower interdependence) for six out of ten cases, contrary to Kang et al. (2017), who find increased short-run correlations among energy, precious metals, and agriculture in both GFC and ESDC periods. In the remaining four cases (NRG-INM, INM-AGR, INM-LIV, AGR-LIV), positive correlations increase, confirming the contagion hypothesis

(*H4*). In the long run, four out of the six lower interdependence cases remain (NRG-PRM and NRG-LIV dependences slightly increase but the change is insignificant since the ESDC average of the monthly correlation is rather stable), and the same four contagion cases occur. During COV, the mean difference tests confirm daily contagion (*H4*) across most intra-commodity pairs, while certain monthly correlations do not follow the daily trend (PRM-AGR, PRM-INM). Negative or close to zero in-crisis correlations are computed for six out of ten metals and energy combinations in the long term, suggesting a long-run safe haven property during COV (*H3*). As a whole, the intra-commodity results demonstrate contagion (although weak in some cases) during GFC and COV and lower interdependences during ESDC for most daily and monthly series. The cyclical variation of the cross-commodity correlations demonstrates their sensitivity to economic dynamics, which, contrary to Casassus et al. (2013), drive not only the short-term but also the long-term co-movement. Precious metals and livestock are less connected to other commodities during crises. This can be attributed to investor strategies under the crisis fear, such as flight-to-quality with hedging vehicles that diversify the portfolio risk. Economic linkages or supply chain effects can also be crisis-vulnerable and move intra-commodity correlations by a lesser extent.

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

Next, comparing short- with long-run dynamics in crises, we notice that a daily COV correlations increase is associated with a decrease in the monthly series for three precious metals pairs (EQU-PRM, PRM-AGR, PRM-INM) and for RE-LIV. This could denote that the pandemic long-term component is not yet adjusted to the daily trend or is more resilient to contagion effects. We also observe the opposite, a short-run decrease with a long-run increase in correlations for three metals pairs (EQU-PRM, RE-INM, PRM-INM) in the GFC, for two intra-commodity pairs (NRG-PRM, NRG-LIV) in the ESDC, and for RE-PRM in the COV. Finally, focusing on the correlation graphs, most insignificant long-run time series changes indicate a rather stable correlation pattern in average terms but not far from the short-run trend. Setting side-by-side EQU-COM with EQU-NRG correlations and RE-COM with RE-NRG, we deduce the dominant role of energy (dominated, in turn, by crude oil) in commodities correlations with the other two asset classes. Aggregate commodities correlations with stocks and real estate are almost fully determined by the evolution of the respective energy correlations. The cyclical patterns of the cross-asset nexus are similar while the interdependence types and safe haven properties are identical across all crises. In what follows, we attempt to explain the evolution of correlations with macro fundamentals in the whole sample and the crisis subsamples separately. From an economic point of view, the macro-relevance of the short- and long-run cross-asset nexus demonstrates that it is attributed to investors' trading behaviour (overreaction to macro news, hedging strategies in crises, attention to assets, speculative demand etc.) apart from the evolution of their economic relationships and their fundamentals' interaction which might be less crisis-vulnerable (Xu and Ye, 2023).

5 Sensitivity Analysis of Dynamic Correlations

Motivated by our conclusions on the counter- and procyclical behaviour of cross-asset correlations, we attribute their variation to global macro and news factors. We first regress the daily and monthly Fisher-transformed correlations on high and low frequency fundamentals (eqs. (12) and (13)) and scrutinise the sensitivity of the macro drivers to the economic uncertainty channel (eq. (14)). Next, we investigate the crisis impact on the correlation determinants (eq. (15)) and the mediating role of uncertainty (eq. (16)).

5.1 The Correlations' Macro Determinants

The correlation macro drivers are traced in well-established metrics tracking the major facets of the business cycle dynamics. We employ sentiment (uncertainty, confidence), infectious disease, credit, news, activity, and prices daily and monthly proxies, based on data availability. The macro sensitivity analysis tests the last two hypotheses (*H6* and *H7*) through eqs. (12) and (13), where we identify the macro effects on the short- and long-run cross-asset nexus. ADF tests reject the unit root hypothesis for both daily and monthly correlations computed by the cDCC-MIDAS model and Fisher-transformed (the test statistics are available upon request). Hence, our dependent and explanatory variables are suitable for the OLS regressions of eqs. (12) and (13).

The short-run correlations are explained by daily fundamentals, which can be useful as early warning signals of imminent crisis episodes when most financial correlations soar (contagion or higher interdependence) or some others drop (flight-to-quality or lower interdependence). The use of high frequency macros is still in its infancy in macro-financial research. Most studies apply common monthly or quarterly macros to explain daily financials (e.g., returns, volatilities, correlations) through MIDAS or aggregation techniques. The superiority of the high frequency domain is its nowcasting advantage. Daily metrics can capture the actual economic stance in a timely manner while lower frequency measures are published with a significant time lag. Therefore, it has become essential to utilise macros that illustrate day-to-day economic developments. This necessity has proved to be urgent, especially during turbulent times like the recent pandemic crisis, when macro deterioration has occurred on a daily basis and policy tools can rely on nowcasting to alleviate the crisis shocks (Diebold, 2020).

Short Run

Table 4 reports the daily correlations regression results (eq. (12)) for the estimated coefficients of the macro regressors of selected asset pairs (see Table A.7 in the Appendix with full regression results for all daily cross-asset correlations). Regarding the significance of the macro regressors, we first notice that the infectious disease effect on financial volatility is significant in six cases only because this particular index increases significantly only during COV. Therefore, its effect on the full period is limited. The activity effect is insignificant in two precious metals combinations while the impact of freights is insignificant in three intra-commodity pairs. The dollar strength is estimated significant in fourteen cases, but is insignificant for both procyclical pairs. Finally, uncertainty, financial stress, and news proxies are always significant with a potent effect on cross-asset co-movements.

