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Financial crises and the dynamic linkages between stock and bond returns

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Non-technical summary

Research Question

This paper investigates the dynamic linkages in terms of the conditional mean and conditional volatility between stock and bond returns, within a wide range of advanced economies, over the different phases of the recent financial crisis. Moreover, it examines the impact of the time-varying volatility transmission between stock and bond markets on the dynamic conditional correlation between these markets as well as on the construction of a minimum variance portfolio in such times.

Contribution

The present paper contributes to the existing literature by analysing the dynamic linkages between stock and bond market returns and volatilities in a completely time-varying framework over the different stages of the recent financial crisis. To this end, we adopt a bivariate volatility model which allows for volatility spillovers of either positive or negative sign. The possibility of negative volatility spillovers between stock and bond returns has been mainly disregarded in the existing literature.

Results

Our results show the existence of a time-varying pattern of mean and volatility spillovers between stock and bond returns over the different stages of the recent financial crisis. In a broad sense, the return spillovers are mainly dominated by the spillover effect from stock to bond returns and get stronger throughout the different stages of the recent crisis. The volatility spillovers, on the other hand, are stronger from bond returns to those of stocks than vice versa, and also exhibit time-variation, especially over the European debt crisis. Our results have important implications for investors and risk managers because portfolio performance comparisons suggest that the portfolio volatility can be reduced by considering the time-varying return and volatility spillovers when calculating the riskminimising weights of the selected assets in the portfolio.

Nichttechnische Zusammenfassung

Fragestellung

Diese Arbeit beschäftigt sich mit der dynamischen Wechselwirkung zwischen bedingtem Mittelwert und bedingter Volatilität von Aktien- und Anleiherenditen in vielen entwickelten Volkswirtschaften über die verschiedenen Phasen der jüngsten Finanzkrise. Darüber hinaus untersucht sie die Auswirkungen der zeitvariablen Volatilitätsübertragung zwischen den Aktien- und Anleihemärkten auf die bedingte dynamische Korrelation zwischen diesen Märkten sowie auf die Erstellung eines Portfolios mit minimaler Varianz.

Beitrag

Die vorliegende Arbeit leistet einen Beitrag zur vorhandenen Literatur, indem sie die dynamischen Verknüpfungen zwischen Aktien- und Anleiherenditen und Volatilitäten in einem völlig zeitvariablen Rahmen über die verschiedenen Phasen der jüngsten Finanzkrise analysiert. Dazu verwenden wir ein bivariates Volatilitätsmodell, welches Volatilitäts-Spillovers von positivem oder negativem Vorzeichen ermöglicht. Die Möglichkeit negativer Volatilitäts-Spillovers zwischen Aktien- und Anleiherenditen wurde in der bisherigen Literatur weitgehend vernachlässigt.

Ergebnisse

Unsere Ergebnisse zeigen das Vorliegen eines zeitvariablen Musters von Rendite- und Volatilitäts-Spillovers zwischen Aktien- und Anleihemärkten über die verschiedenen Phasen der jüngsten Finanzkrise. Im Großen und Ganzen werden die Rendite-Spillovers überwiegend vom Spillover-Effekt von Aktien- zu Anleiherenditen dominiert und verstärken sich im Ablauf der jüngsten Krise. Die Volatilitäts-Spillovers sind dagegen von Anleihe- zu Aktienrenditen stärker als vice versa, und auch sie ändern sich im Zeitablauf, vor allem im Verlauf der europäischen Schuldenkrise. Unsere Ergebnisse haben wichtige Implikationen für Investoren und Risikomanager, denn Portfolio-Performance-Vergleiche lassen darauf schließen, dass die Portfoliovolatilität reduziert werden kann, wenn die zeitabhängigen Rendite- und Volatilitäts-Spillovers bei der Berechnung der risikominimierenden Gewichte der ausgewählten Assets im Portfolio berücksichtigt werden.

Financial Crises and the Dynamic Linkages Between Stock and Bond Returns

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Abstract

This paper investigates the dynamic linkages in terms of the first and second moments between stock and bond returns, within a wide range of advanced economies, over the different phases of the recent financial crisis. The adopted empirical framework is a bivariate volatility model, where volatility spillovers of either positive or negative sign are allowed for. Our results lend support to the existence of a substantial time-variation in the dynamic linkages between these financial assets over the different stages of the recent crisis. In particular, our results of the return spillovers show that such spillovers mostly run from stocks to bonds and exhibit a time-varying pattern over all three stages of the crisis in most countries. Regarding the volatility spillovers, such spillovers from bond returns to those of stocks are stronger than the other way round and also exhibit a time-varying pattern in most countries. Furthermore, the portfolio performance comparison results show that by considering time-varying return and volatility spillovers when calculating the risk-minimising portfolio weights of the selected assets, the portfolio volatility can be reduced despite limited diversification opportunities within national markets in times of financial crises.

Keywords: Bond prices, Financial crisis, Stock prices, Time–varying GARCH models, Volatility spillovers

JEL classification: C32, C58, G15.

