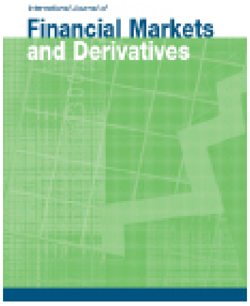

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Dynamic correlations of bond and equity futures and macroeconomic determinants: international evidence

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Abstract: This paper examines whether the dynamic co-movements between stock-bond futures markets may be driven by domestic and international macroeconomic factors. The empirical analysis also investigates whether economic uncertainty and geopolitical risks have an impact on the dynamic conditional correlations of bond and equity futures markets. The results pointed to significance of domestic inflation and industrial production, while the 3M USD Libor and 3M Euribor surfaced as determinants of the dynamic equity-bond futures correlations. Finally, the paper examines the impact of the pandemic on the dynamic correlations with the split of the sample in pre- and post-pandemic periods and it was found that neither the uncertainty nor the geopolitical risk indices emerged as statistically significant in any country.

Keywords: bond-equity futures; DCC-GARCH; macroeconomic variables; economic uncertainty indices; geopolitical risk.

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1 Introduction

The relationship between stock and bond returns has received considerable attention and numerous empirical studies have examined the potential impact of macroeconomic factors on time varying stock-bond correlation. Hence, it is important to understand how those variables relate to the stock-bond returns and specifically to quantify how much of the correlation dynamics can be explained by macroeconomic variables. However, the empirical evidence has been mixed when considering which factors may affect cross asset co-movement and whether they cause positive or negative correlations.

Macroeconomic variables such as inflation, interest rate and market uncertainty have been identified as some of the major determinants of stock-bond correlations. Specifically, it is suggested that high inflation rates positively affect both equity discount rates and bond yields, making the stock-bond correlation positive (Ilmanen, 2003; Yang et al., 2009)[1]. Further research indicates that expected inflation uncertainty has a positive influence on the stock-bond comovement (Li, 2002). Similarly, Andersson et al. (2008) show that stock-bond correlation is positively and significantly related to inflation expectations. In contrast to the evidence reported by previous research, d'Addona and Kind (2006) find that inflation volatility tends to reduce the stock-bond correlation while Baele et al. (2010) report that inflation contributes little to explaining the correlation between stocks and bonds. Moreover, David and Veronesi (2013) examine the effects of inflation news on stock and bond markets and demonstrate that the direction of the stock-bond correlation varies over time turning from positive to negative.

The impact of interest rates on stock-bond correlation has also received considerable attention and a positive relation has been widely documented. For instance, Li (2002) argues that real interest rate uncertainty tends to increase the stock-bond correlation in G7 countries. D'Addona and Kind (2006) suggest that real interest rate volatility leads to a positive correlation between stocks and bonds since both assets are negatively related to interest rates. In a more recent study, Conrad and Stürmer (2017) show that expected interest rate is an important determinant of the stock-bond correlation based on the DCC-MIDAS framework. By using regime switching models, Aslanidis and Christiansen (2012) find that stock and bond returns move in the same direction when the short-term interest rate is high. The empirical findings of other related studies also support the explanatory power of short rate on stock-bond correlation (Yang et al., 2009; Viceira, 2012; Asgharian et al., 2015; Skintzi, 2019).

Concerning the effect of economic growth on stock-bond return correlation, the empirical evidence provides mixed results depending mainly on the proxy used. Andersson et al. (2008) and Conrad and Stürmer (2017) report an insignificant relationship between expected GDP growth and stock-bond comovement. Recently, Skintzi (2019) shows that a decline in the output gap tends to increase the stock-bond correlation which implies that during periods of economic expansion, the relation between stocks and bonds is positive. Other proxies for economic growth that appear to have a significant positive impact on stock-bond return correlations include the industrial production (Asgharian et al., 2015, 2016) and the unemployment rate (Allard et al., 2020).

Another variable of interest is the stock market uncertainty since high levels of stock market uncertainty generate important stock-bond diversification benefits which can be explained by the flight-to-quality shifts from stocks to bonds (Hartmann et al., 2001; Connolly et al., 2005, 2007; Baur and Lucey, 2009). Specifically, high stock market uncertainty increases the risk premium demanded by investors for holding equity (Whaley, 2009). Thus, increases in stock market uncertainty may be associated with higher equity premiums relative to the term premium of bonds, leading to negative stock-bond correlations (Kim et al., 2006; Andersson et al., 2008; Aslanidis and Christiansen, 2012). Moreover, Chiang et al. (2015) has indicated that in periods of high uncertainty in bond market, both equity and bond risk premiums tend to increase, moving stock and bond returns in the same direction.

Overall, the previously mentioned studies apply linear regression models to examine the effect of stock market uncertainty on stock-bond return correlation in developed countries[2]. However, current research emphasises the nonlinear relation between stock market uncertainty and stock-bond comovement and also, in line with prior results, confirms the negative correlation between the two asset classes when the market uncertainty is high (Andrian et al., 2019; Hsu et al., 2020). In addition, most work was on the spot prices of stock and bond indices and not on the futures prices. Consequently, we use futures prices in this paper for various reasons.

First, such data commands lower transaction costs. Second, futures data is more relevant to analysts and policy makers as well as investors. Given that global investors consider the correlations among financial assets when structuring well-diversified, global portfolios, it is of interest to them to understand how these correlations might be caused by fundamental factors within a financially integrated world. Further, investors are more interested in the futures markets instead of the spot markets since stock and bond index futures trading is preferred by investors who participate in speculative transactions (Kawaller et al., 1987). And third, such work on futures data is scant in the empirical literature which our paper aims to fill.

Consequently, the purpose of this paper is threefold. First, to examine how dynamic co-movements between stock-bond futures markets, as opposed to cash (spot) prices, both in a single- and a multi-county context. Another way of stating that examining the dynamic correlations of stocks and bonds using futures data is important is to acknowledge that futures prices respond to news faster than spot prices and thus lead the price-discovery process. Futures prices capture better market and hedging dynamics since short positions do not require the engagement of the repo market. Ahn et al. (2002) find that daily futures returns do not display the positive autocorrelation that is evident in daily spot portfolio returns. In addition, Chui and Yang (2012) claim that trading in futures is preferred by investors that are active traders, and the use of futures data avoids the non-synchronous trading problem. Thus, conclusions regarding investment and risk management strategies can be assessed.

Second, we investigate how various fundamental factors affect the stock-bond futures correlations for a number of countries and under different periods. More specifically, the paper examines whether a set of country-specific and global variables could be used in predicting equity and bond futures correlations in Australia, France, Germany, Italy, Japan, Spain, the UK and the USA. The sample period incorporates the European sovereign debt crisis which has significantly affected the stock-bond correlation. For example, the positive effect of bond market volatility on the stock-bond correlation is also in line with the findings of Skintzi (2019) for both core and peripheral eurozone countries during the EU debt crisis.

