NEWS IMPLIED VOLATILITY AND THE STOCK-BOND NEXUS: EVIDENCE FROM HISTORICAL DATA FOR THE USA AND THE UK MARKETS

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Highlights

- Influence of NVIX on time-varying stock–bond relationship is examined.
- Historical UK and US data used.
- A VAR(p)-BEKK-GARCH(1,1)-in-mean model is used.
- Different types of NVIX affect differently returns, variances and covariance.

Abstract:

Using monthly stock and bond returns data from both the USA and the UK, this study addresses the issue of whether news implied volatility and its main components have affected in any significant manner the time-varying stock–bond covariance, their returns and their variances. The time varying association between the two markets has attracted considerable attention due to its important implications for asset allocation, portfolio selection and risk management. The issue at hand is addressed using a VAR(p)-BEKK-GARCH(1,1)-in-mean model and the results reported herein indicate that different types of news implied volatility as quantified by the NVIX developed by Manela and Moreira (2017) affects differently USA and UK returns, variances and covariance. Common across the two countries is the increased stock market volatility in case of a natural disaster associated uncertainty, and the reduction of bond market volatility in case of the unclassified uncertainty.

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1. INTRODUCTION

Stocks and bonds constitute the two major asset classes traded on capital markets and are the building blocks of most investment portfolios because of their different risk-return characteristics. Due to its important implications for asset allocation, portfolio selection and risk management, the time varying association between stock and bond markets is a theme that has featured in a steadily growing body of literature (*inter alia*: Baele *et al.* 2010; Skintzi, 2017; Ohmi and Okimoto, 2016; Andersson *et al*. 2008; Hassan *et al*. 2017; Baur and Lucey, 2009; Connolly *et al*. 2007). Several economic factors act as driving variables of the dynamic intertemporal relation between the two assets. It has been frequently argued that the relationship between stock and bond returns is positive during periods of macroeconomic stability since both stock and bond markets are influenced by common macroeconomic factors such as inflation expectations or expected economic growth (*inter alia*: Asgharian *et al*. 2015; Macchiarelli, 2014; Ilmanen, 2003; Connolly *et al*. 2005; Dimic *et al*. 2016; Dajcman, 2012; Kim *et al*. 2006). However, there may also be a negative stock–bond association induced by the flight-to-quality phenomenon. Flight-to-quality refers to the phenomenon which, in times of stock market turbulence, investors become more risk averse and adjust their portfolios from risky assets such as stocks into safer assets such as long-term government bonds, thus causing a stock–bond decoupling (*inter alia*: Chang and Hsueh, 2013; Durand *et al*. 2010; Yang *et al*. 2009, 2010; Baur and Lucey 2009; Gulko, 2002; Thomadakis, 2012). In broader terms, reported empirical evidence suggests that periods of market uncertainty and hence high volatility, can trigger-off a flight-to-quality effect with investors fleeing from stocks to bonds since the latter, as already pointed out, are almost invariably considered a more secure and less risky investment. The reverse flow between the two markets, i.e. a flight-from-quality, takes place once uncertainty subsides. Both of these flows bring about a negative effect on the stock-bond covariance and hence result in a decrease in the covariance coefficient.

Apart from the usual cohort of economic factors that can influence this relationship over the long run, exogenous events can also exert an impact on the stock-bond covariance over the short run. As has been shown by a growing number of empirical studies, markets and market agents react to exogenous events such as for instance natural or anthropogenic catastrophes, social unrest, political upheavals, terrorism and other violent events such as conflict and war (*inter alia*: Schneider and Troeger 2006; Apergis *et al*. 2017; Guidolin and La Ferrara 2010; Nikkinnen *et al*. 2008). Although the probability of their occurrence is omnipresent, events like these are largely unanticipated and have the potential to generate uncertainty, adversely influence risk perceptions, and exert a negative effect on investors' sentiment and their concomitant assessment of markets. Hence, markets' volatility and portfolio allocation decisions are influenced and, it follows, the stock-bond association by flights-to-quality induced by such exogenous events (*inter alia*: Brune *et al*. 2015; Aslam and Kang, 2015; Kaplanski and Levy 2010; Kollias *et al*. 2013).

In the broader spirit of such studies, this paper takes up the effect exerted on the stock-bond relationship by uncertainty inducing news. In particular, we use the recently published news implied volatility index (NVIX) of Manela and Moreira (2017) to examine how the nexus between the two markets is affected by news and the concomitant uncertainty they potentially cause. The advantage associated with the Manela and Moreira (2017) NVIX dataset is its forward-looking nature, leaving space for testing its predictability (a) on returns, (b) on variances and (c) on co-variances of the stock and bond markets. Moreover, the fact that it spans many decades and it allows for long-term based analysis and inferences. The point that it is also decomposed into different news sources and events adds further value to the use of this index since different kinds of news can bring about different kinds of effects on the nexus between the two markets. To the best of our knowledge, the question of how NVIX and its main components affect the stock-bond covariance has not been addressed before. We do so here employing a multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) framework[1]. We use the unrestricted Vector Autoregressive - GARCH model in the empirical investigation that follows for two main reasons. First, the VAR representation permits the identification of the causality direction between stock and bond market returns without explicitly assuming a specific direction. Second, heteroskedastic returns are a common characteristic in stock and bond markets disturbing the validity of the estimated parameters. For this reason, modelling time-varying conditional variances and covariance is regarded as the suitable approach in such cases. In the ensuing section, the data and methodology are presented. Section 3 reports and discusses the findings, and section 4 provides concluding remarks.

2. DATA AND METHODOLOGY

The financial data set used in our empirical estimations, consists of monthly data on American and British bond and stock returns. They are two of the largest and important economies worldwide with large and mature bond and stock markets. These two markets present a rich database extending back to 1892 (from July 1892 to March 2016) in US case, and back to 1933 (January 1933 to March 2016) in British case. The US stock log returns are calculated from

[1] Multivariate GARCH models have been widely used to study covariance (Longin and Solnik 1995; Kim *et al*. 2006; Li and Zhou 2008; Bonga-Bonga, 2017).

the S&P500 total return index and the British returns from the FTSE All Share total return index, with returns being computed as the first-differences of the natural logs of these indices. The bond log returns for USA and Britain are extracted from the 10-year government bond total return indices, with data for stocks and bond prices being recovered from the Global Financial Database.