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1 Introduction

The characteristics of stock and bond market returns and their cross-volatility linkages have drawn the attention of practitioners and researchers in applied financial economics for a long time. Moreover, given that stock and bond returns can exhibit a variety of dynamics and that their linkages in terms of the first and second moments may also comprise time-varying properties, more and more attention to these properties has been paid in the past few years in the light of recent historical events, such as the introduction of the euro in 1999, the Great Recession and, more recently, the European sovereign debt crisis.

The existing empirical studies on stock and bond return dynamics mainly focus on their contemporaneous linkages, such as stock-bond return comovements, financial market integration, contagion and flight-to-quality (safe-haven) analysis (see, e.g., [Baur](#page-31-0) [\(2010\)](#page-31-0), [Baele, Bekaert, and Inghelbrecht](#page-31-1) [\(2010\)](#page-31-1) and [Connolly, Stivers, and Sun](#page-31-2) [\(2005,](#page-31-2) [2007\)](#page-31-3) among others). [Baur](#page-31-0) [\(2010\)](#page-31-0) explains the decline of the stock-bond correlation with an increasing portfolio rebalancing due to the globalisation of financial markets. [Baele et al.](#page-31-1) [\(2010\)](#page-31-1) show that liquidity measures play an important role in explaining the time-variation in stock-bond correlation. [Connolly et al.](#page-31-2) [\(2005,](#page-31-2) [2007\)](#page-31-3) find a negative relation between stock market uncertainty and future stock-bond return correlation. Furthermore, [Cap](#page-31-4)[piello, Engle, and Sheppard](#page-31-4) [\(2006\)](#page-31-4), [Connolly et al.](#page-31-2) [\(2005\)](#page-31-2) and [Hartmann, Straetmans,](#page-32-0) [and de Vries](#page-32-0) [\(2004\)](#page-32-0), among others, find evidence for contagion and flight-to-quality be-tween a wide range of stock and bond markets in times of financial turmoil.^{[1](#page-2-0)}

These studies, however, mostly analyse the simultaneous dynamics of stock and bond markets. By contrast, lagged linkages, such as volatility transmission between these markets, have attracted less attention despite their relevance for investment strategies and risk management decisions.[2](#page-2-0) [Fleming, Kirby, and Ostdiek](#page-32-1) [\(1998\)](#page-32-1) indeed support the importance of volatility spillovers using the theoretical model of [Ross](#page-33-0) [\(1989\)](#page-33-0) showing that lagged volatility linkages arise from information spillovers caused by portfolio shifts across stock, bond and money markets. The authors also highlight the prominence of both simultaneous and lagged volatility linkages for a variety of financial decisions from tactical asset allocation via derivative pricing to risk management strategies. Moreover, [Forbes](#page-32-2) [and Rigobon](#page-32-2) [\(2002\)](#page-32-2) note that cross-market correlations are derived from the volatilities of the considered variables, and hence may lead to biased correlation and misleading interpretation of the contagion because stock market volatilities tend to increase in times of financial crisis. Against this backdrop, cross-market volatility spillovers may have a remarkable impact on the overall volatility linkages between stock and bond markets. Given the common interpretation of volatility as a statistical risk measure of an asset, volatility transmission can shed light on how risk spills over across financial markets. Therefore,

¹See also [Kim, Moshirian, and Wu](#page-33-1) [\(2006\)](#page-33-1) who investigate the impact of the introduction of the euro on stock and bond markets showing that it led to an almost perfect correlation among bond markets in the euro area.

²Studies focusing on volatility linkages between financial assets define volatility spillovers as an effect of lagged squared residuals of one asset on the conditional volatility of the other because possible linkages between the lagged variance of one asset and the variance of the other have been mainly disregarded in conventional volatility transmission studies. In order to avoid any misconception, we refer to the former as return shock (ARCH) spillovers and to the latter as volatility (GARCH) spillovers throughout this study.

multi-asset class portfolio managers may consider volatility transmission across different markets by reducing the risk of their holdings.

In addition, [McAleer and da Veiga](#page-33-2) [\(2008\)](#page-33-2) emphasise the importance of volatility spillovers in forecasting Value-at-Risk of portfolios consisting of different risky assets. [Fleming et al.](#page-32-1) [\(1998\)](#page-32-1) and [Diebold and Yilmaz](#page-32-3) [\(2012\)](#page-32-3) also show that volatility linkages have become stronger in the aftermath of the 1987 US stock market crash and the collapse of Lehman Brothers in late 2008, respectively. [Ehrmann, Fratzscher, and Rigobon](#page-32-4) [\(2011\)](#page-32-4) further find strong evidence for the transmission of shocks both within asset classes and across assets at an international level with a focus on the US and the euro area. Notwithstanding this, volatility transmission mechanisms may also play an important role for monetary policy decision-makers in policy setting to stabilise financial markets in times of financial crises. Consequently, policy measures focusing on risk reduction in one market may have a(n) (un)favourable impact on other financial markets if volatilities of these markets are closely linked with each other.