Table 4. Short-run (daily) cross-asset correlations regressions on macro fundamentals, eq. (12).

	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0017^{***}	0.0842^{***}	0.0022^{*}	0.0019^{***}	-0.0276^{***}	-0.0066^{***}	-0.0241^{**}	-0.0008^{*}
	(0.0004)	(0.0184)	(0.0013)	(0.0007)	(0.0109)	(0.0016)	(0.0118)	(0.0005)
EQU-NRG	0.0031^{**}	0.0281^{*}	0.0024	0.0118^{***}	-0.0445^{*}	-0.0074^{**}	-0.0669^{*}	-0.0007^{***}
	(0.0016)	(0.0143)	(0.0018)	(0.0039)	(0.0261)	(0.0037)	(0.0379)	(0.0003)
EQU-PRM	-0.0034^{***}	-0.0492^{***}	-0.0046^{*}	-0.0018^{***}	0.0377^{***}	0.0017^{*}	0.0288^{*}	0.0006
	(0.0014)	(0.0189)	(0.0024)	(0.0005)	(0.0130)	(0.0009)	(0.0162)	(0.0006)
RE-NRG	0.0029^{***}	0.0556^{***}	0.0020	0.0058^{***}	-0.0196^{*}	-0.0136^{**}	-0.0467^{***}	-0.0010^{**}
	(0.0007)	(0.0209)	(0.0017)	(0.0014)	(0.0111)	(0.0058)	(0.0141)	(0.0005)
RE-PRM	-0.0019^{***}	-0.0154^{***}	-0.0013	-0.0046^{***}	0.0364^{***}	0.0079	0.0436^{*}	0.0009
	(0.0003)	(0.0036)	(0.0020)	(0.0006)	(0.0122)	(0.0060)	(0.0236)	(0.0008)
NRG-AGR	0.0074^{*}	0.0108^{**}	0.0011	0.0032^{***}	-0.0084^{**}	-0.0029^{**}	-0.0066^{***}	-0.0007^{*}
	(0.0040)	(0.0046)	(0.0012)	(0.0008)	(0.0040)	(0.0016)	(0.0017)	(0.0004)
PRM-AGR	0.0022^{***}	0.0046^{***}	0.0010	0.0013^{**}	-0.0211^{**}	-0.0032	-0.0068^{***}	-0.0011^{***}
	(0.0004)	(0.0013)	(0.0014)	(0.0006)	(0.0096)	(0.0022)	(0.0018)	(0.0004)

Notes: The table reports the daily correlations regression results (eq. (12)) for the estimated coefficients of the macro regressors of selected pairwise cross-asset combinations. The numbers in parentheses are standard errors. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

The countercyclical correlations confirm *H6*. When the cross-asset co-movements increase in economic slowdowns and are characterised by contagion during crises, we estimate a positive impact of economic and financial uncertainty, infectious disease and financial stress and a negative effect of news sentiment, activity, freights, and dollar value for the whole sample. *H6* is confirmed for most pairwise daily correlations, consistently with the crisis behaviour reported in Table 3. The correlations that increase or remain stable and become or remain positive during most crises (at least in two of the three crises examined) in Panel A of Table 3 exhibit countercyclicality driven by higher uncertainty and disease effects, tighter credit conditions, negative news sentiment, lower activity, freights, and dollar strength. The only cases where the signs of the macro factors are opposite, following *H7*, are the EQU-PRM and RE-PRM. We recall that (Table 3) EQU-PRM daily co-movement decreases significantly during GFC (lower interdependence) and increases but remains negative during COV (safe haven). RE-PRM correlations decrease and become negative during GFC (flight-to-quality and safe haven) and positive but close to zero during COV (lower interdependence and safe haven). Therefore, their procyclical behaviour dominates their whole sample's macro sensitivity. On the one hand, uncertainty, disease, and financial stress exert a negative influence on the two precious metals combinations with equities and real estate. On the other hand, news, activity, freights, and dollar price have a positive impact.

Long Run

Furthermore, the long-run correlations are regressed on monthly fundamentals (EPU, financial stress, confidence, activity, inflation, and freights). Table 5 presents the results (eq. (13)) for the estimated coefficients of the monthly macro regressors of selected asset pairs (see Table A.8 in the Appendix with full regression results for all monthly cross-asset correlations). Regarding the overall significance of the long-run correlation determinants, EPU and credit proxies are always significant. The insignificant cases are two for the activity effect, six for inflation, and eight for freights. The confidence impact is insignificant only in the metals connectedness (PRM-INM). In general, we draw similar conclusions to the daily regression analysis. We demonstrate that the monthly co-movement of precious metals with equities and real estate is procyclical overall, confirming *H7,* and consistently with the daily analysis. Both long-run correlations decrease or are stable on average during the later stages in two out of the three crises, GFC and COV (Table 3, Figures A.4 and A.10). Accordingly, uncertainty and credit coefficients are estimated negative whereas confidence, activity, inflation, and freights parameters are positive.

Table 5. Long-run cross-asset correlations regressions on macro fundamentals, eq. (13).