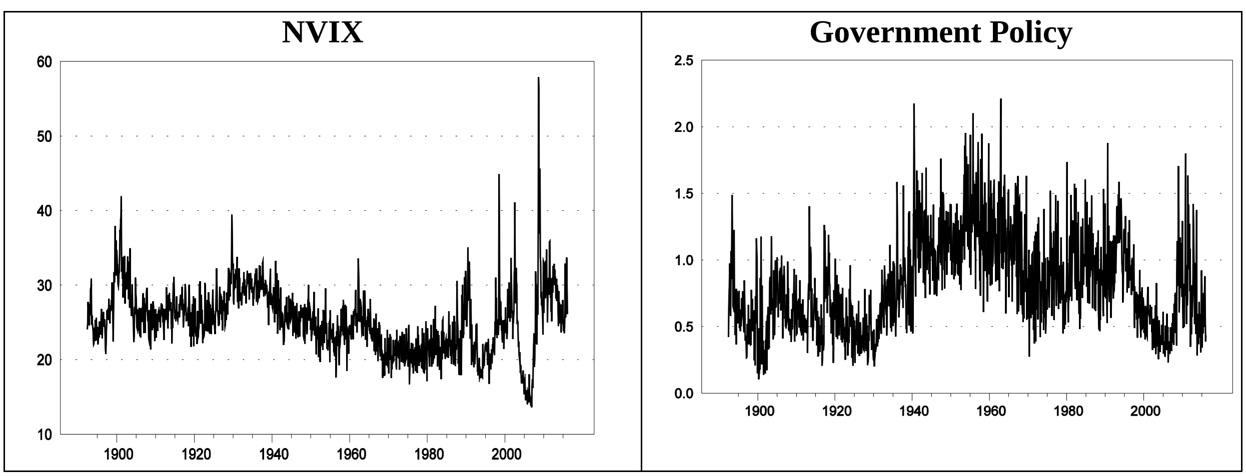
The data on the news-based implied volatility index (NVIX) and its main components are drawn from Manela and Moreira (2017)[2]. The latter, produced a news-based measure of uncertainty derived from the co-movement between the front-page (title and abstract) articles of the Wall Street Journal and options implied volatility (VIX). Manela and Moreira (2017) focus on front-page titles and abstracts in order to ensure feasibility of data collection, and also because these are manually edited and corrected following optical character recognition, which in turn, improves their earlier sample reliability. The NVIX data is found to peak during stock market crashes, times of policy-related uncertainty, world wars and financial crises. Given its forward-looking nature, another significant characteristic of this index is its increased stock market predictability and its rise before transitions into economic sharp downturns. Moreover, the comparative advantage of the index stems from the fact that it is decomposed into different news sources and events that can affect differently the association between the two stock and bond markets. In particular, the NVIX constituent components allow from uncertainty stemming from government policy (henceforth GOV), security markets uncertainty (SecMkts), uncertainty associated with war and conflict (War), natural disaster associated uncertainty (NATDIS), intermediation uncertainty (INTERMED) and finally unclassified uncertainty (Unclass). Intuitively, each of the sub-indices is expected to exert different effects on the stock-bond mean

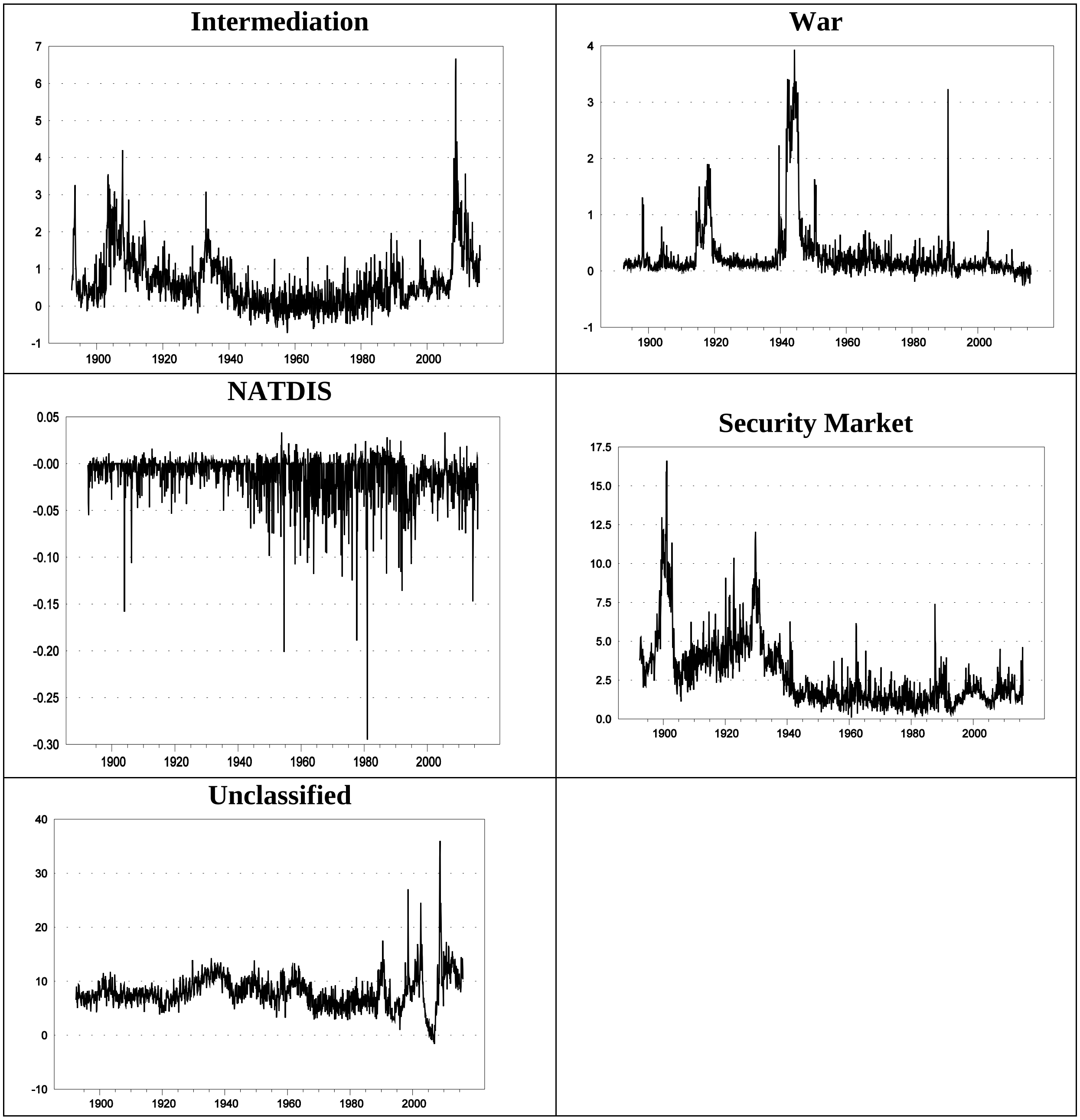
[2] The data are available at: http://apps.olin.wustl.edu/faculty/manela/mm/nvix/nvix_interactive.html.

returns, conditional variance and co-variance between the two markets for the USA and the UK respectively. The start and the end of our analysis is purely driven by the availability of continuous data for the overall NVIX and its components. Note that, even though the NVIX data starts from July 1889, it has missing data between January 1892 to June 1892; hence, we start our analysis from July 1892, even though data for the US economy is available from November 1790.

Figure 1, offers a graphical representation of the NVIX and its six constituent components. As can be observed, each of the indices exhibits an appreciably different pattern and variability. In order to examine the impact of the uncertainty based on news, on the stock-bond covariance, their returns and their variances, the NVIX variable and its components are introduced in both VAR model and multivariate GARCH analysis that follows. In order to allow for the time issue associated given that these indices presents uncertainty over the next month, we introduce the uncertainty indices lagged, at time *t-1*.

Figure 1: Graphical representation of the composite NVIX and its main components





As previously noted, the nexus between the two markets is examined through the use of a multivariate GARCH framework that allows us to estimate time varying variances and covariance in both stock and bond market. The *VECH*[3], the diagonal *VECH* and the *BEKK*

[3] Its name is taken by the vectorized representation of the model. Where VECH( ) denotes the operator that stacks the lower triangular portion of a symmetric N×N matrix into an N(N+1)/2×1 vector of the corresponding unique elements.