And third, the use of recent data enables us to investigate the potential impact of the pandemic on the dynamic cross-asset correlations. This has implications for revising expectations about such stock-bond correlations by global investors. During crisis periods, correlations tend to become more positive which has serious implications for not just policy setting but also for achieving diversification benefits. To the best of our knowledge, we are the first to examine the impact of such a global health crisis (the COVID pandemic) on the dynamic correlations between stock and bond futures markets of selected countries.

The remainder of this study is organised as follows: Section 2 describes the methodology and the data used for the estimation of the dynamic conditional correlations. Section 3 presents the empirical results and discusses the key findings. Finally, section 4 summarises our main findings and concludes the study.

2 Methodology and data

This section lays out the theoretical and empirical methodological design of the study as well as a description of the data and the construction of the variables. We begin with the data description.

2.1 Data

The data are of monthly frequency, starting in January 2010 and ending in March 2021 for Australia's, Germany's, Italy's, Japan's, UK's and USA's bond futures and equity returns. France's bond yield data starts in April 2012 and Spain's in October 2015. All data were obtained from *Bloomberg*.

The raw variables for each country (or country-specific variables) examined are the following: the consumer price index (CPI), the unemployment rate, and industrial production. From these variables, we constructed the rate of inflation (the log differences in the consumer price index), industrial production growth (the log difference in industrial production index) and the change in the unemployment rate. The common, global raw variables are gold prices, crude oil prices, the MSCI World Equity Index of developed countries, the 3-month (3M) Euribor, 3M USD Libor and the EUR 10-year (10Y) interest rate swap (IRS). For the gold and oil prices and the MSCI index, we constructed their log rates of change (as above), whereas for the 3M Euribor, 3M USD Libor and EUR 10Y IRS, we simply took their first differences. All these transformations were necessary to convert the raw variables into stationary series since preliminary statistical investigation for unit roots revealed presence of them in each raw series.[3]

Finally, we employ a number of economic uncertainty/risk indices to assess their impact on the dynamic stock-bond futures correlations. We capture financial uncertainty via two widely-used volatility indicators, the Volatility index (*Vix*) for the USA, and the Eurostoxx 50 (*Eustoxx*) index for Europe. The Vix embeds the level of 'fear' in the stock market (proxied by the S&P500 index) and thus the higher the Vix, the greater the level of fear and uncertainty in the market are. The Eurostoxx 50 index represents the fifty largest companies in the eurozone in terms of market capitalisation. It can be used as a benchmark for many financial products and any stress or fears in Europe's financial market is reflected into that index. Finally, we use a more general uncertainty/risk index which applies to all countries, the Caldara and Iacoviello (2022) geopolitical risk index. In general, elevated geopolitical risks depress global economic activity (such as lower investment and stock prices), create higher downside risks to the global economy and induce changes in the correlations among major financial asset classes.

2.2 Model specifications

The first step in the empirical analysis of the impact of a number of macroeconomic variables, both country-specific and global, on the dynamic conditional correlations between a country's futures on bond yields and stock market returns, is the derivation of these conditional correlations. There is a number of approaches that are suited to derive such correlations such as Bollerslev et al.'s (1988) diagonal VECH and Engle's (2002) dynamic conditional correlation (DCC) GARCH model. The emphasis of the first model is on the estimation of the covariances, which is often difficult to do with restrictions and a high number of variables. In addition, such models do not always ensure that the conditional correlation matrix is positive definite. Hence, the next generation of models focused on the dynamics of the (conditional) correlations among series and guarantee that the estimated conditional correlation matrix is positive definite. Such a model is Engle's DCC-GARCH and Engle and Sheppard's (2001) model.

We define $r_t = [r_{1,t}, r_{2,t}]'$ as a *two-variable* vector of continuously compounding bond yields and equity returns, as the mean equation, as follows. Suppose we have returns, α_t, from n assets with zero expected value and covariance matrix H_t. The conditional mean equation of each asset's returns, can be expressed as:

$$r_t = \mu_t + a_t \tag{1}$$

$$a_t = H_t z_t \tag{2}$$

where r_t is an $n \times 1$ vector of log returns of n assets at time t, μ_t is an $n \times 1$ vector of the expected value of the conditional r_t, a_t is an $n \times 1$ vector of mean-corrected returns of n assets at time t, H_t is an $n \times n$ matrix of conditional standard deviations of a_t at time t and z_t is an $n \times 1$ vector of *iid* errors such that $E(z_t) = 0$ and $E(z_t^2) = I$.

The DCC model is based on the hypothesis that the conditional returns are normally distributed with zero mean and so its multivariate conditional variance is given as follows:

$$H_t = D_t R_t D_t \tag{3}$$

in which D_t is a diagonal matrix with the square root of conditional variances in its diagonal from univariate GARCH(p, q) processes with $\sqrt{h_{ii,t}}$, on the i^{th} diagonal and R_t is the $n \times n$ dynamic correlation matrix. This decomposition ensures that the covariance matrix, H_t, is positive definite. The matrix contains the conditional correlation of the standardised residuals, $e_t = \frac{r_t}{D_t} = \frac{r_t}{\sqrt{h_{it}}}$. The elements of D_t are given by the following standard GARCH(p, q) process:

$$h_{i,t} = c_i + a_i e_{i,t-p}^2 + b_i h_{i,t-q} \tag{4}$$

where a_i represents the short-run persistence of a shock to a series i (ARCH effect) and b_i represents the contribution of a shock to the series' conditional volatility to the long-run persistence (GARCH effect).

The evolution of the conditional correlation in the DCC model is described as follows:

$$Q_t = (1 - a_t - b_t)\rho_t + a e_{t-1} e'_{t-1} + \beta Q_{t-1} \tag{5}$$

in which ρ_t is the unconditional correlation between the analysed series, $Q_t = (q_{ij,t})$ is the $n \times n$ time-varying covariance matrix of e_t, where a_1 and b_1 are the DCC parameters. The term in parentheses $(1 - a_t - b_t)$ shows the restriction to test if the volatility is mean-reverting. These parameters are also known as the volatility decay parameters and we need their sum to be less than one. If the sum is equal to zero, then the model reduces to an integrated GARCH (IGARCH) process.

For ρ_t the conditional covariance of $h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t} h_{ii,t}}$, where $\rho_{ij,t} = q_{ij,t} \big/ \sqrt{q_{ii,t} q_{jj,t}}$ and $q_{ij,t}$ is the conditional covariance between the standardised residuals. When $a_t + b_t < 1$, the model is stationary but if $a + b = 0$ then the DCC model reverts to the constant correlation model.

The model's log-likelihood function to be maximised is given by

$$\begin{aligned} L&\left[-(0.5)\sum_{i-1}^{T}\left(k\log(2\pi) + \log\left(|D_t|^2\right) + r_t' D_t^{-2} r_t\right)\right] \\ &-\left[(0.5)\sum_{i-1}^{T}\left(\log\left(|R_t|\right) + e_t' R_t^{-1} e_t - e_t' e_t\right)\right] = 0 \end{aligned} \tag{6}$$

where the first term represents the volatility component, and the second term represents the correlation component.