	$EPU_{LR,t-1}$	$FS_{LR,t-1}$	$SENT_{LR,t-1}$	$EC_{LR,t-1}$	$INFL_{LR,t-1}$	$FR_{LR,t-1}$
EQU-RE	0.0021^{*}	0.0049^{*}	-0.0126^{**}	-0.0014^{***}	-0.0006^{*}	-0.0127^{***}
	(0.0012)	(0.0027)	(0.0063)	(0.0004)	(0.0004)	(0.0043)
EQU-NRG	0.0012^{***}	0.0040^{***}	-0.0134^{**}	-0.0005^{*}	-0.0003^{**}	-0.0065^{***}
	(0.0002)	(0.0018)	(0.0065)	(0.0003)	(0.0001)	(0.0021)
EQU-PRM	-0.0009^{***}	-0.0045^{**}	0.0109^{***}	0.0012^{**}	0.0006^{*}	0.0101^{**}
	(0.0002)	(0.0016)	(0.0042)	(0.0005)	(0.0004)	(0.0052)
RE-NRG	0.0114^{***}	0.0018^{**}	-0.0297^{***}	-0.0003^{**}	-0.0002	-0.0277
	(0.0033)	(0.0008)	(0.0056)	(0.0001)	(0.0011)	(0.0185)
RE-PRM	-0.0028^{***}	-0.0016^{***}	0.0100^{***}	0.0010^{*}	0.0003	0.0095
	(0.0006)	(0.0005)	(0.0031)	(0.0005)	(0.0004)	(0.0120)
NRG-AGR	0.0061^{***}	0.0035^{***}	-0.0204^{***}	-0.0015^{***}	-0.0003^{*}	-0.0030
	(0.0020)	(0.0012)	(0.0073)	(0.0004)	(0.0002)	(0.0027)
PRM-AGR	0.0036^{***}	0.0029^{***}	-0.0141^{***}	-0.0002	-0.0004	-0.0034^{***}
	(0.0010)	(0.0010)	(0.0051)	(0.0003)	(0.0005)	(0.0010)

Notes: The table reports the long-run correlations regression results (eq. (13)) for the estimated coefficients of the macro regressors of selected pairwise cross-asset combinations. The numbers in parentheses are standard errors. ***, **, * denote significance at the 0.01, 0.05, 0.10 level, respectively.

However, for the other pairs most correlations are positive and increase either across all crisis subsamples or in two crises (Table 3, Panel B) and, therefore, can be characterised as countercyclical, according to *H6*. That is, EPU and financial stress increase correlations while confidence, activity, and prices reduce them. In one case, we further notice mixed signs, partially confirming both *H6* and *H7*. For the two metals pair (PRM-INM), four out of six macro regressors' signs are as expected by *H6* (countercyclicality), with sentiment and activity insignificant. Inflation and freights exert a positive influence, under the context of *H7*, and the latter effect is insignificant. We recall that the long-run correlation among metals is found to decrease during ESDC and COV, but the ESDC average remains positive and not close to zero (Table 3, Panel B). The graphical analysis shows that the PRM-INM monthly series initially decreases in the ESDC and increases in the later ESDC times.

Overall, our baseline regressions reveal the cross-asset correlation determinants in the global macro environment for the whole sample period. The short- and long-run analyses provide quite similar conclusions despite the differences identified in the crisis breakdown among daily and monthly series (Table 3). Most interdependences are countercyclical (*H6*) while certain correlations of precious metals (safe havens) with financial and financialised assets exhibit procyclical behaviour. The countercyclical correlation results are in line with previous studies, which have revealed the negative business cycle impact on asset dependences (Conrad et al., 2014, Mobarek et al., 2016, Karanasos and Yfanti, 2021). Similarly, our findings on the procyclical cases are consistent with correlation determinant studies with safe havens involved (e.g. stock-bond correlations) where economic slowdown leads to flights-to-quality or a decrease in interdependences (see, among others, Asgharian et al., 2016).

The Uncertainty Channel

Next, we focus on the uncertainty channel of the economy. The well-documented power of uncertainty in moving or leading the business cycle is further examined in the case of cross-asset correlations. The direct EPU effect is always significant in the short- and long-run co-movements (Tables 4 and 5), which demonstrates that EPU can be considered a powerful correlation determinant and contagion or flight transmitter in contagion or flight-to-quality phenomena during crises. Higher EPU levels increase countercyclical correlations and reduce the procyclical patterns. Given the ample empirical evidence on the wider devastating EPU impact on macros and financials, we explore the indirect EPU effect on correlations. The baseline macro regressions (eqs. (12) and (13)) have unveiled the direct EPU influence, confirming the significant uncertainty effect on countercyclical correlations (Pastor and Veronesi, 2013) and on procyclical or flight-to-quality cases (Costantini and Sousa, 2022). The indirect influence reveals the EPU impact on the remaining macro regressors and their role in driving the correlation pattern. We estimate eq. (14) for the daily correlations (similar results for long-run correlations are available upon request) by including each EPU interaction term separately for each explanatory variable (estimation of restricted forms of eq. (14) for the EPU indirect effect on each macro).

Table 6 reports the estimated interaction terms for selected asset combinations (see also Table A.9 in the Appendix for the indirect EPU impact on all correlation pairs). The uncertainty channel intensifies all macro effects by adding an increment to each macro parameter, in line with Pastor and Veronesi (2013) and Karanasos and Yfanti (2021). The positive / negative economic effects increase in absolute terms by higher uncertainty levels across all correlations, either countercyclical or procyclical. For the countercyclical cases, given increased EPU, the financial uncertainty, disease, and credit effects become more positive while the news, activity, freights, and dollar value effects become more negative. In the two procyclical correlation series (EQU-PRM and RE-PRM), we estimate the opposite signs for the EPU interaction terms, as expected. The overall significance of the indirect uncertainty effects is similar to the significance of the respective macro effect in the baseline regression (Table 4). The EPU sensitivity analysis confirms the decisive effect of uncertainty and provides clear evidence about the potent indirect impact of uncertainty on the cross-asset nexus, beyond the direct one already estimated in eq. (12).

Table 6. The EPU effect on the macro drivers of daily cross-asset correlations, eq. (14).