(Baba, Engle, Kraft and Kroner)[4] models[5] are among the several multivariate GARCH formulations that have been proposed and used in the relevant literature. For the purposes of our empirical investigation, the bivariate unrestricted BEKK-GARCH(1,1) model as proposed by Engle and Kroner (1995) is used in order to probe into the effects exerted by news implied uncertainty on the stock-bond association in the case of the USA and UK markets. This type of models is not frequently used in empirical studies because of their complexity that often leads to severe convergence problems (Bauwens *et al*. 2006). Nevertheless, in broad terms, the bivariate version of the general BEKK (p,q) model with p=q=1 represents a good compromise between conducting a multivariate analysis and still achieving robust convergence. In addition, the *BEKK* model by Engle and Kroner (1995) adequately addresses the difficulty associated with *VECH*, ensuring that the conditional variance-covariance matrix is always positive definite. The joint process governing the two variables in question is modeled with the bivariate Vector Autoregressive (VAR) unrestricted BEKK-GARCH(1,1)-in-mean model. The news implied uncertainty variable, as encapsulated by NVIX and its components, is included each time in the construction of the mean, variances and covariance matrices. Equation (1) depicts the expression for the conditional mean.

$$\mathbf{x_t} = \boldsymbol{\gamma} + \boldsymbol{\delta}\sum_{j=1}^{p}\mathbf{x_{t-1}} + \boldsymbol{\lambda} y_{\mathbf{t-1}} + \boldsymbol{\zeta}\mathbf{h_t} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{1}$$

where vector $\mathbf{x} = (RB, RS)$ includes the returns of the bond (RB) and stock (RS) markets, respectively, for each of the two countries examined herein. In each case, the lag length, defined as "*p*" is based on the Akaike (AIC) criterion. Variable *y* includes the NVIX index or its constituent component in each model version based on decomposition and classification offered

[4] The BEKK acronym refers to a specific parameteriztion of the multivariate GARCH model developed in Engle and Kroner (1995).
[5] For a more detailed discussion and survey see among others Bauwens *et al*. (2006)

by Manela and Moreira (2017). The y is an exogenous variable presented in both equations[6]. $\mathbf{h} = (h_{11}, h_{22}, h_{21})$ is the GARCH-in-mean vector. The residual vector $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2)$ is bivariate and student t distributed with $\boldsymbol{\varepsilon}_t \mid \Phi_{t-1} \sim T(0, \mathbf{H}_t)$ and the corresponding conditional variance covariance matrix given by:

$$\mathbf{H_t} = \begin{bmatrix} h_{11t} \, h_{12t} \\ h_{21t} \, h_{22t} \end{bmatrix}.$$

The second moment will take the following form:

$$\mathbf{H_t} = \mathbf{C_0 C_0'} + \mathbf{A}' \boldsymbol{\varepsilon}_{\mathbf{t-1}} \boldsymbol{\varepsilon}'_{\mathbf{t-1}} \mathbf{A} + \mathbf{B}' \mathbf{H_{t-1}} \mathbf{B} + \mathbf{K} \bullet y_{t-1} \,, \tag{2}$$

where the conditional variance-covariance matrix depends on its past values and on past values of error terms defined in matrix $\boldsymbol{\varepsilon}_{t\text{-}1}$. C_0 is a 2 × 2 matrix, the elements of which are zero above the main diagonal; and $\mathbf{A}$, $\mathbf{B}$ are 2 × 2 matrices. **K**, is the coefficient matrix for the NVIX or its components indices respectively, and the operator "•" is the element-by-element (Hadamard) product. More analytically:

$$\mathbf{H_t} = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix} \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}' + \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}' \boldsymbol{\varepsilon}_{t\text{-}1} \boldsymbol{\varepsilon}'_{t\text{-}1} \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}' \mathbf{H}_{t\text{-}1} \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} + \begin{pmatrix} k_{11} & k_{12} \\ 0 & k_{22} \end{pmatrix} \bullet y_{t-1} \tag{3}$$

The main advantage of the BEKK-GARCH vis-a-vis the VECH-GARCH model is that it guarantees by construction that the covariance matrices in the system are positive definite. The positive definiteness of the covariance matrix is ensured owing to the quadratic nature of the terms on the equation's (2) right hand sight.

[6] Preliminary Granger causality tests between NVIX and stock-bond returns do present a univariate direction from the former to the later. For reasons of brevity, the results are not presented here but are available upon request.

The maximum likelihood is used to jointly estimate the parameters of the mean and the variance equations. In a single equation format, the model may be written as follows:

$$h_{11,t} = c_{11}^2 + \alpha_{11}^2\varepsilon_{1,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{21}^2\varepsilon_{2,t-1}^2 + \beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta_{21}^2 h_{22,t-1} + \kappa_{11}y_{t-1} \quad (4)$$

$$h_{12,t} = c_{11}c_{21} + \alpha_{11}\alpha_{12}\varepsilon_{1,t-1}^2 + (\alpha_{21}\alpha_{12} + \alpha_{11}\alpha_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{21}\alpha_{22}\varepsilon_{2,t-1}^2 + \beta_{11}\beta_{12}h_{11,t-1} + (\beta_{21}\beta_{12} + \beta_{11}\beta_{22})h_{12,t-1} + \beta_{21}\beta_{22}h_{22,t-1} + \kappa_{12}y_{t-1} \quad (5)$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + \alpha_{12}^2\varepsilon_{1,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{22}^2\varepsilon_{2,t-1}^2 + \beta_{12}^2 h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1} + \beta_{22}^2 h_{22,t-1} + \kappa_{22}y_{t-1} \quad (6)$$

Therefore, the main research hypotheses in our case can be formulated as follows:

H_0^A: NVIX does not predict stock returns, λ=0

H_0^B: NVIX does not predict bond market conditional volatility, k_{11}=0

H_0^C: NVIX does not predict stock market conditional volatility, k_{22}=0

H_0^D: NVIX does not predict stock-bond conditional covariance, k_{12}=0

3. THE FINDINGS

We start the presentation of the findings with the descriptive statistics for the return series in both markets in each of the two countries examined here. These are shown in Table 1. As it can be seen, the stock and bond mean monthly returns are positive, statistically significant and, on the basis of the ADF tests statistic, are characterized as *I(0)* processes. As one would have intuitively expected, the bond market volatility is lower compared to the stock market volatility. Broadly speaking, the Jarque-Bera values are high and statistically significant. In the bond markets the degree of skewness measured in absolute terms is higher compared to stock markets.

The Ljung–Box statistics on level returns present evidence for auto covariances in all cases. Moreover, this statistic on squared returns indicates evidence for time varying variability of returns.

Table 1 Descriptive Statistics of Bond and Stock Returns

	US Bond Return	US Stock Return	UK Bond Return	UK Stock Return
Mean	0.393	0.397	0.558	0.499
Median	0.297	0.752	0.385	0.928
Maximum	11.945	40.746	8.019	42.319
Minimum	-8.243	-30.753	-5.109	-30.924
Std. Dev.	1.643	4.238	1.329	4.857
Skewness	0.604	-0.463	0.831	-0.155
Kurtosis	8.629	14.146	7.503	11.722
ADF t-statistic	-20.9***	-28.4***	-27.7***	-24.9***
J-B test	2050.6***	7739.7***	958.8***	3170.8***
Q(12)	48.54***	137.3***	93.60***	28.08***
Qsq(12)	565.7***	417.9***	398.1***	147.4***
# Obs.	1485	1485	999	999

Note: Mean, Median, Maximum and Minimum figures are in percentages; ADF the augmented Dickey Fuller test; J-B the Jarque-Bera Test provides evidence against normally distributed returns; Q(12) and Q^2 (12) are the Ljung-Box statistic based on the returns and the squared returns respectively up to the 12^{th} order.