Once the dynamic conditional correlations among the series, each country's bond yields and equity returns have been computed, we then regress them on a number of macroeconomic variables for the period (and subperiod) under investigation. The general specification of that regression model is

$$\rho_{ij} = \beta_0 + \beta_i X_i + u_t \tag{7}$$

where ρ_{ij} is the series conditional correlation, β_0 is the intercept or constant, X_i is a matrix of the country-specific and global set of macroeconomic variables and u_t the error term with its usual properties. The focus here is on the economic and statistical significance of the estimated β_i parameters.

We expect to find the following signs for the macroeconomic variables we employ. First, we expect that the impact of inflation on the stock-bond correlations may be positive or negative. For example, inflation shocks are associated with positive stock/bond correlations because higher inflation raises the discount factor for stocks and the bond risk premia, hence depressing bonds and stocks. By contrast, Andersson et al. (2008) found that negative/positive stock-bond correlations coincide with periods of high/low inflation expectations via the interest rate component. Second, the expected sign of economic growth proxied by industrial production or unemployment is positive since economic expansions have been found to have a significant positive impact on stock-bond return correlations. Third, interest rates are expected to positively affect the stock-bond correlations because higher rates are reflected in inflation (expectations). Finally, it is expected that major commodities such as crude oil and gold negatively affect the stock-bond correlations because these are typically viewed as hedging instruments when hedging is less profitable between stocks and bonds.

3 Empirical results

In this section, we present some preliminary statistical analysis namely, the descriptive of each series, their correlation matrices, and their graphs, in Subsection 3.1. In Subsections 3.2 the main empirical analysis is reported and in Subsection 3.3 analysis in the pre- and COVID-19 subperiod is undertaken.

3.1 Preliminary statistical investigation

We begin with some descriptive statistics for the main series, that is, the equity-bond futures returns, for each country. Table 1 depicts these statistics. Panel A contains the equity returns, and we observe the following. First, all mean equity returns are positive (except for Spain's) during the period under investigation, with the highest values seen in the USA and Japan and the lowest in Italy and Spain (negative). Second, it appears that high standard deviation values do not always go with higher returns since the highest value is seen in Italy and the lowest in the UK, followed by the USA. Third, all equity returns exhibit negative skewness and excess kurtosis, results largely expected, which imply that they not just deviate from normality but also seem to have experienced sharp spikes in their returns (that is, fat tails). For example, a negative skew with a negative mean implies an overall negative performance for the investment or that an investor can expect frequent small gains and few large losses from that financial asset (as in the case of Spain). Finally, the Jarque-Bera statistic's values for normality clearly show that these series depart from normality (the statistic's prob values are all zero).

As far as the bond returns' descriptive are concerned (panel B), we observe several differences from those of equity returns. First, some series show positive skewness which means that along with a positive mean, this would be a good thing for investors (as in the cases of Australia, France, Germany, and the USA). That is, they may expect frequent small losses and a few large gains from their investment. Second, excess kurtosis is not far above the normal distribution's value of 3 suggesting that these yields are not highly leptokurtic. Finally, the normality requirement is satisfied for these series based on the Jarque-Bera statistic's values and their corresponding probabilities. Hence, these series seem to behave closer to the normal distribution compared to the equity returns series.

Table 1 Descriptive statistics

	AUSTRALIA	*FRANCE*	*GERMANY*	*ITALY*	*JAPAN*	*SPAIN*	*UK*	*USA*
Panel A: Equity futures returns								
Mean	0.2847	0.3173	0.6761	0.0320	0.7849	–0.2150	0.1675	0.9523
Std. dev.	4.0673	4.8346	5.1410	6.3338	5.1782	5.9375	3.7600	4.0263
Skewness	–1.7134	–0.3301	–0.8183	–0.5217	–0.4696	–0.2337	–0.5024	–0.5133
Kurtosis	11.034	4.9815	5.6550	4.7188	3.1096	6.0919	4.5925	4.2413
Jarque-Bera	422.85	24.175	53.911	22.406	4.9553	54.190	19.650	14.381
Probability	0.0000	0.0000	0.0000	0.0000	0.0839	0.0000	0.0000	0.0007
Observations	133	133	133	133	133	133	133	133
Panel B: Bond futures returns								
Mean	0.0335	0.2653	0.2724	0.2023	0.0639	0.2413	0.1112	0.1114
Std. dev.	0.2153	1.8018	1.6310	2.6322	0.4938	1.4303	2.0790	1.3685
Skewness	0.3698	0.2582	0.0901	–0.3678	–0.6771	–0.4152	–0.7519	0.0569
Kurtosis	3.3464	3.7498	2.6212	4.9355	4.1169	3.9398	7.9243	3.1163
Jarque-Bera	3.6971	3.6613	0.9753	23.759	17.077	4.1944	146.91	0.1468
Probability	0.1574	0.1603	0.6140	0.0000	0.0001	0.1227	0.0000	0.9292
Observations	133	106	133	133	133	64	133	133

Notes: Sample is from January 2010 to March 2021 for Australia, Germany, Italy, Japan, UK and USA; for France data begin in April 2012 and for Spain in October 2015.

Table 2 shows the correlation matrices of the main series as follows. In panel A, the below-diagonal values are each country's equity returns correlations while the above-diagonal (in bold) values are each country's the bond returns correlations. Panel B contains two outputs, the equity-bond pairwise correlations, which are below the diagonal, and the own-country equity-bond correlations (in italics), which are the diagonal. The below-diagonal pairwise equity-bond correlations are each country's dynamic conditional correlations with those of the other countries. From the values in Panel A, we see a significant extent of linkage among these countries' equity returns, as expected, in a highly integrated world. By contrast, the degree of connectedness among the futures' returns is smaller across borders (countries) compared to the equity returns. From panel B, we observe that the highest positive equity-bond futures correlations were detected in the Spain-Japan and followed by the Spain-UK country pairs, while the lowest one in the Spain-Germany pair and followed by the Japan-Germany pair. Perhaps, these negative/positive findings entail significant/non-significant diversification benefits across countries regarding these financial markets. Finally, on the own-country correlations we can state that relatively safe countries (Australia, Germany, Japan, UK and USA) exhibit negative correlations, whereas riskier ones (France, Italy and Spain) display positive correlations. Again, such an interesting contrast naturally makes sense from the perspective of achieving efficient diversification.