$EPU_{SR,t-1}\times$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-RE	0.0030^{***}	0.0005^{*}	0.0004^{**}	-0.0039^{***}	-0.0026^{***}	-0.0046^{***}	-0.0006^{*}
	(0.0011)	(0.0003)	(0.0002)	(0.0009)	(0.0011)	(0.0018)	(0.0004)
EQU-NRG	0.0023^{***}	0.0007	0.0019^{***}	-0.0093^{***}	-0.0012^{***}	-0.0122^{**}	-0.0004^{*}
	(0.0006)	(0.0010)	(0.0004)	(0.0030)	(0.0003)	(0.0056)	(0.0003)
EQU-PRM	-0.0034^{***}	-0.0014^{*}	-0.0010^{***}	0.0124^{***}	0.0005^{*}	0.0062^{*}	0.0004
	(0.0011)	(0.0008)	(0.0004)	(0.0047)	(0.0003)	(0.0032)	(0.0004)
RE-NRG	0.0167^{***}	0.0007	0.0039^{***}	-0.0072^{***}	-0.0061^{**}	-0.0234^{***}	-0.0005^{*}
	(0.0040)	(0.0008)	(0.0011)	(0.0020)	(0.0029)	(0.0050)	(0.0003)
RE-PRM	-0.0023^{***}	-0.0006	-0.0014^{***}	0.0141^{**}	0.0025^{***}	0.0030^{***}	0.0004
	(0.0007)	(0.0008)	(0.0004)	(0.0068)	(0.0010)	(0.0009)	(0.0004)
NRG-AGR	0.0031^{*}	0.0004^{*}	0.0004^{***}	-0.0020^{***}	-0.0014^{***}	-0.0007^{**}	-0.0004^{*}
	(0.0018)	(0.0003)	(0.0001)	(0.0007)	(0.0004)	(0.0003)	(0.0003)
PRM-AGR	0.0041^{***}	0.0005^{**}	0.0005^{***}	-0.0085^{***}	-0.0010	-0.0010^{***}	-0.0004^{**}
	(0.0013)	(0.0002)	(0.0002)	(0.0029)	(0.0008)	(0.0003)	(0.0002)

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

5.2 The Correlations' Crisis Vulnerability

The EPU sensitivity analysis has clearly shown the incremental effect of uncertainty in magnifying the impact of all correlations' macro drivers. In this Section, we proceed with a crisis sensitivity analysis on the correlation determinants. Consistently with the indirect effect of higher EPU levels, mostly observed during crises, we expect that the crisis shock will also add a significant increment to all macro effects. Therefore, we estimate eq. (15). The crisis intercept dummies

($D_{C,t}$), estimated separately from the slope dummies, confirm our conclusions about the direct crisis shock on correlation levels (Table 3, Panel A). For most contagion cases, we estimate a positive and significant dummy, while for correlation decreases the dummies are estimated negative or insignificant (see Table A.10 in the Appendix). The crisis impact on the macro drivers' effect is captured by the slope dummies. We estimate the crisis slope dummies of each macro effect separately. Table 7 presents our estimation results for selected daily correlations (see also Table A.11 in the Appendix for the crisis impact on all correlation pairs) and the three crisis periods examined (similar conclusions in the long-run correlation analysis are available upon request). The number of significant cases per crisis period and per macro effect does not vary substantially, with the exception of the infectious disease effect. The disease news effect on financial volatility is significant during COV for all correlations, while in the first two crises it is insignificant for most cases (see also Table A.13 in the Appendix for a recap of the significant macro coefficients estimated across all macro models).

Our initial crisis analysis in Section 4.2 (Table 3, Panel A), has identified the correlations' response to crises, with contagion and flight-to-quality phenomena, lower or higher dependences, and safe haven asset properties. For most cases with significant correlation increases to positive levels (contagion / countercyclicality), the crisis slope dummy adds a significant increment to all macro effects, confirming Karanasos and Yfanti (2021), who show the GFC impact on correlation drivers. The economic impacts are magnified under the crisis shock: positive effects (EPU, FU, ID, FS) become more positive and negative ones (NS, EC, FR, FX) become more negative. For the procyclical correlations, we observe the opposite-signed macro effects during the crisis subsample, where we observe procyclicality (correlations decrease during crises). The crisis slope dummies demonstrate that the crisis also intensifies the procyclical macro impact. Therefore, the negative uncertainty, disease, and credit effects become more negative during crises and the positive news, activity, and price effects become more positive. For EQU-PRM and RE-PRM, the two procyclical pairs, we estimate the opposite GFC and COV incremental effects to the contagion cases for most regressors (see Tables 7, Panel A and C). In the ESDC period, the procyclical cases are identified in five intra-commodity pairs (three of which involve PRM, see Table 7, Panel B). Accordingly, the slope dummies magnify most drivers' impact, with the opposite sign from the countercyclical cases. Comparing in-crisis correlation increases with decreases, we notice more insignificant macro regressors in the procyclical cases, indicating a more profound macro sensitivity for the countercyclical combinations.

Overall, the crisis vulnerability analysis confirms our results on the correlations' response to crises and demonstrates that the economic determinants play a key role in correlation dynamics in normal and crisis times. In crises, the determinants' effect is significantly amplified, intensifying contagion or flight episodes, in line with the findings of Mobarek et al. (2016), who focused on the long-run low frequency correlation determinants during crises for contagion cases only (stock markets cross-border correlations).

Similarly, the indirect EPU effect under crisis, estimated by eq. (16), becomes stronger during market stress conditions for both countercyclical and procyclical correlations. Table A.12 in the Appendix reports the EPU interaction terms for each crisis subsample. The uncertainty channel's magnifying power on the macro drivers of correlations is intensified during all crisis periods, as expected from the macro and crisis sensitivity analyses so far. All signs of the crisis interaction terms are the same as the signs of the respective crisis slope dummies (Table 7), with the exception of some insignificant effects. The significant cases of the indirect EPU under crisis effects are similar to the significant cases of the crisis impact on the macro regressors (Table A.13, Panels C and D). In the second crisis, the ID effect is significant in more cases under the EPU moderation. Although financial uncertainty under the ESDC shock is always significant, it becomes insignificant with the EPU interaction for two procyclical cases (NRG-AGR and NRG-LIV). All in all, for most crisis-EPU interaction terms, we estimate slightly more significant coefficients than in the crisis slope dummies of the respective macro effect.