However, unlike the contagion analysis, there are very few studies on the time-varying dynamics of cross-asset volatility transmission between stock and bond markets. Relevant studies include [Scruggs and Glabadanidis](#page-33-3) [\(2003\)](#page-33-3), [Cappiello et al.](#page-31-4) [\(2006\)](#page-31-4) and [Kim et al.](#page-33-1) [\(2006\)](#page-33-1), who conclude that bond return shocks have a stronger impact on stock returns and that the introduction of the common currency led to almost perfect correlation among bond markets in the euro area. However, these studies focus only on return shock spillovers and do not consider possible volatility spillovers via lagged conditional variances between assets. In fact, [Conrad and Weber](#page-31-5) [\(2013\)](#page-31-5) emphasise that return shock spillovers may be offset or amplified by the volatility spillovers. It follows that a more thorough investigation of the dynamic linkages between the two assets is of paramount interest, particularly work which can identify clear causal volatility transmission mechanisms.

Moreover, previous studies on the linkages between stock and bond markets also disregard possible time-variation in the return shock spillovers and volatility transmission mechanism, even though the time-varying pattern of the dependence between financial assets is well-known by now. For example, the theoretical trading model of [Fleming](#page-32-1) [et al.](#page-32-1) [\(1998\)](#page-32-1) supports the time-varying characteristics of volatility transmission indicating stronger volatility spillovers when the benefits of cross-market hedging are greater than practical considerations, such as transaction costs. [Kim et al.](#page-33-1) [\(2006\)](#page-33-1) also note that their new findings on return shock spillovers may arise from using different time periods compared to related studies. Similarly, [Conrad and Weber](#page-31-5) [\(2013\)](#page-31-5) and [Karanasos,](#page-33-4) [Paraskevopoulos, Menla Ali, Karoglou, and Yfanti](#page-33-4) [\(2014\)](#page-33-4) find evidence for changing persistence of stock market volatilities and time-varying volatility spillovers during financial crises, respectively.

Finally, Chuliá and Torró [\(2008\)](#page-31-6) emphasise the economic value of volatility transmission defining a trading rule based on news content of volatilities from stock and bond markets in the euro area. This trading decision is based on a time-invariant volatility news impact curve. However, the information content of macroeconomic news affecting both stock and bond markets may be subject to remarkable changes as bad news for stock markets can be considered good news for bond markets (and vice versa) in times of financial turmoil. This may also give rise to negative volatility spillovers across different markets which have been mainly ignored in the related literature. Indeed, [Kim et al.](#page-33-1) [\(2006\)](#page-33-1) document negative return shock spillovers between national stock and bond markets in the euro area consistent with the interpretation of negative spillovers as volatility trade-off between markets by [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7).

The present paper contributes to the existing literature by analysing the dynamic linkages between stock and bond returns in terms of the first and second moments in a completely time-varying framework. In particular, the time-varying pattern of the linkages between financial returns is explored over the different stages of the recent financial crisis, using daily data from a wide range of developed countries over the period from January 1999 to September 2015. That is, the different stages of the most recent crisis considered include the subprime mortgage crisis in the US, the peak of the global financial crisis, and the European sovereign debt crisis. These stages are defined on the basis of the timeline of the global financial crisis of [BIS](#page-31-8) [\(2009\)](#page-31-8) and our own interpretation of the timing of the more recent sovereign debt crisis in the euro area. To the best of our knowledge, the time-varying dynamic linkages between stock and bond market returns in terms of the first and second moments during the recent financial crises are yet to be explored in the literature, and this paper aims to fill this gap.

The adopted framework is a bivariate volatility model. Specifically we model the conditional mean equation in a VAR-framework - replacing it by a vector error correction model (VECM) in cases where stock and bond prices are cointegrated -, and then build the conditional variance equations with an unrestricted extended dynamic conditional correlation (UEDCC) AGARCH model. We refer to this model as VAR (VECM) UEDCC-AGARCH. It follows that the adopted model employs the DCC-framework of [Engle](#page-32-5) [\(2002\)](#page-32-5) to capture the time-varying characteristics of the conditional correlation, and is flexible enough to examine return and volatility linkages simultaneously allowing for shifts in volatility spillovers over the recent turbulent periods, in the sense of [Karanasos et al.](#page-33-4) [\(2014\)](#page-33-4).[3](#page-2-0) Finally, our bivariate model allows for volatility spillovers of either positive or negative sign by imposing the non-negativity conditions of [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7). The possibility of negative volatility spillovers between stock and bond returns has been mainly disregarded in the existing literature. Hence, allowing for negative volatility spillovers and shifts in stock and bond market returns and volatility linkages may unveil new results which might be missed in exploring the volatility transmission pattern between these assets.