Table 2 Equity and bond futures correlation matrices

	AUSTRALIA	*FRANCE*	*GERMANY*	*ITALY*	*JAPAN*	*SPAIN*	*UK*	*USA*
				Panel A: series correlations				
AUSTRALIA	1.000	**0.623**	**0.540**	**0.300**	**0.586**	**0.377**	**0.655**	**0.734**
FRANCE	0.713	1.000	**0.507**	**0.309**	**0.469**	**0.431**	**0.657**	**0.523**
GERMANY	0.647	0.882	1.000	**0.314**	**0.648**	**0.398**	**0.688**	**0.524**
ITALY	0.636	0.891	0.791	1.000	**0.267**	**0.563**	**0.280**	**0.205**
JAPAN	0.559	0.697	0.715	0.615	1.000	**0.330**	**0.512**	**0.569**
SPAIN	0.621	0.860	0.723	0.900	0.614	1.000	**0.451**	**0.252**
UK	0.712	0.820	0.753	0.703	0.584	0.706	1.000	**0.649**
USA	0.720	0.775	0.766	0.660	0.708	0.646	0.770	1.000
				Panel B: pairwise correlations				
AUSTRALIA	*–0.194*							
FRANCE	–0.010	*0.052*						
GERMANY	–0.055	0.128	*–0.209*					
ITALY	–0.185	–0.125	–0.225	*0.335*				
JAPAN	0.433	–0.265	–0.524	–0.002	*–0.440*			
SPAIN	0.124	–0.025	–0.722	0.214	0.564	*0.244*		
UK	–0.020	0.279	–0.100	0.158	0.128	0.527	*–0.112*	
USA	–0.176	–0.102	–0.092	0.141	–0.119	0.352	0.313	*–0.377*

Notes: Panel A: each country's equity returns correlations are below the diagonal, while in bold above the diagonal are each country's bond returns correlations.
Panel B: the equity-bond pairwise correlations are below the diagonal, and the own-country equity-bond correlations are in italics.

3.2 Main empirical analysis

We begin with the DCC-GARCH model to obtain the dynamic conditional correlations for each returns pair for each country over the entire period. For the sake of completeness, we only report selected results from the estimation of each country's model but the main focus here is to obtain and subsequently use the estimated dynamic correlations between the equity and bond futures returns.

Table 3 contains the estimates for the volatility decay parameters (or the values that are used to obtain the dynamic conditional correlations), α and β, their t-ratios, the value of the maximised log likelihood function (*LogL*) and evidence of the series' stationarity by subtracting the sum of α and β from unity. From these results we infer that, in all cases, the GARCH effect or the volatility persistence parameter (β) is statistically significant while the ARCH effect parameter (α) is not. Further, the sum of these volatility decay parameters for each country is less than 1, which shows that conditional volatilities are mean-reverting with gradual decay of volatility.

Figure 1 shows the dynamic conditional correlations of the equity-bond futures series for each country derived from the DCC-GARCH model. Note that those for France and Spain begin later compared to the other series (see Table 1). Several observations can be made from these graphs. First, the correlations in the Australian and French series began as negative (alternating between weak and moderate strength), then turning positive before alternating between positive and negative afterwards. Second, the dynamic correlations for Germany, Japan, the UK and the USA were consistently negative, turning from weak to strong occasionally, mostly during the recent years. Third, the Italian series consistently exhibited positive correlation becoming very strong on occasion such as during the 2011 and 2018 periods. Finally, Spain's series started out as showing a moderately positive correlation switching to negative during the last couple of years. Overall, we can say that there exists heterogeneity in the nature (positive or negative) and extent of strength (weak, moderate or strong) in these series' correlations both over time and across countries.

Table 3 Selected DCC-GARCH estimates

Country	α_t	*T-ratio*	β_t	*T-ratio*	$(1 - \alpha_t - \beta_t)$	*LogL*
Australia	0.168	1.067	0.549***	2.889	0.283	–456.44
France	0.011	0.215	0.774***	2.470	0.219	–667.90
Germany	0.019	0.611	0.912***	3.222	0.069	–645.96
Italy	–0.197	–0.201	0.680***	3.011	0.517	–733.86
Japan	0.050	0.667	0.801***	2.778	0.015	–876.32
Spain	0.103	0.223	0.850*	2.112	0.047	–785.22
UK	0.090	0.103	0.805*	1.998	0.105	–454.23
USA	0.050	0.098	0.795*	2.067	0.155	–643.34

Notes: Parameter α is the ARCH effect whereas parameter β is the GARCH effect; *, *** denote statistical significance at the 5% and 1% levels, respectively.

It has been observed that the US equity indices and treasury bonds futures prices have shown an inverse relationship since the bull market of the early 2010s. Besides, it is known that the best way to get a good understanding on how the equity markets would open is to observe early trading in the Treasury bond market. Recent research has corroborated some of our findings. Specifically, Chui and Yang (2012) examined the time-varying correlations of stock and futures data for the USA, the UK and Germany and found that there was positive correlation in the USA and the UK when the markets were bearish or bullish. German correlation, on the other hand, was negative, as in our findings above, implying a deterioration in investor diversification benefits when the stock (futures) market advances.

Next, we will perform two types of regressions, the stepwise and the robust regressions, and then contrast their results. We begin with regressions of all explanatory variables on the pairwise dynamic correlations for all countries examined employing the (forward) stepwise regression methodology. In this context, all variables entered in the equation simultaneously from which the most statistically significant ones emerged and remained in the final model. The results from this methodology are displayed in Table 4. The regressions' R-squared values ranged from 8%, in the cases of Italy and the USA, to 16% for Germany, and from 28% to mid-30% for Australia, France and the UK. Spain had the highest value of the R-squared, 62%. As seen from the Table 4, not all country-specific and common variables, surfaced as statistically significant for each country. What is common in these results is that both sets of variables (country-specific and global) were statistically significant for all countries but the USA, in which only global variables were significant. Specifically, for the most part, inflation was significant for all but the USA and emerged with a negative sign except for Spain. Industrial production growth was relevant for only Australia, Spain and UK. 3M USD Libor was significant for France, Italy, Spain, UK and USA and is seen with a positive sign. The unemployment rate and the MSCI index were only significant for Spain and Italy, respectively. Finally, the crude oil prices variable was significant for France, Italy and Japan only.

Figure 1 Equity-bond futures dynamic conditional correlations (see online version for colours)

Table 4 Country stepwise regression results

Country	*Variable*									
	Constant	*INF*	*IPG*	*GOLD*	*OIL*	*LIBOR*	*EURIBOR*	*EUR10*	*UR*	*MSCI*
Australia	–0.222*	–0.081*	0.073*	–0.053*						
	(0.057)	(0.018)	(0.015)	(0.021)						
France	0.107*	–0.035*		0.108*	0.101*	0.436*		–0.075*		
	(0.008)	(0.006)		(0.058)	(0.041)	(0.150)		(0.035)		
Germany	–0.199*	–0.012*								
	(0.005)	(0.003)								
Italy	0.352*	–0.010*			0.209**	0.142**				0.002**
	(0.008)	(0.004)			(0.111)	(0.050)				(0.001)
Japan	–0.463*	–0.020*			–0.235*					
	(0.102)	(0.009)			(0.094)					
Spain	0.134*	0.039*	–0.014*			0.403*			–0.338*	
	(0.018)	(0.012)	(0.008)			(0.131)			(0.074)	
UK	–0.040*	–0.036*	0.004**			0.167*	0.277*			
	(0.129)	(0.005)	(0.002)			(0.076)	(0.120)			
US	–0.404*			–0.001**		0.167*				
	(0.004)			(0.001)		(0.044)				

Notes: Estimates derived via the stepwise regression methodology; *, ** denote statistical significance at the 1% and 5% levels, respectively; INF is inflation, IPG is industrial production growth, LIBOR is the 3M USD Libor, EURIBOR is the 3M Euribor, EUR10 is the 10-year EUR IRS and UR is the unemployment rate; sample period January 2010 to March 2021.