Table 7. The Crisis effect on the macro drivers of daily cross-asset correlations, eq. (15).

Panel A. The GFC effect								
$D_{GFC,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-PRM	-0.0014^{***}	-0.0047^{***}	-0.0011	-0.0063^{***}	0.0113^{***}	0.0049^{***}	0.0091^{*}	0.0004
	(0.0003)	(0.0010)	(0.0032)	(0.0020)	(0.0030)	(0.0015)	(0.0049)	(0.0010)
RE-PRM	-0.0022^{***}	-0.0027^{*}	-0.0025	-0.0015	0.1187^{**}	0.0217	0.0050	0.0011
	(0.0005)	(0.0015)	(0.0050)	(0.0023)	(0.0523)	(0.0198)	(0.0043)	(0.0015)
NRG-AGR	0.0016^{***}	0.0025^{***}	0.0015	0.0017^{*}	-0.0217^{**}	-0.0030^{***}	-0.0014^{***}	-0.0001
	(0.0004)	(0.0010)	(0.0012)	(0.0009)	(0.0105)	(0.0011)	(0.0003)	(0.0004)
Panel B. The ESDC effect								
$D_{ESDC,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-PRM	0.0018^{***}	0.0151^{*}	0.0112	0.0021^{***}	-0.0371^{***}	-0.0033^{*}	-0.0026^{***}	-0.0011^{***}
	(0.0007)	(0.0086)	(0.0133)	(0.0005)	(0.0098)	(0.0018)	(0.0008)	(0.0004)
RE-PRM	0.0024^{***}	0.0038^{***}	0.0123	0.0014^{***}	-0.0683^{*}	-0.0122^{***}	-0.0046^{***}	-0.0009
	(0.0009)	(0.0010)	(0.0192)	(0.0004)	(0.0363)	(0.0031)	(0.0018)	(0.0010)
NRG-AGR	-0.0013^{***}	-0.0035^{*}	-0.0041	-0.0057^{**}	0.0012^{**}	0.0031	0.0010	0.0004
	(0.0004)	(0.0017)	(0.0063)	(0.0028)	(0.0005)	(0.0044)	(0.0008)	(0.0007)
Panel C. The COV effect								
$D_{COV,t-1}\times$	$EPU_{SR,t-1}$	$FU_{SR,t-1}$	$ID_{SR,t-1}$	$FS_{SR,t-1}$	$NS_{SR,t-1}$	$EC_{SR,t-1}$	$FR_{SR,t-1}$	$FX_{SR,t-1}$
EQU-PRM	-0.0032^{***}	-0.0176^{***}	-0.0035^{***}	0.0009	0.0434^{***}	-0.0132	-0.0071^{***}	-0.0015
	(0.0008)	(0.0052)	(0.0010)	(0.0021)	(0.0127)	(0.0145)	(0.0028)	(0.0032)
RE-PRM	-0.0014^{***}	-0.0131^{***}	-0.0011^{***}	-0.0024^{***}	0.0926^{***}	0.0018	0.0004	0.0043
	(0.0005)	(0.0035)	(0.0002)	(0.0006)	(0.0278)	(0.0034)	(0.0021)	(0.0039)
NRG-AGR	0.0035^{***}	0.0084^{***}	0.0012^{***}	0.0025^{***}	-0.0488^{*}	-0.0156^{*}	-0.0013^{**}	-0.0028^{**}
	(0.0010)	(0.0020)	(0.0004)	(0.0007)	(0.0282)	(0.0084)	(0.0006)	(0.0012)

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

6 Model Evaluation

The main objective of the present study is to investigate the dynamics of the cross-asset nexus and the short- and long-term determinants of the co-movement between financial and financialised assets. Accordingly, we have demonstrated the macro-sensitive and crisis-vulnerable counter- and procyclical interdependences among global equity, real estate, and commodity markets. However, in this Section, we go a step further and provide important evidence on the superiority of our proposed specification for time-varying correlations modelling over competitive conditional correlation models in terms of forecasting performance and portfolio and risk management implications.

We first compare the in-sample estimation of the cDCC-MIDAS with the nested DCC-MIDAS without Aielli's correction, and the two models without the MIDAS component in correlations, the cDCC and the DCC, based on three diagnostics: the log likelihood ($logL$), the Akaike and Schwartz Information Criteria (AIC and BIC, respectively). Table A.14 in the Appendix reports the correlation equation results for our first trivariate system, the EQU-RE-COM combination. The variance equations are similarly estimated with the GARCH-MIDAS for all competitors. The novel cDCC-MIDAS model outperforms the three benchmarks with the highest log likelihood and the lowest information criteria values (underlined). We also observe significant improvements of the cDCC over the DCC and of the DCC-MIDAS over both cDCC and DCC, in line with the extant literature (Colacito et al., 2011, Aielli, 2013, Conrad et al., 2014). Most importantly, we reach identical conclusions on the cDCC-MIDAS in-sample superiority with all ten trivariate systems estimated in this study (results available upon request) and show the significant contribution of Aielli's correction added in the DCC-MIDAS framework.