Our results show the existence of a time-varying pattern of mean and volatility spillovers between stock and bond returns over the different stages of the recent financial crisis. In a broad sense, the return and shock spillovers are mainly dominated by the spillover effect from stock to bond returns and get stronger on the onset of the recent crisis and throughout its different stages. The volatility spillovers, on the other hand, show that such spillovers from bond returns to those of stocks are stronger and also exhibit timevariation, especially over the European debt crisis (e.g., they turn from positive in the pre-crisis to negative during the European debt crisis in most countries). Overall, the findings indicate limited diversification opportunities for investors, especially during the

³Similar UEDCC-GARCH models have been recently used in [Caporale, Hunter, and Menla Ali](#page-31-9) [\(2014\)](#page-31-9), [Karanasos et al.](#page-33-4) [\(2014\)](#page-33-4) and [Rittler](#page-33-5) [\(2012\)](#page-33-5). Our VAR-UEDCC-AGARCH specification models the mean equation in a VAR-framework and allows for asymmetries in the conditional variances in the sense of [Caporale et al.](#page-31-9) [\(2014\)](#page-31-9) and [Rittler](#page-33-5) [\(2012\)](#page-33-5), respectively, while it allows for shifts in the coefficients of return and volatility spillovers based on [Karanasos et al.](#page-33-4) [\(2014\)](#page-33-4). Moreover, [Karanasos et al.](#page-33-4) [\(2014\)](#page-33-4) also allow for regime switches between increasing and decreasing stock market returns compared to our specification. Overall, [Karanasos et al.](#page-33-4) [\(2014\)](#page-33-4) can be considered as a generalisation of our specification.

European sovereign debt crisis period. However, our results have important implications in terms of the construction of a minimum variance portfolio. Accordingly, the portfolio performance comparison results suggest that the portfolio volatility can be reduced considering the time-varying return and volatility spillovers in calculating the risk-minimising weights of the selected assets in the portfolio despite limited diversification opportunities within national financial markets.

The remainder of this paper is set out as follows. Section [2](#page-8-0) describes the data and provides a preliminary analysis. Section [3](#page-9-0) introduces the econometric framework used in this paper, while Section [4](#page-15-0) discusses the empirical findings and practical implications of our study. Section [5](#page-27-0) concludes.

2 Data description and preliminary analysis

We employ daily data to analyse the time-varying dynamic linkages between stock and bond returns and volatilities over the recent financial crisis. Hence, we consider a wide range of developed economies, including Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US over the period from January 1, 1999 to September 30, 2015.[4](#page-2-0) We use the main local stock exchange indices for stock prices, while bond prices are the DataStream benchmark indices for 10-year government bond prices in each economy. The stock and bond prices in levels are given in logarithm and denoted by the variables s_t and b_t , respectively. Figure [1](#page-10-0) plots the time series data over the period under investigation. Moreover, log returns of stocks and bonds are continuously compounded, multiplied by 100, and hence given in percentages. That is, they are calculated as $R_{s,t} = 100 * (s_t - s_{t-1})$ and $R_{b,t} = 100 * (b_t - b_{t-1})$ for stock and bond markets, respectively. Tables $A.1-A.4$ $A.1-A.4$ in [A](#page-34-1)ppendix A report a wide range of descriptive statistics for return series. All time series have been obtained from Thomson DataStream.

In order to account for shifts in return and volatility spillovers between stock and bond markets, we consider a pre-crisis period from January 1, 1999 to August 8, 2007 and a crisis period from August 9, 2007 to September 30, 2015. Moreover, we further divide the crisis period into three different stages based on the international financial crisis timeline of [BIS](#page-31-8) [\(2009\)](#page-31-8) and our own evaluation of the timing of the sovereign debt crisis in the euro area. The first phase of the crisis period covers the subprime mortgage crisis in the US starting on August 9, 2007 as subprime problems spread to interbank markets. Consequently, stock prices in the US, the euro area, the UK and Japan declined by approximately 18%, 26%, 17% and 30%, respectively, while bond prices started to rise remarkably. The second stage refers to the peak of the global financial crisis which covers the period from the collapse of Lehman Brothers on September 15, 2008 to the first signs of stabilisation and recovery in mid-March 2009. The collapse of Lehman Brothers triggered a rapid sell-off on global stock markets, which fuelled the stock market downturns across developed economies. In this period, stock prices dropped by 34%, 33%, 22% and 30% in the US, the euro area, the UK and Japan, respectively. On the other hand, bond prices rose by 9%, on average, in these economies. In line with the [BIS](#page-31-8) [\(2009\)](#page-31-8), we consider

⁴The sample period for Greece reduces to April 1, 1999 – September 30, 2015, as the bond price index for Greece is only available from April 1, 1999 onwards.

March 2009 as the end of the global financial crisis, also consistent with the empirical studies of [Baur](#page-31-10) [\(2012\)](#page-31-10) and [Dimitriou, Kenourgios, and Simos](#page-32-6) [\(2013\)](#page-32-6). Thus, we regard the period from April 2009 to May 2010 as a non-crisis period similar to the pre-crisis one. In addition to the subprime mortgage crisis and the global financial crisis, we also consider the euro area debt crisis starting with the Greek bailout on May 2, 2010. Against the background of ongoing political and economic uncertainties in the euro area, we assume that our third stage of the global financial crisis, referred as the euro area debt crisis, lasts until the end of our sample period. Compared to the other two financial crises, stock and bond markets seem to exhibit different dynamics during the sovereign debt crisis in the euro area. While increased global liquidity backed by expansive monetary policies across developed economies appears to rally the stock markets $(+60\%, +57\%)$ $+10\%$ and $+43\%$ in the US, Germany, the UK and Japan, respectively), bond prices also increased significantly $(+20\%, +32\%, +5\%$ and $+15\%$ in the US, Germany, the UK and Japan, respectively). The strong price increase of German government bonds, which are considered among the safest in the euro area, may reflect financial markets' perception of ongoing economic and political uncertainties related to the common currency area.