Figures 2 and 3 also provide evidence for time varying variances for bond and stock returns in both countries. Noteworthy is that since the mid-70s the bond variability seems to have increased significantly. This is true both in the case of the US bond market (Figure 2) as well as the UK one (Figure 3). Moreover, the distribution of these is fat-tailed because excess kurtosis is greater than zero. These results are more pronounced on stock compared to bond returns. In view of this, adopting the VAR(p)-BEKK-GARCH(1,1)-in-mean model in our analysis emerges as an appropriate choice in order to take into account all of the above mentioned data characteristics and the well-known risk-return relationship in finance literature. According to most models used in finance there is a positive relationship between risk and return. The investors should be rewarded on their risk taken in their investment decisions. This main finance principle can be covered by the ARCH-M model, firstly suggested by Engle, Lillien and Robins (1987). In the

GARCH-M model the conditional variance of asset returns is directly related to asset returns since it enters into the conditional mean equation.

Figure 2: US Bond and Stock Monthly Returns

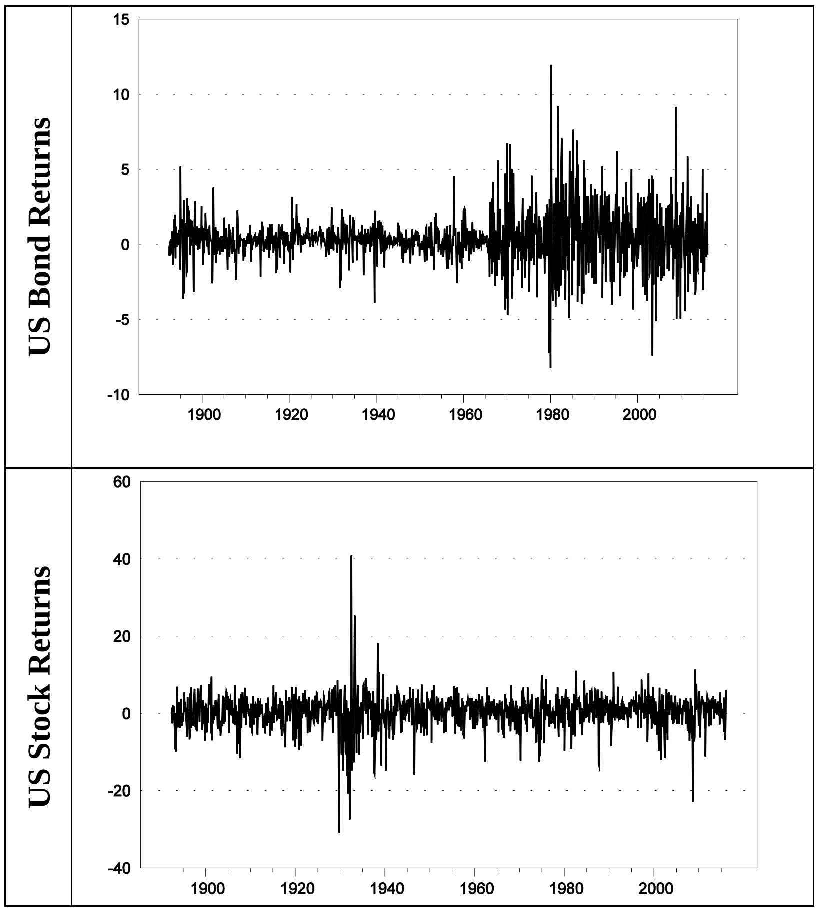
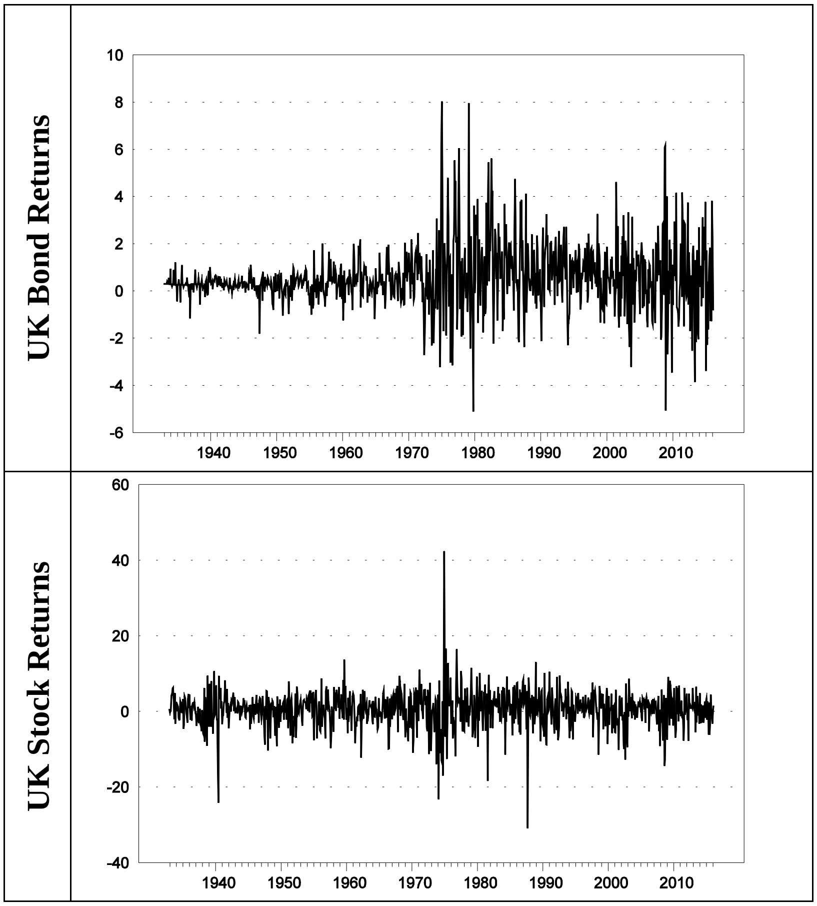


Figure 3: UK Bond and Stock Monthly Returns



The estimation results for the VAR-unrestricted BEKK-GARCH(1,1)-in-mean model are presented in Table 3 for the US bond and stock markets and in Table 4 for the UK ones. The upper part of the tables presents the estimated coefficients and their statistical significance while the lower part the diagnostic tests applied on the residuals are shown. We assume the return residuals follow a bivariate student t density and the relevant t-distribution parameter is presented in this lower part of Tables 3 and 4. Based on the diagnostic tests the problems of autocorrelations and heteroscedasticity previously presented in Table 1 concerning the series of interest have been resolved following the proposed modelling. In the cases where such problems persist the Newey and West (1987) standard errors are calculated in order to ensure that reliable inferences are made.