6.1 Forecasting Performance

We further investigate whether the in-sample superiority of our extended model ensures its predictive power over the three DCC benchmarks. We initially re-estimate all models with an in-sample period ending on 18/07/2016 and calculate our multistep-ahead variance and covariance forecasts for the out-of-sample period from 19/07/2016 until 27/07/2020. We proceed with a rolling window in-sample estimation using $4,056$ observations (the initial in-sample length). All specifications are re-estimated daily with the same rolling sample length, and we compute 1-, 5- and 20-step-ahead forecasts from each re-run. We end up with $1,050$ 1-step-ahead, $1,046$ 5-step-ahead, and $1,031$ 20-step-ahead predictions of the variance-covariance matrix under each of the four competing DCC specifications. Next, we compute the corresponding correlations from the forecasted variance-covariance matrices and compare them with the actuals from our in-sample estimations for the whole sample. Among the various loss functions established for multivariate volatility models (see, for example, Ledoit et al., 2003, Golosnoy et al., 2012, Laurent et al., 2013), we apply the Frobenius loss function as the main criterion for the forecasting evaluation of the alternative models (see also Conrad et al., 2014, Llorens-Terrazas and Brownlees, 2022, Bauwens and Xu, 2023). By comparing the losses based on the Frobenius metric for correlations and covariances, we identify the best specification with the lowest out-of-sample loss. Finally, the Diebold-Mariano test (Diebold and Mariano, 1995) compares the forecasted series of the competing models and demonstrates whether their differences are statistically significant (see, for example, Engle and Colacito, 2006, Colacito et al., 2011, Conrad and Stürmer, 2017).

Table 8 presents the forecasting evaluation for the EQU-RE-COM combination (similar results and conclusions are obtained from all trivariate systems' forecasts). In line with Llorens-Terrazas and Brownlees (2022) and Bauwens and Xu (2023), we compute the Frobenius loss function for each correlation point forecast. Next, for each specification and each horizon, we calculate the ratio of the average losses over the DCC average forecast losses. The Frobenius loss ratio is lower than the unity when the competing model has a lower forecast error than the benchmark one. In Table 8, Panel A, we observe all three models with lower losses than the DCC benchmark and identify the cDCC-MIDAS (underlined) as the one with the best out-of-sample performance across all horizons and the three correlation pairs (lowest ratios in bold). The forecasting accuracy of the proposed model is significantly higher than the nested DCC-MIDAS, showing that adding Aielli's correction is important in terms of out-of-sample gains. We further show the improvement of the cDCC compared to DCC and the MIDAS component's importance with and without Aielli's correction, similar to our in-sample evaluation. For robustness purposes, we also apply Euclidean distance for variances and covariances (Conrad et al., 2014). Our conclusions on the forecasting superiority of each competing model are identical to the ones extracted from our main criterion on correlation losses. Finally, in Table 8, Panel B, we demonstrate that the difference between the forecasted series of all models is significantly different from zero with the Diebold-Mariano (DM) test's p-values lower than 0.100 in all cases of model comparison pairs, horizons, and asset correlation pairs. Given that the models are nested, we also run the Harvey-Leybourne-Newbold (HLN) forecast encompassing test (Harvey et al., 1998), a modification of the DM test that accounts for the fact that the alternative specifications are nested. The HLN test results confirm the significant differences among the forecast series and the superiority of the extended model compared to the nested one.

Overall, our forecasting exercise provides strong evidence that the correction we introduce to the DCC-MIDAS framework is important, with a significant improvement in the forecasting accuracy. Comparing all DCC competing models, we further show that both the MIDAS component and Aielli's correction in time-varying correlations are critical for the out-of-sample performance of multivariate volatility modelling. They both add an increment when incorporated into the correlation equation and make the proposed cDCC-MIDAS the best-performing model in- and out-of-sample.

Table 8. Forecasting performance: EQU-RE-COM Correlation forecasts.

Panel A. Frobenius loss ratios									
	EQU-RE			EQU-COM			RE-COM		
models ↓ m-steps ⟶	1	5	20	1	5	20	1	5	20
<u>cDCC-MIDAS</u>	0.756	0.758	0.783	0.696	0.730	0.767	0.674	0.705	0.717
DCC-MIDAS	0.821	0.832	0.836	0.733	0.771	0.792	0.742	0.761	0.784
cDCC	0.964	0.960	0.972	0.952	0.963	0.950	0.911	0.934	0.952
DCC	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Panel B. Diebold-Marano test									
	EQU-RE			EQU-COM			RE-COM		
models ↓ m-steps ⟶	1	5	20	1	5	20	1	5	20
cDCC-MIDAS vs. DCC-MIDAS	0.042	0.043	0.048	0.044	0.045	0.043	0.041	0.038	0.040
cDCC-MIDAS vs. cDCC	0.007	0.008	0.007	0.005	0.005	0.006	0.002	0.002	0.002
cDCC-MIDAS vs. DCC	0.006	0.006	0.005	0.004	0.005	0.005	0.000	0.001	0.001
DCC-MIDAS vs. cDCC	0.015	0.016	0.015	0.010	0.015	0.011	0.013	0.013	0.017
DCC-MIDAS vs. DCC	0.017	0.017	0.018	0.014	0.016	0.014	0.011	0.013	0.014
cDCC vs. DCC	0.052	0.058	0.055	0.050	0.051	0.045	0.039	0.040	0.048

Notes: The table reports the out-of-sample model evaluation. Panel A reports the ratios of the losses based on the Frobenius norm for the correlation forecasts of the EQU-RE-COM trivariate system. The ratios are computed by dividing the average forecast losses for each DCC specification (cDCC-MIDAS, DCC-MIDAS, cDCC, DCC), forecast horizon (1-, 5-, 20-step-ahead), and correlation series (EQU-RE, EQU-COM, RE-COM) over the losses of the DCC benchmark. A ratio less than one indicates the out-of-sample superiority of the model compared to the benchmark. Bold values denote the lowest ratios for the best model in terms of predictive power, that is, the cDCC-MIDAS here (underlined). Panel B reports the p-values of the Diebold-Mariano test, which compares the predictive accuracy of the alternative models. All models are tested in pairs, and given the low p-values reported (< 0.100), the forecasted series are significantly different from each other.