Alternatively, we applied the methodologies of [Bai and Perron](#page-31-11) (2003) and Inclán and [Tiao](#page-32-7) [\(1994\)](#page-32-7) to test for breaks in stock and bond returns in a preliminary analysis. However, these procedures result in too many potential break dates for a proper econometric analysis within a multivariate GARCH framework.^{[5](#page-2-0)} Hence, we rely on commonly accepted crisis phases in our empirical analysis enabling us to observe whether global stock-bond return and volatility spillovers have changed during these stages.

3 The econometric methodology

In this paper, we employ a bivariate VAR (VECM) UEDCC-AGARCH model to investigate the joint return and volatility dynamics between stock and bond prices. While our framework is able to capture the time-varying characteristics of the correlation structure, it also allows for different spillover dynamics in the conditional mean and volatility equations during the recent financial crises. In the first step, we specify the conditional mean equation in a VAR-framework. However, when detecting a cointegrating relationship between stock and bond prices, the mean equation is instead specified as a VECM. The conditional variances, on the other hand, are modelled as the unrestricted extended dynamic conditional correlation (UEDCC) GARCH specification to capture the joint volatility dynamics of stock and bond returns. Furthermore, the conditional mean as well as volatility equations allow for shifts in spillover dynamics to capture the variation throughout the financial turmoil.

3.1 Modelling the mean equation

We model the conditional mean equation by employing a VAR model. The vector $r'_t = [r_{s,t}, r_{b,t}]$ contains the stock and bond returns, denoted as $r_{s,t}$ and $r_{b,t}$, respectively. Accordingly, the conditional mean equation is specified as

⁵The results of the variance break tests of the Inclán and Tiao [\(1994\)](#page-32-7) and [Bai and Perron](#page-31-11) [\(2003\)](#page-31-11) methods for choosing break dates are available upon request from the authors.

Figure 1: Log of stock and bond prices

Notes: The graphs plot the daily stock (solid black line, left axis) and bond (grey dashed line, right axis) prices in logarithm for selected economies over the period 1999:1:1−2015:9:30.

Figure 1 (continued): Log of stock and bond prices

Notes: The graphs plot the daily stock (solid black line, left axis) and bond (grey dashed line, right axis) prices in logarithm for selected economies over the period 1999:1:1−2015:9:30.

$$
\boldsymbol{r_t} = \boldsymbol{\mu} + \sum_{i=1}^p \boldsymbol{\psi_i r_{t-i}} + \sum_{i=1}^p \sum_{l=1}^3 \boldsymbol{\psi_l}^D d_l \boldsymbol{r_{t-i}} + \epsilon_t
$$
\n
$$
\boldsymbol{\mu} = \begin{bmatrix} \mu_s \\ \mu_b \end{bmatrix}, \quad \boldsymbol{\psi_i} = \begin{bmatrix} \psi_{ss,i} & \psi_{sb,i} \\ \psi_{bs,i} & \psi_{bb,i} \end{bmatrix}, \quad \boldsymbol{\psi_l}^D = \begin{bmatrix} 0 & \psi_{sb,i}^{dl} \\ \psi_{bs,i}^{dl} & 0 \end{bmatrix}, \quad \epsilon_t = \begin{bmatrix} \epsilon_{s,t} \\ \epsilon_{b,t} \end{bmatrix}
$$
\n(1)

where μ is a vector of constants and ψ_i is the 2 \times 2 coefficient matrix for the lagged time period which is denoted with the subscript i. The coefficients $\psi_{ss,i}$ and $\psi_{bb,i}$ are the autoregressive coefficients indicating the response of stock and bond returns to their own lagged values, respectively. The off-diagonal elements of ψ_i matrix, $\psi_{sb,i}$ and $\psi_{bs,i}$, measure the mean or return spillovers from bond to stock market, and vice versa. Moreover, ψ_l^D is a cross-diagonal matrix with non-zero elements $\psi_{i,j,l}^{dl}$ for $i, j = s, b, s \neq b$ capturing the spillovers between stock and bond returns in times of the different stages of the recent crisis modelled with the shift dummies d_l for $l = 1, 2, 3$ for the subprime mortgage crisis, the global financial crisis and the euro area debt crisis, respectively. Finally, $\epsilon_t | \mathcal{F}_{t-1} \sim$ $N(0, H_t)$ is the normally distributed innovation vector with the corresponding conditional covariance matrix H_t . According to the weak form of the efficient market hypothesis, which goes back to Fama (1965), past returns do not have predictive power on future asset returns. However, [we set the la](#page-32-8)g length to $p = 1$ (if necessary, further lags are added) to eliminate any serial correlation based on the multivariate Q−statistic of Hosking (1981).