Table 2: Summary of results

USA							
	NVIX	GOV	INTERMED	NATDIS	SecMkts	War	Unclass
Bond market Returns		-			+		
Stock market Returns			-			+	
Bond market Volatility	-						-
Stock market Volatility	+			+			+
Covariance			+		+		
UK							
	NVIX	GOV	INTERMED	NATDIS	SecMkts	War	Unclass
Bond market Returns							
Stock market Returns					-		-
Bond market Volatility	-		+	+			-
Stock market Volatility			+	+			
Covariance	+			+		-	+

We start with a bird's eye view summary of the results presented in Table 2 before we move to a more detailed presentation and discussion. As can be seen, from the two bond markets, only the US market returns are positively affected by uncertainty news concerning the corresponding security markets. Stock market returns respond positively to war news uncertainty and negatively on INTERMED news in USA. In UK, stock returns are mainly reduced after implied uncertainty from security market news and uncertainty from unclassified news. Bond market volatility is reduced significantly based on NVIX and unclassified news both in the US and the UK. Stock market volatilities in both cases are affected positively due to NATDIS news. However, in the case of US unclassified news adds to stock market volatility while in UK case a similar effect is brought about by INTERMED news. Finally, covariance between stock and bond market is usually increased due to uncertainty news. However, different types of news are responsible for this increase between stock and bond markets, across the two countries. Only in the case of the UK the bond and stock market are negatively correlated in cases of War news uncertainty.

We now turn to a more detailed presentation and discussion of the results yielded from estimating the mean equation for the US bond and stock returns. The well-known risk-return result is shown, according to which investors require high return for the risk undertaken. This is present only in the bond market but not in the stock market (see Table 3). In particular, bond volatility coexists with high bond returns and this result does not appear to be affected when different components of NVIX are used in the bond equation as can be deduced from coefficients H(1,1). Stock market conditional volatility does not affect bond returns as indicated by coefficients H(2,2) while the covariance of the two markets contributes positively to bond returns according to NVIX as shown by coefficients H(1,2). This is the case with all the uncertainty news components of NVIX with the exception of uncertainty news associated with government policy (GOV) and security markets (SecMkts) as can be observed in the relevant columns of Table 3. Generally speaking, bond returns present first order autocorrelation in most of the times, while stock market is characterised by a higher order of autocorrelation (see coefficients of lagged bond and stock returns). Stock returns are positively affected by bond returns with one and five time lags while the opposite is not the case. This implies a unidirectional relationship from bond market to stock market.