6.2 Portfolio Hedging Performance

Multivariate volatility modelling is mainly used in daily business operations of trading front rooms and risk back offices, such as the asset allocation process and risk mitigation techniques. Portfolio professionals seek to diversify the portfolio risk by investing in multiple asset classes and risk managers to cover the trading positions with effective hedging strategies, using the variance-covariance projections computed by multivariate volatility models. In this vein, our model evaluation proceeds with an empirical application of dynamic correlations in portfolio choice problems and the risk management practice and sheds further light on the implications of our proposed methodology and our findings on cross-asset dependences. We will identify which DCC specification outperforms the competing models when used in real-world risk and portfolio analytics.

Based on the $1,051$ one-step-ahead forecasts of the variance-covariance matrix, we construct a hedge portfolio (p) consisting of a one-dollar long position on one asset (i) hedged by a short position on another asset (j). Since cross-asset interdependences do not remain constant and move with the business cycle dynamics, the optimal hedge ratio or hedging cost is time-varying. Its computation relies on the variance/covariance forecasts. The portfolio payoff, $r_{p,t}$, equals $r_{i,t} - b_{ij,t}r_{j,t}$, where $r_{i,t}$ and $r_{j,t}$ are the daily returns of asset i and j, respectively. The weight of the hedge position, the time-varying beta coefficient ($b_{ij,t}$), is the optimal hedge ratio we need to estimate daily in order to minimise the variance (risk) of the portfolio (see, for example, Engle, 2016). The one-dollar long position on i is covered by beta-dollars short on j, that is, beta-dollars hedging cost. Following Kroner and Sultan (1993), risk minimisation is achieved by solving the first derivative of the portfolio variance w.r.t. beta. Hence, the daily optimal hedge ratio series is calculated as follows: $b_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}}$, where $h_{ij,t}$ is the covariance of the two assets and $h_{jj,t}$ is the variance of the hedge position j, both extracted from the variance-covariance matrix. Given that we test the out-of-sample performance of our models, we will use the variance/covariance forecasts instead of the in-sample estimations. The DCC specification proved to be superior in predictive power is the one which will give the lowest portfolio variance significantly different from the other models. That is the best model for out-of-sample portfolio hedging.

Table 9. Hedge Portfolio with Equities, Real Estate, and Commodities.

	EQU-RE			EQU-COM			RE-COM		
Panel A. Out-of-sample hedging effectiveness									
models ↓ portfolio metrics ⟶	Var	H.R.	H.E.	Var	H.R.	H.E.	Var	H.R.	H.E.
<u>cDCC-MIDAS</u>	0.762	0.587	0.443	0.960	0.162	0.298	0.896	0.051	0.190
DCC-MIDAS	0.781	0.540	0.429	0.975	0.151	0.288	0.898	0.051	0.188
cDCC	0.878	0.557	0.358	1.008	0.159	0.263	0.949	0.048	0.142
DCC	0.919	0.522	0.329	1.017	0.149	0.257	0.962	0.047	0.130
Panel B. Out-of-sample gain/loss									
cDCC-MIDAS vs. DCC-MIDAS (b)		1.25***			0.78***			0.12**	
cDCC-MIDAS vs. cDCC (b)		7.34***			2.47***			2.91***	
cDCC-MIDAS vs. DCC (b)		9.77***			2.93***			3.65***	
DCC-MIDAS vs. cDCC (b)		6.01***			1.68***			2.79***	
DCC-MIDAS vs. DCC (b)		8.41***			2.14***			3.52***	
cDCC vs. DCC (b)		2.27***			0.45***			0.71**	

Notes: The table reports the hedge portfolio results for the EQU-RE-COM combination. Three portfolios are constructed: 1) equities hedged by real estate (EQU-RE), 2) equities hedged by commodities (EQU-COM), and 3) real estate hedged by commodities (RE-COM). The variance-covariance matrix one-step-ahead forecasts of four alternative models are used: cDCC-MIDAS, DCC-MIDAS, cDCC, DCC. Panel A presents three portfolio risk metrics. Var, H.R., and H.E. denote the average variance of the hedge portfolio, the average optimal hedge ratio (average beta), and the average hedging effectiveness, respectively. The cDCC-MIDAS (underlined) outperforms the other three competing models with the lowest Var and the highest H.E. Panel B reports the out-of-sample Gains/Losses (G/L) in portfolio risk when we use the enriched DCC models compared to the benchmark one (b). The Diebold-Mariano (DM) type of test compares the forecasted portfolio variances estimated by the alternative models. It indicates whether their difference is significantly different from zero, which is the case for all pairs. ***, **, * denote the significance of the DM test at the 0.01, 0.05, 0.10 level, respectively.

Table 9 presents the portfolio results of the EQU-RE-COM trivariate models. We build 3 hedge portfolios: 1) equities hedged by real estate (EQU-RE), 2) equities hedged by commodities (EQU-COM), and 3) real estate hedged by commodities (RE-COM). We use the variance/covariance forecasts of the four alternative DCC models and compare their out-of-sample hedging performance. Panel A reports the variance of the hedged position (Var), the average optimal hedge ratio (H.R.), and the average hedging effectiveness ($H.E. = 1 - \frac{Variance_{hedge\_portfolio}}{Variance_{unhedged\_position}}$). The higher the H.E. ratio is estimated, the higher the risk reduction will be from the hedge used in the portfolio. The cDCC-MIDAS (underlined) outperforms the other three competitors. It minimises the variance of all portfolios and maximises the hedging effectiveness. Moving from the simpler DCC specification to the ones with Aielli's correction and the MIDAS component, we observe significant improvements with lower variances and higher H.E. ratios. This is strong evidence of the incremental benefits both extensions add to dynamic correlation modelling.