Note that the conditional mean equation, Eq. (1), is instead specifie[d as a VECM in](#page-32-9) cases where stock and bond prices (in logs) are cointegrated. We test for cointegration between stock and bond prices employing the Engle and Granger (1987) two-step procedure and the Johansen (1995) trace test as well as the [Gregory and Han](#page-32-10)sen (1996) method which al[lows for a](#page-33-6) s[tructu](#page-33-6)ral break at an unknown [date in the cointegrati](#page-32-11)n[g rela](#page-32-11)tionship. Accordingly, the VECM takes the following form:

$$
\boldsymbol{r_t} = \boldsymbol{\mu} + \sum_{i=1}^{p} \boldsymbol{\psi_i} \boldsymbol{r_{t-i}} + \sum_{i=1}^{p} \sum_{l=1}^{3} \boldsymbol{\psi_l}^D d_l \boldsymbol{r_{t-i}} + \eta c t_{t-1} + \eta^* c t_{t-1} + \epsilon_t
$$
 (2)

where ect_{t-1} is the lagged error correction term, and $\boldsymbol{\eta'} = [\eta_s, \eta_b]$ is the vector consisting of coefficients capturing the short-term adjustments towards the long-run relationship, whereas η^* captures the shifts in the adjustment coefficients in cases where the Gregory [and Hansen](#page-32-11) [\(1996\)](#page-32-11) test detects a structural break in the cointegrating relationshi[p, if any.](#page-32-11)

3.2 Modelling volatility spillovers

 μ_b

In financial econometrics, multivariate GARCH models are widely used to investigate linkages between different asset classes, such as correlation structure and volatility spillovers between assets.⁶ In this paper, we employ the (asymmetric) unrestricted extended dynamic conditio[na](#page-2-0)l correlation (UEDCC) AGARCH framework similar to Karanasos et al. [\(2014\)](#page-33-4). This specification uses the dynamic conditional correlation st[ructure of](#page-33-4) [Engle](#page-32-5)

 6 The reader is referred to Bauwens, Laurent, and Rombouts (2006), Tsay (2006) and [Silvennoinen](#page-33-8) and Teräsvirta (2009) for a m[ore detailed survey on the multivariate GA](#page-31-12)[RCH family.](#page-33-7)

[\(2002\)](#page-32-5) allowing for volatility transmission between stock and bond returns. In addition, the adoption of the non-negativity conditions of [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7) for the conditional variance enables volatility spillovers of either positive or negative sign. Finally, we include three dummy variables to capture potential shifts in the volatility transmission between the two variables.

More specifically, the conditional covariance matrix is given by (see [Engle](#page-32-5) [\(2002\)](#page-32-5))

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

where $\mathbf{D_t} = diag\{\sqrt{h_{i,t}}\}$ is the $n \times n$ diagonal matrix of conditional volatilities with elements $\sqrt{h_{i,t}}$, while the conditional correlation matrix $\boldsymbol{R_t}$ is time-varying.^{[7](#page-2-0)}

In the initial DCC-GARCH model of [Engle](#page-32-5) [\(2002\)](#page-32-5), the conditional variances are obtained from the univariate GARCH process which implicitly does not allow for volatility transmission between the variables. In contrast, we compute conditional variances from a multivariate GARCH model allowing for volatility spillovers. Following [Karanasos et al.](#page-33-4) (2014) and [Rittler](#page-33-5) (2012) , we employ the UEDCC-AGARCH $(1,1)$ framework to model the conditional variances specified as

$$
\mathbf{h}_{t} = \boldsymbol{\omega} + \mathbf{A} \epsilon_{t-1}^{2} + \sum_{l=1}^{3} \mathbf{A}_{l} \mathbf{d}_{l} \epsilon_{t-1}^{2} + \boldsymbol{\Gamma} \mathbb{1} \epsilon_{t-1}^{2} + \mathbf{B} \mathbf{h}_{t-1} + \sum_{l=1}^{3} \mathbf{B}_{l} \mathbf{d}_{l} \mathbf{h}_{t-1}
$$
(4)

where $\boldsymbol{\omega} = [\omega_i]_{i=s,b}$ is the two-dimensional vector of constants, while $\boldsymbol{\Gamma}$ is a diagonal matrix with elements γ_{ii} for $i = s, b$ and 1 is a diagonal matrix consisting of indicator functions with $\mathbb{1}_{\epsilon_{ii,t-1}<0}$ being equal to one if $\epsilon_{ii,t-1}<0$ and zero otherwise for $i=s,b$. Note that the model is able to capture asymmetric responses of the conditional variances to negative shocks. However, the model reduces to a symmetric one where there is no evidence for asymmetry. Moreover, **A** and **B** are (2×2) ARCH and GARCH parameters matrices, respectively. Furthermore, A_1 and B_1 are (2×2) cross-diagonal matrices with non-zero elements α_{ij}^l and β_{ij}^l for $i, j = s, b, s \neq b$ capturing the shifts in volatility spillover parameters during the financial crises. The different stages of the recent global crisis correspond to the dummied periods \mathbf{d}_1 for $l = 1, 2, 3$. The parameter matrices take the following form:

$$
\mathbf{\omega} = \begin{bmatrix} \omega_s \\ \omega_b \end{bmatrix}, \quad \mathbf{A} = \begin{bmatrix} \alpha_{ss} & \alpha_{sb} \\ \alpha_{bs} & \alpha_{bb} \end{bmatrix}, \quad \mathbf{A}_1 = \begin{bmatrix} 0 & \alpha_{sb}^{dl} \\ \alpha_{bs}^{dl} & 0 \end{bmatrix},
$$

$$
\mathbf{\Gamma} = \begin{bmatrix} \gamma_{ss} & 0 \\ 0 & \gamma_{bb} \end{bmatrix}, \quad \mathbf{1} = \begin{bmatrix} \mathbb{1}_{\epsilon_{ss,t-1} < \mathbf{0}} & 0 \\ 0 & \mathbb{1}_{\epsilon_{bb,t-1} < \mathbf{0}} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} \beta_{ss} & \beta_{sb} \\ \beta_{bs} & \beta_{bb} \end{bmatrix}, \quad \mathbf{B}_1 = \begin{bmatrix} 0 & \beta_{sb}^{dl} \\ \beta_{bs}^{dl} & 0 \end{bmatrix}.
$$

In the initial conditional correlation models, parameter matrices A and B are assumed to be non-negative definite diagonal matrices. [Jeantheau](#page-32-12) [\(1998\)](#page-32-12) generalised the diagonal CCC-GARCH framework allowing for non-negative off-diagonal elements in A and B matrices, named as extended constant conditional correlation (ECCC) models by [He and](#page-32-13) Teräsvirta [\(2004\)](#page-32-13). Furthermore, [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7) showed in a multivariate

⁷The initial CCC-GARCH model of [Bollerslev](#page-31-13) [\(1990\)](#page-31-13) assumes that the conditional correlations between time series in the model are constant over time, and thus the conditional covariance matrix reduces to $H_t = D_t R D_t$.

case that not all elements in **B** need to be positive for the conditional covariance matrix H_t to be positive definite for all t and named their model an unrestricted extended constant conditional correlation (UECCC) GARCH model. Moreover, [Rittler](#page-33-5) [\(2012\)](#page-33-5) extended the UECCC-model to an UEDCC-AGARCH model adopting the non-negativity conditions of [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7).

Following [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7), we also impose the four necessary and sufficient conditions of the bivariate process of order $(1, 1)$ to ensure the positive definiteness of the conditional covariance matrix H_t almost surely for all t without placing any sign restriction on the coefficients in the B matrix. Assuming that the model described in equation (4) is identified and invertible^{[8](#page-2-0)} in the sense of [Jeantheau](#page-32-12) [\(1998\)](#page-32-12) and [Conrad and](#page-31-7) [Karanasos](#page-31-7) [\(2010\)](#page-31-7), respectively, the non-negativity conditions are (i) $(1-\beta_{bb})\omega_s+\beta_{sb}\omega_b > 0$ and $(1 - \beta_{ss})\omega_b + \beta_{bs}\omega_s > 0$, (ii) ϕ_1 and ϕ_2 are real and $\phi_1 > |\phi_2|$, (iii) $\mathbf{A}^* \geq 0$ and (iv) $[\mathbf{B}-\max(\phi_2,0)\mathbf{I}]$ $\mathbf{A}^* > 0$ where $\mathbf{A}^* = \mathbf{A} + \mathbf{\Gamma} \mathbb{1}$ is the sum of parameter matrices and $>$ (\geq) denotes the elementwise inequality operator. Overall, these conditions do not place a priori any sign restriction on the coefficients in the B matrix, and hence enable us to analyse volatility spillovers of both positive and negative signs.^{[9](#page-2-0)}

Moreover, we use the DCC model of [Engle](#page-32-5) [\(2002\)](#page-32-5) to model the conditional covariance matrix which takes the following form:

$$
Q_t = (1 - \alpha^{DCC} - \beta^{DCC})\bar{Q} + \alpha^{DCC} z_{t-1} z'_{t-1} + \beta^{DCC} Q_{t-1}
$$
(5)

where z_t is the standardised residuals vector. While $Q_t = (q_{ij,t})$ is the time-varying covariance matrix of z_t , \overline{Q} is the unconditional covariance matrix of the standardised residuals. Moreover, α^{DCC} and β^{DCC} are assumed to be positive scalars with α^{DCC} + β^{DCC} < 1 satisfying the stationarity condition. Furthermore, the time-varying covariance matrix Q_t is transformed into the correlation matrix R_t by

$$
\boldsymbol{R_t} = diag\{\boldsymbol{Q_t}\}^{-1/2}\boldsymbol{Q_t}diag\{\boldsymbol{Q_t}\}^{-1/2}
$$
\n(6)

where $diag\{Q_t\}$ is a diagonal matrix which ensures that R_t is the correlation matrix where $diag(\mathbf{Q}_t)$ is a diagonal matrix which ensures that \mathbf{P}_{t_i} is the correlation matrix with diagonal elements $\rho_{i,j,t} = q_{i,j,t}/\sqrt{q_{ii,t}q_{jj,t}} < |1|$ for $i, j = s, b, i \neq j.$

We estimate all the bivariate models using the quasi-maximum likelihood estimator of [Bollerslev and Wooldridge](#page-31-14) [\(1992\)](#page-31-14) in order to compute non-normality robust standard errors. Thus, the assumption on normally distributed innovation vector can be dropped and $\text{Var}[\epsilon_t | \mathcal{F}_{t-1}] = H_t$ states the conditional variance matrix.