Table 5 Robust regression results by country

Country	Variable									
	Constant	*INF*	*IPG*	*GOLD*	*OIL*	*LIBOR*	*EURIBOR*	*EUR10*	*UR*	*MSCI*
Australia	–0.222*	–0.078*	0.071*	–0.007**				0.225**		
	(0.067)	(0.022)	(0.017)	(0.003)				(0.109)		
France	0.097*	–0.030*			0.123*	0.113*	0.416*			
	(0.008)	(0.006)			(0.057)	(0.045)	(0.150)			
Germany	–0.209*	–0.009*	0.004*						0.078**	
	(0.005)	(0.003)	(0.001)						(0.042)	
Italy	0.352*	–0.009*				0.126*				
	(0.006)	(0.003)				(0.040)				
Japan	–0.443*	–0.299*			–0.294*	–0.316*				
	(0.009)	(0.008)			(0.081)	(0.088)				
Spain	0.188*	–0.031*							–0.314*	
	(0.011)	(0.004)							(0.044)	
UK	–0.041*	–0.037*	0.006*			0.324*				
	(0.012)	(0.005)	(0.002)			(0.082)				
USA	–0.4047*				–0.155*	0.173*				
	(0.010)				(0.043)	(0.047)				

Notes: Estimates derived via the stepwise regression methodology; *, ** denote statistical significance at the 1% and 5% levels, respectively; INF is inflation, IPG is industrial production growth, LIBOR is the 3M USD Libor, EURIBOR is the 3M Euribor, EUR10 is the 10-year EUR IRS and UR is the unemployment rate; sample period January 2010 to March 2021.

Table 5 presents the results using the robust regression methodology. The R-squared values (not shown) ranged from 25% for Australia, 21% for France, 14% for Germany, 10% for Italy, 16% for Japan, 19% for Spain, 33% for the UK and 13% for the USA. As with the stepwise regression results, inflation was the common and most statistically significant variable and always with a negative sign, followed by industrial production growth. Gold was only significant for Australia and oil for France, Japan and the USA. 3M USD Libor was again significant for France, Italy, Japan, the UK and the USA, mostly with a positive sign except for Japan. Finally, contrary to the stepwise regression results, the MSCI index did not surface as statistically significant for any country.

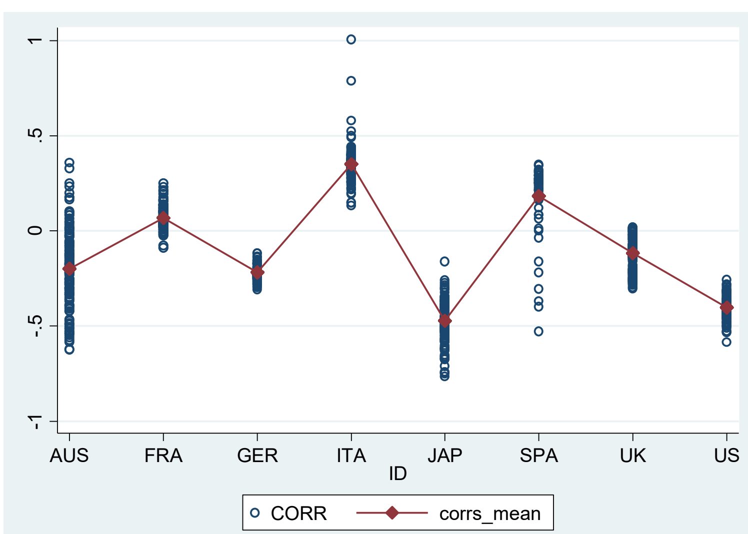
To ascertain whether the above magnitudes are also statistically significant for all countries simultaneously, we estimated a fixed-effects panel specification. Fixed effects are used whenever one is only interested in analysing the impact of variables that vary over time. In other words, we wish to explore the relationship between predictor and outcome variables within a country where each country has its own individual characteristics that may or may not influence the predictor variables. Typically, we assume that something within the country may impact or bias the predictor or explanatory variables and we need to control for this and thus, fixed effects remove the effect of those time-invariant characteristics so we can assess the net effect of the explanatory variables on the outcome variable. Another assumption is that those time-invariant characteristics are unique to the country and should be uncorrelated with other country characteristics. Stated differently, each country is different and hence its constant, which captures individual country characteristics, and error term should not be correlated with the others.

The general panel model specification is as follows:

$$\rho_{it} = \alpha_i + x_{it}'\beta + u_{it} \qquad i = 1, \ldots, N \tag{8}$$

where α_i are individual country intercepts (which are fixed for given N) and assuming that $E(x_{it}u_{it}) = 0$.

Figure 2 Heterogeneity across countries (see online version for colours)



To check whether there exists significant heterogeneity among countries, Figure 2 shows the differences in the correlations among the countries when assuming fixed effect. The graph indeed shows marked differences in the correlations and their means where some countries (France, Italy and Spain) exhibit positive correlations while others (Australia, Germany, Japan, UK and USA) negative correlations. Furthermore, observing the statistics for the between and within variations in countries, we conclude that there are significant differences among these eight countries since the min and max values are far apart (see Table 6). Moreover, the between-country variations are greater that within-country variations.

Table 6 Overall, between and within differences among countries

Variable		*Mean*	*Std. dev.*	*Min*	*Max*	*Observations*
corrs	Overall	–0.1253	0.2895	–0.7661	1.0000	N = 984
	Between		0.2847	–0.4729	0.3521	n = 8
	Within		0.1133	–0.8348	0.5282	T-bar = 123

Table 7 Panel regression results

Variable	*Coefficient*	*Std. error*	*t-stat*	*P > |t|*	*95% conf. interval*	
EUR10	0.0104	0.0243	0.45	0.667	–0.0373	0.0586
EURIBOR	0.1514*	0.0703	2.15	0.032	0.0130	0.2897
LIBOR	0.1001***	0.0360	2.77	0.006	0.0230	0.1783
GOLD	–0.0012	0.0010	–1.39	0.142	–0.0028	0.0042
MSCI	–0.0013	0.0008	–1.35	0.180	–0.0034	0.0007
INF	–0.0146***	0.0031	–3.83	0.000	–0.0218	–0.0065
IPG	0.0010	0.0010	1.00	0.320	–0.0018	0.0038
UR	–0.0103	0.0094	–1.12	0.252	–0.0297	0.0076
OIL	–0.0379	0.0282	–1.34	0.183	–0.0937	0.0177
Constant	–0.1047***	0.0064	–16.93	0.000	–0.1168	–0.0925

F(7, 967) = 792.35	Prob > F = 0.0000
R^2	Obs per group:
within = 0.0417	min = 67
between = 0.0133	avg = 123.0
overall = 0.0071	max = 135
F(9,967) = 4.68	Prob > F = 0.0000
corr(ui, X) = 0.0001	
rho = 0.8656	
$\chi^2(8) = 2.74$	Prob > chi-squ = 0.0500

Notes: For variable definitions, see Table 5; *, *** denote statistical significance at the 5% and 1% levels, respectively.