Table 3: VAR-BEKK-GARCH(1,1)-in-mean model estimation results for US data

		Exogenous $NVIX_{t-1}$		Exogenous GOV_{t-1}		Exogenous $INTERMED_{t-1}$		Exogenous $NATDIS_{t-1}$		Exogenous $SecMkts_{t-1}$		Exogenous War_{t-1}		Exogenous $Unclass_{t-1}$	
		R_{Bonds}-R_{Stocks}		R_{Bonds}-R_{Stocks}		R_{Bonds}-R_{Stocks}		R_{Bonds}-R_{Stocks}		R_{Bonds}-R_{Stocks}		R_{Bonds}-R_{Stocks}		R_{Bonds}-R_{Stocks}	
	Variable	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*
Bond Mean Return Equation	Const.	-0,1423	0,45	**0,2757**	**<0.01**	**0,1979**	**<0.01**	**0,1664**	**<0.01**	**0,1092**	**<0.01**	**0,2002**	**<0.01**	0,1120	0,04
	H(1,1)	0,0574	**<0.01**	**0,0495**	**<0.01**	**0,0542**	**<0.01**	**0,0520**	**<0.01**	**0,0562**	**<0.01**	**0,0503**	**<0.01**	**0,0553**	**<0.01**
	H(1,2)	0,0641	**0,01**	-0,0252	0,43	0,0534	**0,01**	0,0495	**0,02**	-0,0206	**0,44**	0,0483	**0,01**	0,0520	**0,01**
	H(2,2)	-0,0016	0,29	0,0018	0,23	0,0002	**0,78**	0,0005	0,65	0,0010	0,52	0,0002	0,89	-0,0005	0,70
	RB_{t-1}	**0,1524**	**<0.01**	**0,1552**	**<0.01**	**0,1556**	**<0.01**	**0,1551**	**<0.01**	**0,1547**	**<0.01**	**0,1527**	**<0.01**	**0,1524**	**<0.01**
	RB_{t-2}	-0,0353	0,15	**-0,0459**	**0,05**	-0,0398	0,07	-0,0395	0,08	**-0,0491**	**0,04**	-0,0411	0,07	-0,0367	0,11
	RB_{t-3}	0,0291	0,20	**0,0486**	**0,02**	0,0325	0,11	0,0328	0,10	**0,0464**	**0,04**	0,0309	0,13	0,0303	0,17
	RB_{t-4}	0,0014	0,95	-0,0124	0,58	0,0045	0,85	0,0055	0,81	-0,0136	0,63	0,0048	0,83	0,0043	0,85
	RB_{t-5}	0,0055	0,79	0,0023	0,92	0,0046	0,82	0,0064	0,75	0,0000	1,00	0,0062	0,76	0,0067	0,74
	RS_{t-1}	-0,0028	0,58	-0,0027	0,62	-0,0039	0,41	-0,0035	0,47	-0,0015	0,77	-0,0032	0,50	-0,0042	0,38
	RS_{t-2}	-0,0047	0,29	-0,0058	0,20	-0,0040	0,32	-0,0040	0,32	-0,0054	0,26	-0,0034	0,48	-0,0038	0,40
	RS_{t-3}	0,0022	0,64	0,0019	0,69	0,0014	0,75	0,0009	0,84	0,0022	0,68	0,0009	0,84	0,0019	0,68
	RS_{t-4}	-0,0007	0,89	-0,0011	0,82	-0,0020	0,70	-0,0017	0,73	-0,0007	0,89	-0,0012	0,81	-0,0022	0,70
	RS_{t-5}	-0,0011	0,83	-0,0033	0,52	-0,0017	0,73	-0,0015	0,75	-0,0036	0,48	-0,0014	0,76	-0,0020	0,66
	Exog. Indicator $_{t-1}$	0,0133	0,06	**-0,1153**	**<0.01**	-0,0300	0,13	-1,0277	0,15	**0,0236**	**<0.01**	-0,0232	0,07	0,0098	0,15
Stock Mean Return Equation	Const.	1,0362	0,06	0,2201	0,48	**0,3413**	**<0.01**	0,2934	0,14	**0,4577**	**0,03**	0,1624	0,12	**0,3845**	**<0.01**
	H(1,1)	0,0034	0,96	0,0508	0,51	-0,0068	0,90	0,0096	0,87	0,0614	0,41	-0,0054	0,92	-0,0102	0,86
	H(1,2)	0,0186	0,26	-0,0026	0,86	**0,0109**	**0,01**	0,0032	0,79	0,0076	0,63	0,0042	0,56	0,0144	0,19
	H(2,2)	-0,0233	0,44	-0,0152	0,52	-0,0101	0,48	-0,0123	0,53	-0,0273	0,37	0,0011	0,93	-0,0116	0,52
	RB_{t-1}	**0,2903**	**<0.01**	**0,2858**	**<0.01**	**0,2799**	**<0.01**	**0,2812**	**<0.01**	**0,2926**	**<0.01**	**0,2760**	**<0.01**	**0,2850**	**<0.01**
	RB_{t-2}	0,0035	0,93	0,0286	0,49	0,0045	0,91	0,0069	0,86	0,0269	0,52	0,0046	0,91	0,0070	0,87
	RB_{t-3}	0,0968	0,02	0,0861	0,05	0,0921	**0,03**	0,0867	0,03	0,0949	0,03	0,0916	0,03	0,0960	0,02
	RB_{t-4}	0,0006	0,99	0,0118	0,78	0,0084	0,85	0,0074	0,86	0,0069	0,87	0,0079	0,86	0,0046	0,92
	RB_{t-5}	**0,1083**	**0,01**	**0,1222**	**0,01**	**0,1102**	**0,01**	**0,1071**	**0,01**	**0,1176**	**0,01**	**0,1122**	**0,01**	**0,1091**	**0,01**
	RS_{t-1}	**0,2370**	**<0.01**	**0,2465**	**<0.01**	**0,2372**	**<0.01**	**0,2383**	**<0.01**	**0,2425**	**<0.01**	**0,2392**	**<0.01**	**0,2383**	**<0.01**
	RS_{t-2}	-0,0491	0,03	-0,0616	**<0.01**	-0,0459	0,02	-0,0453	**0,02**	-0,0656	**0,00**	-0,0469	**0,03**	-0,0474	**0,02**
	RS_{t-3}	-0,0035	**0,88**	-0,0023	0,92	-0,0077	**0,72**	-0,0078	0,72	0,0014	0,95	-0,0072	0,75	-0,0043	0,85
	RS_{t-4}	0,0277	0,16	0,0200	0,32	0,0273	0,16	0,0275	0,17	0,0185	0,40	0,0287	0,15	0,0293	0,15
	RS_{t-5}	**0,0759**	**<0.01**	**0,0843**	**<0.01**	**0,0744**	**<0.01**	**0,0754**	**<0.01**	**0,0829**	**<0.01**	**0,0772**	**<0.01**	**0,0768**	**<0.01**
	Exog. Indicator $_{t-1}$	-0,0368	0,16	0,1595	0,43	-0,2315	**0,02**	-1,7943	0,43	-0,0806	0,18	**0,3670**	**<0.01**	-0,0302	0,09
Variances-Covariance equations	c_{11}	**1,1662**	**<0.01**	-0,0675	0,14	**0,0924**	**<0.01**	**0,0975**	**<0.01**	**-0,1069**	**<0.01**	**0,1148**	**<0.01**	**0,5317**	**<0.01**
	c_{21}	-0,6100	0,32	**1,0126**	**<0.01**	0,1709	0,42	0,4097	0,11	**0,7394**	**<0.01**	0,1927	0,26	-0,0399	0,82
	c_{22}	0,0423	0,88	0,0000	1,00	**0,8825**	**<0.01**	0,9695	<0.01	0,0000	1,00	**0,8866**	**<0.01**	**0,7275**	**<0.01**
	α_{11}	**0,3649**	**<0.01**	**0,3770**	**<0.01**	**0,3634**	**<0.01**	**0,3715**	**<0.01**	**0,3670**	**<0.01**	**0,3825**	**<0.01**	**0,3720**	**<0.01**
	α_{12}	-0,0014	0,98	-0,0011	**0,98**	0,0197	**0,65**	0,0170	0,70	-0,0262	0,64	0,0155	0,73	0,0118	0,81
	α_{21}	0,0116	**0,10**	-0,0016	0,84	0,0123	0,01	0,0115	**0,05**	-0,0003	**0,97**	**0,0114**	**0,01**	**0,0110**	**<0.01**
	α_{22}	0,2685	**<0.01**	0,2221	**<0.01**	0,2659	**<0.01**	0,2626	**<0.01**	**0,2301**	**<0.01**	**0,2653**	**<0.01**	**0,2738**	**<0.01**
	β_{11}	0,9289	**<0.01**	0,9360	**<0.01**	0,9381	**<0.01**	0,9352	**<0.01**	**0,9388**	**<0.01**	**0,9310**	**<0.01**	**0,9296**	**<0.01**
	β_{12}	0,0170	0,49	0,0766	0,53	0,0005	0,97	0,0009	0,95	0,0888	0,45	0,0016	0,91	0,0064	0,68
	β_{21}	-0,0025	0,14	**-0,0320**	**0,03**	**-0,0047**	**0,05**	**-0,0046**	**0,04**	**-0,0322**	**0,02**	-0,0042	0,06	**-0,0028**	**0,03**
	β_{22}	0,9216	**<0.01**	-0,9523	**<0.01**	0,9339	**<0.01**	0,9334	**<0.01**	-0,9445	**<0.01**	0,9364	**<0.01**	0,9239	**<0.01**
	κ_{11}	**-0,0421**	**<0.01**	-0,0174	0,71	-0,0010	0,97	0,0747	0,95	0,0083	0,37	-0,0224	0,29	**-0,0601**	**<0.01**
	κ_{12}	0,0240	0,35	-0,2340	0,11	**0,2472**	**0,02**	6,8416	0,19	**0,0632**	**0,02**	0,1028	0,42	0,0257	0,18
	κ_{22}	**0,0409**	**0,01**	0,0000	**1,00**	-0,0311	0,79	**8,4569**	**0,01**	0,0000	1,00	-0,0382	0,64	**0,0376**	**0,05**
Diagnostics	*T-Dist. Parameter*	**5,2743**	**<0.01**	**5,0367**	**<0.01**	**5,1226**	**<0.01**	**5,1774**	**<0.01**	**5,0603**	**<0.01**	**5,0945**	**<0.01**	**5,2119**	**<0.01**
	Usable Obs.	1480		1480		1480		1480		1480		1480		1480	
	Log Likelihood	-6211,62		-6235,96		-6221,50		-6219,62		-6231,01		-6219,86		-6219,65	
		Res. Bond eqn.	Res. Stock eqn.	Res. Bond eqn.	Res. Stock eqn.	Res. Bond eqn.	Res. Stock eqn.	Res. Bond eqn.	Res. Stock eqn.	Res. Bond eqn.	Res. Stock eqn.	Res. Bond eqn.	Res. Stock eqn.	Res. Bond eqn.	Res. Stock eqn.
	Ljung-Box Q(12) p-value	0,49	0,70	0,5657	0,92	0,4221	0,86	0,4451	0,82	0,57	0,83	0,4513	0,84	0,5681	0,75
	McLeod-Li(12) p-value	0,44	0,15	0,6576	0,06	0,5702	0,13	0,5487	0,14	0,6946	0,07	0,7862	0,18	0,4724	0,11
	ARCH(12) Test p-value	0,51	0,23	0,706	0,10	0,628	0,18	0,603	0,19	0,746	0,14	0,817	0,24	0,541	0,17

Notes: Bold numbers indicates statistical significance

Focusing on the coefficients of the uncertainty news indicators, it appears that the effect exerted depends on the type of news. In particular, they reveal a direct positive effect on bond returns emanating from increased uncertainty concerning security markets news and a negative effect from uncertainty induced by government policy news. In a similar manner, stock market returns are positively affected by uncertainty induced by War news and negatively affected by intermediation news implied uncertainty. Worth mentioning is that for both stock and bond markets the aggregate index of NVIX does not indicate any significant impact. This result highlights the importance of disaggregating news implied uncertainty into different types and uncertainty generating sources. Let us now turn to the direct effects of news-implied uncertainty on variance equation of both bond and stock returns (see Variance-Covariance section of Table 3). As a general observation, an increase of the NVIX has a significant reduction on bond variability (as implied by the negative and statistically significant coefficient $k_{1,1}$) and a significant rise on stock variability (as implied by the positive and statistically significant coefficient $k_{2,2}$). The former result may be attributed to the last category, entitled as "unclassified news" when comparing the results across the different categories. While, the latter may be attributed to NATDIS news and unclassified news also. News implied uncertainty concerning intermediation policy and security markets bring about a significant increase in the correlation of the two markets (see coefficient $k_{1,2}$) reducing any diversification benefits for portfolio managers.