In Table 9, Panel B, we present the gains from using the alternative models compared to the benchmarks in terms of portfolio volatility (Colacito et al., 2011, Conrad and Stürmer, 2017). The gain/loss is computed as follows: $G/L = 100(\sigma_{BM} - \sigma_1)/\sigma_1\%$, where σ_{BM} is the volatility of the benchmark portfolio (the hedge portfolio estimated with the benchmark model) and σ_1 is the volatility of the alternative portfolio (the hedge portfolio estimated with the alternative extended model). The G/L ratio is positive when the alternative model outperforms the benchmark in portfolio hedging. This is the case for all comparisons in Panel B, where we have gains when we compare each enriched model with the simpler one used as benchmark (b) for the hedge portfolio constructed. The cDCC-MIDAS minimises the portfolio's risk compared to all benchmarks, and each extended DCC specification outperforms the simpler ones, confirming our conclusions in Panel A. Finally, the Diebold-Mariano test demonstrates that the differences between the forecasted portfolio variances are always significantly different from zero. Finally, for robustness purposes, we did the same hedging exercise by using the in-sample estimations of the variance-covariance matrices instead of the forecasts (results available upon request). Our findings lead to identical conclusions on the superiority of the proposed model for all portfolios.

7 Results Discussion and Implications

On the whole, a broader lesson is that policymakers and market practitioners should closely watch cross-asset interdependences, which mostly increase in times of financial and health crises and soaring EPU levels. The crisis slope dummies and the EPU interaction terms manifest the fact that the supplemental rise in the absolute size of the macro and news drivers' impact on correlations' increase is to some extent attributed to poor fundamentals. Such fundamentals serve as contagion transmitters that tighten the cross-asset nexus, giving rise to systemic risk and jeopardising financial stability. Lower short- and long-term interlinkages with safe haven assets and flight episodes provide some protection in turbulent times for investors to eliminate massive losses, by anchoring, for example, to precious metals during GFC and COV. Similarly, in the GFC shock, real estate investments guarantee safety when combined with commodities (flights and safe havens), while in the ESDC and COV cases, contagion becomes more apparent. Financial integration and financialisation progress at an accelerating pace, eroding the diversification benefits from investing in multiple financial and financialised asset classes. In the European crisis, only intra-commodity correlations drop and the recent pandemic-induced turmoil drives most correlations higher. In the COV subsample, precious metals act as safe havens in the short and long run whereas real estate - commodities remain uncorrelated only in the long run but mainly with increased interdependences relative to the pre-crisis period.

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

The insights we glean from the short- and long-term correlation determinants, defining the counter- or procyclical behaviour of asset markets' interdependences, project important policy implications. Systemic supervisors should recognise as early warning signals of imminent disruptions the high and low frequency fundamentals which drive the time-varying co-movement of global equities, real estate, and commodities. Weaker economic conditions trigger crisis dominos, where countercyclical correlations explode and procyclical combinations with safe havens provide insurance against extreme losses. In the meantime, such signals should warn traders and risk managers, as well, to redesign investment tactics for an imminent collapse of diversification benefits due to financial contagion. When the economic outlook gradually deteriorates and agents' expectations become gloomier, a flight to safe haven assets can be a solution for market practitioners' profit and loss forward-looking considerations and a stabilising factor for policymakers' oversight of the whole financial system. Our results further show more contagion and fewer flights or safe haven cases as we pass from the first to the second and the third crisis. Therefore, market and policy experts should also account for the fact that financial integration has dramatically increased interconnectedness, and as we go forward to future crises, the asset markets' synchronicity will be undermining hedging effectiveness and stabilising forces. The significant impact of the macroeconomic environment and the crisis shocks on the cross-asset momentum demonstrates that we cannot rely only on economic linkages to predict this momentum. Investors' overreaction, extrapolative beliefs, and herding in response to macro news are major drivers of markets' correlation dynamics.

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

8 Conclusions

Our empirical analysis has examined the cyclical variation of the cross-asset nexus. We investigated the short- and long-run correlations among equities, real estate, and commodities, aggregated and disaggregated into five broad categories: energy, precious and industrial metals, agriculture, and livestock. The time-varying co-movement of a risky financial instrument with two major financialised assets and the intra-commodity interdependence are attributed to high and low frequency economic fundamentals. We have demonstrated the macro sensitivity and crisis vulnerability of the correlation dynamics, computed by the cDCC-MIDAS setting, a new corrected DCC-MIDAS specification we are proposing. Commodity markets are more closely interconnected with equities than with real estate. Short- and long-run contagion phenomena identified for most asset pairs imperil the whole financial stability, while we find that the long-term correlation components remain more resilient to crisis shocks for certain asset pairs and turbulent periods. The precious metals correlations with equities and real estate are involved in flight-to-quality episodes during the 2008 turmoil and the recent pandemic. Such safe havens can stabilise the markets through increased diversification benefits, reducing the systemic risk build-ups induced by enormous losses across multiple economic sectors. However, massive flights to safe havens induce contagion among riskier assets and propagate the domino effects of the crisis further.

Our study makes an important contribution with a broad investigation of the short- and long-run co-movements of financial and financialised instruments and concludes on their hedging properties and interdependence types, establishing and implementing an improved econometric correlations specification. The novel results on countercyclical and procyclical correlation dynamics should alert market practitioners and policymakers to account for cross-asset correlations in their risk assessments and proactive policy interventions. The correlations' macro and news drivers can serve a critical signalling role for imminent crises, while both higher and lower interdependences can threaten financial stability. Cross-asset economic linkages are not enough to predict markets' co-movement. Investors' trading behaviour in response to crisis fears and macro news is the primary determinant. Reinforcing macro-financial resilience backstops can encounter the negative externalities of financial integration and globalisation. Both regulatory authorities and markets should build the financial system's resilience on a global and local basis. Therefore, a further research path in the cross-asset nexus study could involve the regional perspective, by investigating the cross-border dependences alongside the cross-asset dimension.

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