Table 7 displays the fixed-effects, panel regression results (using the robust option to control for heteroskedasticity). At the bottom of the table, the diagnostics show no issues about the estimation of this specification. Specifically, the F test that all $u_i = 0$ is accepted (based on the high F-test value), and the hypothesis that there is zero correlation between the u_i and explanatory variables, X, is also accepted (based on the practically zero correlation value). The rho coefficient shows that 86.56% of the variance is due to differences across panels ('rho' is also known as the intra-class correlation). Finally, the chi-squared value (with eight degrees of freedom) of 2.74, after conducting the Hausman model specification test (for fixed- or random-effects model), indicates appropriateness of the fixed-effects model.

In general, the results from the panel regression show that Euribor, Libor and inflation were the common variables statistically significant for all countries. This finding agrees with the above findings using the stepwise and robust regression models (reported in Tables 4 and 5). However, the high statistical significance of the constant term suggests that other magnitudes, not explicitly accounted for in the model, could be relevant in explaining the dynamic correlations between these countries' equity-bond futures returns.

3.3 The impacts of COVID-19, financial uncertainty and risk

In this subsection, we explore the impacts of the pandemic, financial uncertainty and geopolitical risk on the dynamic correlations of these major series using weekly data. We capture the pandemic period both via a dummy variable (set on 1 January 2020) and via split regressions, pre- and post-COVID-19 periods. Financial uncertainty is captured by two widely used volatility indicators, the volatility index (*Vix*) for the USA, and the Eurostoxx 50 (*Eustoxx*) index for Europe, whereas geopolitical risk by the Caldara and Iacoviello (2022) geopolitical risk index (*GPR*).

Figure 3 Equity-bond futures dynamic correlations (see online version for colours)

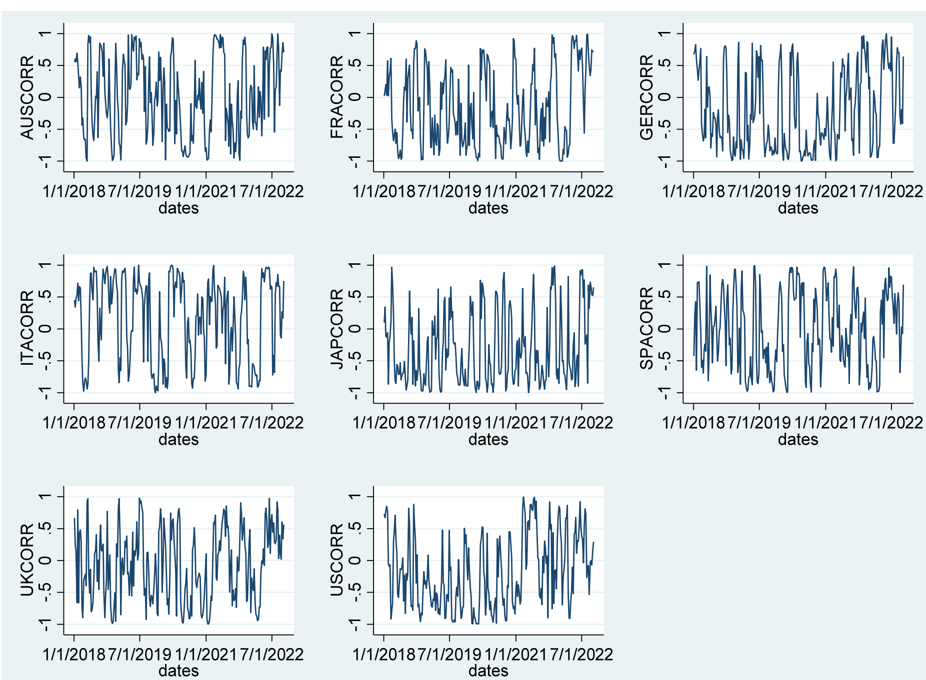


Table 8 Pre- and post-COVID regression results

	Pre-COVID [Jan 2018–Dec 2020]					*Post-COVID [Jan 2020–Aug 2022]*				
	Constant	*EUSTOXX*	*VIX*	*GPR*	R^2	*Constant*	*EUSTOXX*	*VIX*	*GPR*	R^2
Australia	–0.3550*	–0.0126			0.002	–0.2124*	0.0051			0.020
	(0.041)	(0.010)				(0.074)	(0.003)			
	–0.3248*		–0.0075*		0.003	–0.2444*		0.0085		0.030
	(0.052)		(0.003)			(0.067)		(0.003)		
	0.0123			–0.125	0.017	–0.0778			0.0613	0.020
	(0.098)			(0.094)		(0.067)			(0.047)	
France	–0.2289*	0.0032			0.011	–0.2291*	0.0030			0.011
	(0.056)	(0.002)				(0.003)	(0.003)			
	–0.2301*		0.0061**		0.033	–0.2281*		0.0036		0.013
	(0.051)		(0.003)			(0.067)		(0.003)		
	–0.2208*			0.1620	0.021	–0.0889			0.0781	0.002
	(0.081)			(0.101)		(0.078)			(0.051)	
Germany	–0.2770*	0.0000			0.001	–0.4391*	0.0051			0.036
	(0.058)	(0.000)				(0.061)	(0.003)			
	–0.2781*		0.0031		0.007	–0.4386*		0.0054		0.036
	(0.058)		(0.003)			(0.062)		(0.003)		
	–0.2898*			0.0382	0.008	–0.0167			–0.0241	0.002
	(0.092)			(0.023)		(0.009)			(0.011)	
Japan	–0.4250*	–0.0016			0.003	–0.2624*	0.0045			0.022
	(0.046)	(0.002)				(0.069)	(0.003)			
	–0.4248*		–0.0015		0.003	–0.2614*		0.0055		0.032
	(0.045)		(0.003)			(0.070)		(0.003)		
	–0.3678*			0.0998	0.011	–0.2859*			–0.802	0.002
	(0.070)			(0.107)		(0.060)			(0.671)	

Notes: Data frequency weekly; *, **significant at 5% and 10% levels, respectively.

Table 8 Pre- and post-COVID regression results (continued)

	Pre-COVID [Jan 2018–Dec 2020]					Post-COVID [Jan 2020–Aug 2022]				
	Constant	*EUSTOXX*	*VIX*	*GPR*	R^2	*Constant*	*EUSTOXX*	*VIX*	*GPR*	R^2
Italy	0.1682*	0.0034			0.002	0.2101*	0.0011			0.001
	(0.066)	(0.003)				(0.070)	(0.003)			
	0.1672*		0.0037		0.007	0.2117*		–0.0004		0.000
	(0.067)		(0.004)			(0.070)		(0.001)		
	0.1878			–0.1077	0.005	0.1400			–0.700	0.001
	(0.125)			(0.097)		(0.098)			(0.055)	
Spain	–0.0897	0.0019			0.003	0.1108	0.0024			0.006
	(0.059)	(0.002)				(0.073)	(0.003)			
	–0.9011		0.0087		0.005	0.1113		0.0023		0.003
	(0.581)		(0.003)			(0.073)		(0.003)		
	–0.0245			–0.0137	0.001	0.0770			0.1718	0.001
	(0.017)			(0.010)		(0.056)			(0.155)	
UK	–0.0761	0.0007			0.003	–0.1550*	0.0034			0.013
	(0.056)	(0.003)				(0.069)	(0.003)			
	–0.0768		0.0022		0.004	–0.1544*		0.0034		0.013
	(0.052)		(0.003)			(0.069)		(0.003)		
	–0.1010			0.0718	0.004	–0.0500			0.2001	0.016
	(0.096)			(0.056)		(0.045)			(0.170)	
USA	–0.3587*	–0.0048**			0.030	–0.1703*	0.0045			0.019
	(0.047)	(0.002)				(0.075)	(0.003)			
	–0.3587*		–0.0026		0.007	–0.1692*		0.0034		0.010
	(0.047)		(0.002)			(0.075)		(0.004)		
	–0.3455*			–0.0506	0.002	–0.0541			–0.0061	0.000
	(0.022)			(0.039)		(0.044)			(0.004)	