Table 4: VAR-BEKK-GARCH(1,1)-in-mean model estimation results for UK data

		Exogenous $NVIX_{t-1}$ R_{Bonds}-R_{Stocks}		Exogenous GOV_{t-1} R_{Bonds}-R_{Stocks}		Exogenous $INTERMED_{t-1}$ R_{Bonds}-R_{Stocks}		Exogenous $NATDIS_{t-1}$ R_{Bonds}-R_{Stocks}		Exogenous $SecMkts_{t-1}$ R_{Bonds}-R_{Stocks}		Exogenous War_{t-1} R_{Bonds}-R_{Stocks}		Exogenous $Unclass_{t-1}$ R_{Bonds}-R_{Stocks}	
	Variable	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*	*Coeff*	*T-Stat. p-value*
Bond Mean Return Equation	Const.	0.2153	0.05	0.1450	0.06	0.1606	0.00	**0.1576**	**<0.01**	**0.1746**	**<0.01**	**0.1795**	**<0.01**	**0.1719**	**<0.01**
	H(1,1)	**0.0665**	**0.01**	0.0547	0.30	0.0504	0.17	**0.0646**	**<0.01**	**0.0592**	**<0.01**	**0.0523**	**0.02**	**0.0643**	**<0.01**
	H(1,2)	0.0452	0.07	0.0586	0.68	0.0760	0.22	**0.0430**	**0.02**	**0.0440**	**<0.01**	**0.0560**	**0.01**	**0.0465**	**<0.01**
	H(2,2)	**0.0017**	**0.04**	0.0010	0.62	0.0013	0.38	**0.0017**	**0.02**	**0.0020**	**0.04**	0.0013	0.25	0.0014	0.10
	RB_{t-1}	**0.2556**	**<0.01**	**0.2558**	**<0.01**	**0.2572**	**<0.01**	**0.2597**	**<0.01**	**0.2603**	**<0.01**	**0.2563**	**<0.01**	**0.2576**	**<0.01**
	RB_{t-2}	-0.0423	0.09	-0.0408	0.14	-0.0375	0.09	**-0.0487**	**0.01**	**-0.0472**	**0.02**	**-0.0479**	**0.02**	**-0.0413**	**0.02**
	RB_{t-3}	**0.0861**	**<0.01**	**0.0789**	**0.03**	**0.0800**	**<0.01**	**0.0879**	**<0.01**	**0.0885**	**<0.01**	**0.0875**	**<0.01**	**0.0861**	**<0.01**
	RS_{t-1}	-0.0018	0.64	0.0001	0.97	-0.0002	0.97	-0.0016	0.68	-0.0020	0.60	-0.0013	0.74	-0.0011	0.78
	RS_{t-2}	0.0039	0.26	0.0038	0.45	0.0045	0.27	0.0043	0.23	0.0034	0.37	0.0037	0.30	0.0037	0.28
	RS_{t-3}	**-0.0110**	**0.02**	**-0.0106**	**0.01**	**-0.0113**	**<0.01**	**-0.0115**	**0.01**	**-0.0112**	**0.01**	**-0.0112**	**0.02**	**-0.0114**	**0.01**
	Exog. Indicator $_{t-1}$	-0.0019	0.64	0.0287	0.73	0.0075	0.84	-0.8199	0.15	-0.0070	0.34	-0.0020	0.85	-0.0002	0.97
Stock Mean Return Equation	Const.	1.1013	0.06	0.2009	0.93	0.4091	0.21	**0.4468**	**0.04**	**0.7320**	**<0.01**	**0.3242**	**0.05**	**0.7538**	**<0.01**
	H(1,1)	0.0221	0.74	0.0170	0.97	0.0769	0.65	0.0313	0.53	0.0344	0.46	0.0550	0.46	0.0245	0.56
	H(1,2)	0.0074	0.50	-0.0014	0.99	0.0117	0.39	0.0083	0.43	0.0073	0.38	0.0092	0.26	0.0064	0.17
	H(2,2)	0.0259	0.69	0.0750	0.84	0.0520	0.60	0.0140	0.65	0.0128	0.69	0.0414	0.45	0.0309	0.35
	RB_{t-1}	0.1301	0.11	**0.2735**	**0.01**	**0.2393**	**<0.01**	0.1299	0.06	0.1279	0.08	0.1324	0.08	0.1395	0.09
	RB_{t-2}	0.1753	0.06	0.1353	0.52	0.1685	0.14	**0.1821**	**0.03**	**0.1663**	**0.04**	0.1551	0.07	0.1819	0.07
	RB_{t-3}	0.0608	0.53	-0.0612	0.69	-0.0140	0.88	0.0642	0.43	0.0505	0.57	0.0221	0.82	0.0622	0.47
	RS_{t-1}	0.0023	0.94	0.0122	0.83	0.0027	0.93	0.0033	0.90	0.0009	0.97	0.0094	0.72	0.0005	0.98
	RS_{t-2}	**-0.0709**	**0.01**	-0.0590	0.38	-0.0533	0.07	**-0.0692**	**0.01**	**-0.0724**	**0.01**	**-0.0730**	**0.01**	**-0.0723**	**0.01**
	RS_{t-3}	-0.0075	0.78	0.0026	0.93	0.0026	0.92	-0.0058	0.83	-0.0051	0.86	-0.0067	0.81	-0.0101	0.72
	Exog. Indicator $_{t-1}$	-0.0263	0.29	0.3762	0.40	-0.3494	0.08	-0.2355	0.95	**-0.1430**	**0.05**	0.1626	0.16	**-0.0360**	**0.04**
Variances-Covariance equations	c_{11}	**0.4919**	**<0.01**	-0.0050	0.91	**-0.0745**	**<0.01**	0.0052	0.49	0.0109	0.64	0.0066	0.70	0.2276	0.00
	c_{21}	-0.5413	0.15	3.3201	0.26	**-3.5622**	**<0.01**	0.0821	0.75	**0.9869**	**<0.01**	1.1098	0.02	-0.2116	0.31
	c_{22}	1.0893	0.06	-0.0001	1.00	-0.4312	0.61	**1.1950**	**<0.01**	-0.2393	0.80	0.4260	0.68	**0.8914**	**<0.01**
	α_{11}	**0.3026**	**0.00**	**0.3178**	**<0.01**	**0.3231**	**<0.01**	**0.3024**	**<0.01**	**0.3102**	**<0.01**	**0.3196**	**<0.01**	**0.3048**	**<0.01**
	α_{12}	0.1557	0.46	-0.3943	0.86	-0.1269	0.75	0.1684	0.33	0.1364	0.22	0.0515	0.75	0.1856	0.28
	α_{21}	0.0003	0.92	0.0031	0.37	0.0024	0.41	0.0000	0.99	-0.0019	0.75	0.0013	0.77	0.0012	0.75
	α_{22}	**0.3211**	**<0.01**	0.3598	0.42	**0.4017**	**<0.01**	**0.3254**	**<0.01**	**0.3173**	**<0.01**	**0.2831**	**<0.01**	**0.3223**	**<0.01**
	β_{11}	**0.9551**	**<0.01**	**0.9608**	**<0.01**	**0.9583**	**<0.01**	**0.9582**	**<0.01**	**0.9599**	**<0.01**	**0.9575**	**<0.01**	**0.9563**	**<0.01**
	β_{12}	-0.0303	0.52	0.9656	0.65	**0.7258**	**0.01**	-0.0418	0.30	-0.0263	0.23	-0.0032	0.93	-0.0337	0.35
	β_{21}	0.0004	0.56	-0.0061	0.77	-0.0072	0.21	0.0002	0.77	0.0013	0.30	0.0001	0.94	0.0003	0.61
	β_{22}	**0.9250**	**<0.01**	-0.6799	0.43	-0.5258	0.08	**0.9210**	**<0.01**	**0.9275**	**<0.01**	**0.9320**	**<0.01**	**0.9242**	**<0.01**
	κ_{11}	**-0.0175**	**<0.01**	0.0420	0.51	**0.0752**	**<0.01**	**2.2409**	**<0.01**	-0.0074	0.23	-0.0140	0.09	**-0.0230**	**<0.01**
	κ_{12}	**0.0307**	**0.03**	-0.3310	0.73	0.2968	0.58	**12.2269**	**0.03**	0.0123	0.78	**-0.3743**	**0.03**	**0.0475**	**0.01**
	κ_{22}	-0.0038	0.86	0.0000	0.99	**1.3620**	**0.00**	**15.4887**	**<0.01**	0.0737	0.86	0.0225	0.95	0.0144	0.50
Diagnostics	T-Dist. Parameter	**5.0556**	**<0.01**	**4.5929**	**<0.01**	**4.5119**	**<0.01**	**5.0735**	**<0.01**	**4.9718**	**<0.01**	**4.9301**	**<0.01**	**4.9666**	**<0.01**
	Usable Observations	996		996		996		996		996		996		996	
	Log Likelihood	-4078.89		-4119.77		-4114.49		-4077.50		-4083.51		-4078.48		-4079.73	
		Res. Bond eqn.	*Res. Stock eqn.*	*Res. Bond eqn.*	*Res. Stock eqn.*	*Res. Bond eqn.*	*Res. Stock eqn.*	*Res. Bond eqn.*	*Res. Stock eqn.*	*Res. Bond eqn.*	*Res. Stock eqn.*	*Res. Bond eqn.*	*Res. Stock eqn.*	*Res. Bond eqn.*	*Res. Stock eqn.*
	Ljung-Box Q(12) p-value	0.49	0.28	0.25	0.35	0.30	0.25	0.39	0.14	0.32	0.28	0.32	0.26	0.40	0.28
	McLeod-Li(12) p-value	0.62	0.75	0.80	**<0.01**	0.75	**<0.01**	0.74	0.50	0.68	0.75	0.65	0.56	0.68	0.75
	ARCH(12) Test p-value	0.60	0.75	0.79	**<0.01**	0.72	**<0.01**	0.73	0.51	0.68	0.75	0.65	0.54	0.68	0.75