Notes: Data frequency weekly; *, **significant at 5% and 10% levels, respectively.

Figure 3 shows the equity-bond futures dynamic correlations for Australia, France, Germany, Italy, Japan, Spain, the UK and the USA, from January 2018 to August 2022. As seen from these graphs, there was great variability in these correlations ranging from high positive to low negative very often. However, a bit more frequent variability is observed for Japan, Italy and Spain.

Table 8 contains the results from the pre- and post-COVID subperiods regressions along with both uncertainty indices and the geopolitical risk index. We used both uncertainty indices for the sake of comprehensiveness and because there was a difference in the results for France and the USA in the pre-COVID subperiod. Finally, although not reported in the table, the dummy variable was statistically insignificant for France, Italy and the UK but significant (at the 5% level) for the remaining countries. Specifically, the dummy variable's coefficients were negative for Germany and positive for Spain, Japan and the USA. The general message from the table is that the two uncertainty indices were not statistically significant, which suggests that post-COVID the dynamic correlations between the equity and bond futures were not impacted by financial uncertainty but by other factors, not explicitly captured in the regressions, as implied by the statistical significance of the regressions' constant terms. Similarly, the geopolitical risk index, GPR, was not found to be statistically significant in any country and in any subperiod. However, we can note that its coefficient surfaced as negative in many cases (such as Italy and the USA) in both subperiods, which implies that correlations may be negatively affected by general, global geopolitical risks in these countries.

The low linkages between the dynamic correlations and the volatility indices are also corroborated by looking at the simple correlations between them, in Table 9. The lowest (positive) correlation with the Eurostoxx was for Germany, the highest with Japan while a negative one is observed for the USA. As regards the correlations with the Vix, the smallest was for Spain and the largest for France. Finally, we observe even lower correlations with the geopolitical risk index for many countries, which again proves that these global events may not be relevant in these countries' equity-bond futures dynamic correlations. Although this is not reported in the table, the correlations between the geopolitical risk index with the Vix, during the same period, was negative, while that with the Eustoxxx index was positive, albeit small in both cases.

Hence, once again we see different results between the two indices besides low correlation which imply that they are not a major contributor the movements of the equity-bond futures dynamic correlations (at least during this subperiod).

Table 9 Correlations between volatility indices and equity-bond futures dynamic correlations

	AUSTRALIA	*FRANCE*	*GERMANY*	*ITALY*	*JAPAN*	*SPAIN*	*UK*	*USA*
EUSTOXX	0.0862	0.0612	0.0042	0.0342	0.0991	0.0303	0.0245	–0.0305
VIX	0.1567	0.1642	0.1100	0.0223	0.1388	0.0166	0.0996	0.0262
GPR	–0.0417	0.0868	0.0081	–0.0572	0.0467	0.0296	0.0578	–0.0042

Note: Full sample.

4 Summary and conclusions

This paper examined whether the dynamic co-movements between stock-bond futures markets, both in single country and a multi-country context, may be driven by domestic and international macroeconomic factors. The empirical analysis also entailed the investigation of whether macroeconomic variables have an impact on the dynamic conditional correlations of bond and equity futures markets. The data used cover the period from January 2010 to March 2021 for Australia, Germany, Italy, Japan, UK, USA, France since April 2012, and Spain since October 2015. The main macroeconomic variables used are consumer price index, unemployment rate, and industrial production. Finally, the paper explored the impact of the pandemic on the dynamic correlations with the split of the sample in the pre- and post-pandemic periods.

The full period under investigation is characterised by positive equity and bond returns, the static correlations for the period under examination confirm the significant linkage of equity and bonds futures markets between the countries, especially the equity markets. Concerning the own country static bond-equity futures correlations, results are mixed with riskier countries exhibiting positive correlations (France, Italy, Spain), while the relatively safer countries exhibiting negative correlations (Australia, Germany, Japan, UK, USA). This finding has implications for achieving effective diversification in portfolio construction and management.

In the estimation of the dynamic conditional correlations, the conditional volatilities are mean-reverting with gradual decay. The estimated dynamic conditional correlations confirm the material fluctuation of correlations throughout the entire period. In Australia, France, and Spain dynamic conditional correlations exhibit both negative and positive signs. Germany, Japan, UK, and USA exhibit consistently negative correlations, while Italy is the only country in the sample with consistently positive correlation.

From the country-specific variables, inflation was the common and most statistically significant variable in the bond-stock correlations, and mainly with a negative sign. The empirical evidence also indicates that industrial production also has an impact in the bond-stock correlation mainly with a positive sign. Unemployment rate appears to contribute less in determining the bond-stock correlation. This empirical evidence is in line with previous studies that report the high impact of inflation in the determination of stock-bond correlations. One remarkable exemption in the analysis is the US market where country-specific economic variables had no significant impact on the US stock-bond correlation. This might be determined by the global status of the US markets and this also suggests that the US market should be analysed in a global, rather local, economic framework.

From the international macroeconomic variables used, the 3M USD Libor is the key determinant in the country-specific stock-bond correlations, which surfaced as significant with a positive sign. This is consistent with previous research that has reported a positive relation between interest rates and stock-bond correlations. The finding that the 3M USD Libor, rather the 3M Euribor, is a key determinant in the bond-stock correlations highlights the global impact of the Fed's monetary policy.

To further ascertain whether the country-specific and the global variables are also statistically significant for all countries simultaneously, the fixed-effects panel specification is estimated. The panel regression results show that inflation, 3M USD Libor, and 3M Euribor are the common statistically significant variables for all countries. These results, especially for inflation and the 3M USD Libor, are consistent with the findings of the individual country regressions.

Finally, the analysis suggests that post-COVID the dynamic correlations between the equity and bond futures were not impacted by financial uncertainty or geopolitical risks but by other factors, not explicitly identified in the regressions, as implied by the statistical significance of the regressions' constant terms.

References

Ahn, D., Boudoukh, J. Richardson, M. and Whitelaw, R.F. (2002) 'Partial adjustment or stale prices? Implications from stock index and futures return autocorrelations', *The Review of Financial Studies*, Vol. 15, No. 2, pp.655–689.

Allard, A., Leonardo, I. and Kristien, S. (2020) 'Time frequency Stock-bond return correlations: moving away from 'one-frequency-fits-all' by extending the DCC-MIDAS approach', *International Review of Financial Analysis*, Vol. 71, No. 2, pp.15–57.

Andersson, M., Krylova, E. and Vähämaa, S. (2008) 'Why does the correlation between stock and bond returns vary over time?', *Applied Financial Economics*, Vol. 18, No. 2, pp.139–151.

Andrian, T., Crump, E., and Vogt, E. (2019) 'Nonlinearity and flight-to-safety in the risk-return trade-off for stocks and bonds', *The Journal of Finance*, Vol. 74, No. 4, pp.1931–1973.

Asgharian, H., Christiansen, C. and Hou, A.J. (2015) 'Effects of macroeconomic uncertainty on the stock and bond markets', *Finance Research Letters*, Vol. 13, No. 1, pp.10–16.

Asgharian, H., Christiansen, C. and Hou, A.J. (2016) 'Macro-finance determinants of the long-run stock-bond correlation: The DCC-MIDAS specification', *Journal of Financial Econometrics*, Vol. 14, No. 3, pp.617–642.

Aslanidis, N. and Christiansen, C. (2012) 'Smooth transition patterns in the realized stock bond correlation', *Journal of Empirical Finance*, Vol. 19, No. 4, pp.454–464.

Baele, L., Bekaert, G. and Inghelbrecht, K. (2010) 'The determinants of stock and bond return comovements ', *Review of Financial Studies*, Vol. 23, No. 6, pp.2374–2428.

Baur, D.G. and Lucey, B.M. (2009) 'Flights and contagion – an empirical analysis of stock bond correlations', *Journal of Financial Stability*, Vol. 5, No. 4, pp.339–352.

Bianconi, M., Yoshino, J.A. and Machado de Sousa, M.O. (2013) 'BRIC and the U.S. financial crisis: an empirical investigation of stock and bond markets', *Emerging Market Review*, Vol.14, No. 1, pp.76–109.

Bollerslev, T., Engle, R.F. and Wooldridge, J. (1988) 'A capital asset pricing model with time varying covariances', *Journal of Political Economy*, Vol. 96, No. 1, pp.116–131.

Caldara, D. and Iacoviello, M. (2022) 'Measuring geopolitical risk', *American Economic Review*, Vol. 112, No. 4, pp.1194–1225.

Chiang, T.C., Li, J. and Yang, S.Y. (2015) 'Dynamic stock-bond correlations and financial market uncertainty', *Review of Quantitative Finance and Accounting*, Vol. 45, No. 1, pp.59–88.

Chui, C.M., and Yang, J. (2012) 'Extreme correlation of stock and bond futures markets: international evidence', *Financial Review*, Vol. 47, No. 3, pp.565–587.

Connolly, R.A., Stivers, C. and Sun, L. (2005) 'Stock market uncertainty and the stock-bond return relation', *Journal of Financial and Quantitative Analysis*, Vol. 40, No. 1, pp.161–194.

Connolly, R.A., Stivers, C. and Sun, L. (2007) 'Commonality in the time-variation of stock-stock and stock-bond return comovements ', *Journal of Financial Markets*, Vol. 10, No. 2, pp.192–218.

Conrad, C. and Stürmer, K. (2017) *On the Economic Determinants of Optimal Stock-Bond Portfolios: International Evidence*, Department of Economics Discussion Paper Series No. 636, University of Heidelberg.

d'Addona, S. and Kind, A.H. (2006) 'International stock-bond correlations in a simple affine asset pricing model', *Journal of Banking and Finance*, Vol. 30, No. 10, pp.2747–2765.

David, A. and Veronesi, P. (2013) 'What ties return volatilities to price valuations and fundamentals?', *Journal of Political Economy*, Vol. 121, No. 4, pp.682–746.

Engle, R. (2002) 'Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models', *Journal of Business and Economic Statistics*, Vol. 20, No. 3, pp.339–350.

Engle, R. and Sheppard, K. (2001) *Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH*, Working Papers, No. 8554, National Bureau of Economic Research, Cambridge, MA.

Hartmann, P., Straetmann, S. and de Vries, C.G (2001) *Asset Market Linkages in Crisis Periods*, Working paper, No. 71, European Central Bank.

Hsu, C., Lee, H. and Lien, D. (2020) 'Stock market uncertainty, volatility connectedness of financial institutions, and stock-bond return correlations', *International Review of Economics and Finance*, Vol. 70, No. 4, pp.600–621.

Ilmanen, A. (2003) 'Stock-bond correlations', *The Journal of Fixed Income*, Vol. 13, No. 2, pp.55–66.

Kawaller, I., Koch, P. and Koch, T. (1987) 'The temporal price relationship between S&P 500 futures and the S&P 500 Index', *Journal of Finance*, Vol. 42, No. 5, pp.1309–1329.

Kim, S-J., Moshirian, F. and Wu, E. (2006) 'Evolution of international stock and bond market integration: influence of the European Monetary Union', *Journal of Banking and Finance*, Vol. 30, No. 5, pp.1507–1534.

Li, L. (2002) *Macroeconomic Factors and the Correlation of Stock and Bond Returns*, Working paper, Yale International Center for Finance.

Nebojsa, D., Jarno, K., Vanja, P. and Janne, A. (2016) 'Impact of financial market uncertainty and macroeconomic factors on stock-bond correlation in emerging markets', *Research in International Business and Finance*, Vol. 36, No. 1, pp.41–51.

Panchenko, V. and Wu, E. (2009) 'Time-varying market integration and stock and bond return concordance in emerging markets', *Journal of Banking and Finance*, Vol. 33, No. 6, pp.1014–1021.

Skintzi, V. (2019) 'Determinants of stock-bond comovement in the eurozone under market uncertainty', *International Review of Financial Analysis*, Vol. 61, No. 1, pp.20–28.

Viceira, L.M. (2012) 'Bond risk, bond return volatility, and the term structure of interest rates', *International Journal of Forecasting*, Vol. 28, No. 1, pp.97–117.

Whaley, R.E. (2009) 'Understanding the VIX', *Journal of Portfolio Management*, Vol. 35, No. 3, pp.98–105.

Yang, J., Zhou, Y., and Wang, Z. (2009) 'The stock-bond correlation and macroeconomic conditions: one and a half centuries of evidence', *Journal of Banking and Finance*, Vol. 33, No. 4, pp.670–680.

Notes

1 Inflation rate changes affect both expected cash flows and discount rates and depending on which effect dominates, stock and bonds move in the same or in the opposite direction. An increase in the inflation rate is expected to increase the bond's discount rate, thus causing bond prices to decline. However, the impact of inflation on stock prices is uncertain since discount rates and stock dividends are jointly determined by inflation changes.

2 Evidence on stock-bond correlation in the emerging markets is rather limited (e.g., Panchenko and Wu, 2009; Bianconi et al., 2013; Nebojsa et al., 2016) while such evidence is extensively available for developed economies.

3 Results from the unit root tests are available upon request.