Notes: Bold numbers indicates statistical significance

Let us now turn to the results in the case of the UK presented in Table 4. The positive risk-return relationship is also present to a certain degree only for the bond market but in the cases of uncertainty news concerning government policy and intermediation this positive relationship disappears. Additionally, the increased variability on stock market has a significant positive effect on bond returns and this is mainly attributed to the NATDIS and SecMkts components of NVIX. Bond returns present a notable persistence as indicated by the statistical significance of its lagged values. Worth mentioning is the negative effect of stock returns present under a three period delay. Unlike the US case, stock returns have a positive impact after one period on bond returns, in only two cases: the uncertainty induced by government policy news and by intermediation policy news. Furthermore, the NATDIS and SecMkts components present a significant positive effect on stock returns in a two time-lag specification. When it comes to the direct effects of news-implied indicators on bond returns and in line with the US case, there are no significant results. Nevertheless, negative effects on stock returns can be observed because of security markets and unclassified factors-stemming uncertainty news. Just as in the case of the US result, the NVIX exerts a negative and statistically significant effect on bond volatility that is mainly attributed to the unclassified news factor. However, positive effects on bond volatility are based on the effects of the intermediation and NATDIS components. The same applies when examining the stock volatility. When examining the covariance effects of uncertainty news on the UK case, it can be argued that the positive sign of NVIX coefficient on the covariance equation may be attributed to the NATDIS and unclassified news components. Notably, the correlation between the two markets is significantly reduced over the war-invoked news. This latter result implies substantial diversification benefits between the two markets during war periods. As far as the other coefficients in the variance equations are concerned, it can be observed that both the stock and bond markets present a similar high volatility persistence (compare the β_{11} to the β_{22} coefficients). Moreover, the α_{11} coefficients can in broad terms be characterised as being higher in magnitude in US case compared to UK. While the α_{22} coefficients are, lower in the US versus the UK markets. This implies that the impact of news on bond variability is higher in US compared to UK and the opposite for the impact of news on stock variability (compare in Tables 3 and 4 the magnitude of the α_{11} and α_{22} coefficients respectively).

4. Concluding Remarks

The effects of news based uncertainty on the stock-bond covariance, their returns, and their variances were the focus of the paper. To this effect, the news implied volatility index – NVIX- was used. To allow for different effects that depend on the source of uncertainty, the index was also decomposed into its six sub-indices that account for uncertainty emanating from war and conflict, securities markets, natural disasters, government and intermediation policy as well as unclassified uncertainty (Manela and Moreira, 2017). Uncertainty news may trigger a capital movement from risky assets to more safe assets, i.e a flight-to-quality effect. Using VAR methodology and a multivariate GARCH-in-mean framework that allows the modelling of the variance with the covariance, we investigated the effect of uncertainty news on bond and stock returns and their variances. Moreover, their time varying correlation was also examined in this framework. In a nutshell, our findings indicate a positive risk return relationship for US bond market and to a lesser extend in the case of the British bond market. Stock returns were found to influence negatively bond market returns in both countries and, interestingly, the effect is unidirectional only in the case of the USA. Bond returns are positively influenced by the increased uncertainty concerning security markets news and negatively influenced from uncertainty induced by government policy news. No effect is traced on UK bond returns. When it comes to the effects exerted by NVIX and its constituent components the findings are mixed. This should not come as a surprise since different news can and do affect in different ways the bond and stock markets. The results reported herein seem to corroborate this intuitive expectation. A more prominent result is provoked on bond and stock variability by the uncertainty news in case of the US. More specifically, the negative effect of NVIX on bond variability is attributed to unclassified news while the positive effect on stock variability is also laid on unclassified news and NATDIS news. Albeit appreciably feebler, this result applies in the UK but the sign of the effect is more dependent on the type of uncertainty news. Bond returns are positively influenced by the increased uncertainty concerning security markets news and negatively influenced from uncertainty induced by government policy news. No effect is traced on UK bond returns. Correlation between the two markets is found to be increased significantly over specific type of uncertainty news for both UK and US. However, in case of UK uncertainty news about war trigger diversification benefits implied by the appearance of a negative correlation between stock and bond market.

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