⁸The invertibility assumption indicates that the inverse roots of $|I - B(L)|$, denoted by ϕ_1 and ϕ_2 , lie inside the unit circle with I and L being the identity matrix and lag operator, respectively. For more details, see Assumption A2 in [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7).

⁹Our bivariate UEDCC-AGARCH model reduces to the baseline DCC-GARCH model of [Engle](#page-32-5) [\(2002\)](#page-32-5) for $\alpha_{ij} = \alpha_{ij}^l = \beta_{ij} = \beta_{ij}^l = \gamma_{ii} = 0$ with $i, j = s, b, i \neq j$. Therefore, the baseline model is nested in our framework and can also be considered as a special case of our model without all the spillover effects and asymmetry.

4 Empirical results

We start our empirical analysis by testing for possible cointegrating relationships between stock and bond prices (in logs) before we proceed with bivariate model estimations. Accordingly, we specify the conditional mean equations in the next step. Then we build the conditional variance equations considering the possible volatility linkages. Finally, we estimate our bivariate models and present a summary of our results in Tables [1](#page-17-0) and [2.](#page-19-0)

4.1 Cointegration test results

We first investigate whether stock and bond prices exhibit a long-run relationship in order to model the conditional mean equations properly. The [Engle and Granger](#page-32-10) [\(1987\)](#page-32-10), [Johansen](#page-33-6) [\(1995\)](#page-33-6) and [Gregory and Hansen](#page-32-11) [\(1996\)](#page-32-11) tests are employed in this regard.

While the [Engle and Granger](#page-32-10) [\(1987\)](#page-32-10) and [Johansen](#page-33-6) [\(1995\)](#page-33-6) procedures test for a timeinvariant cointegrating relationship between the two variables, they may fail to detect any long-run relationship between stock and bond prices if it is subject to structural changes. Hence, we also apply the [Gregory and Hansen](#page-32-11) [\(1996\)](#page-32-11) method which allows for a structural break in the cointegrating relationship at an unknown date. [Gregory and](#page-32-11) [Hansen](#page-32-11) [\(1996\)](#page-32-11) consider three types of structural shift in the cointegrating relationship under the alternative hypothesis. In particular, they allow for a shift in the intercept, denoted as Model C, a shift in the intercept and the trend, denoted as Model C/T, and a regime shift, which the authors define as a shift in the intercept and the slope coefficient of the cointegrating relationship and denote it as Model C/S.

The results of the [Engle and Granger](#page-32-10) [\(1987\)](#page-32-10) and [Johansen](#page-33-6) [\(1995\)](#page-33-6) trace tests cannot reject the null hypothesis of no cointegration between stock and bond prices in any of the cases. The test results are presented in Tables [A.5](#page-36-0) and [A.6](#page-37-0) in Appendix [A.](#page-34-1) On the other hand, the [Gregory and Hansen](#page-32-11) [\(1996\)](#page-32-11) tests reject the null hypothesis of no cointegration between both series in favour of a cointegrating relationship with a break in the intercept and the slope coefficient in the US, Canada and Japan. The corresponding Tables [A.7](#page-38-0)[–A.10](#page-39-0) present the test results with related alternative hypotheses in Appendix [A.](#page-34-1) Moreover, the suggested break date for the US is late 2011, which is shortly after the first downgrade of the US sovereign debt rating in history. The suggested break dates for Canada and Japan, on the other hand, are late 2011 and early 2013, respectively. Both countries had general elections before the related break dates, and thus the change in both long-run relationships may reflect financial market uncertainty associated with the economic policies linked to the election outcomes.

4.2 Return spillover results

The estimation results of the return spillover coefficients are summarised in Table [1](#page-17-0) for all countries. The full model estimations of the bivariate VAR (VECM) UEDCC-AGARCH models are presented in Tables [A.11–](#page-40-0)[A.30,](#page-59-0) respectively, in Appendix [A](#page-34-1) for Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Denmark, Norway, Sweden, Switzerland, the UK, the US, Canada, Japan and Australia (the insignificant parameters are dropped).^{[10](#page-2-0)} Note that in many cases, a lag length of 1

¹⁰The dropped parameters from each model were jointly insignificant, at least at the 10% level.

is enough to avoid serially correlated residuals. However, to eliminate autocorrelations, we add further lags and use a lag length of $p = 2$ in the mean equations of Germany, Italy, Portugal, Spain and the UK as well as a lag length of $p = 3$ in the mean equation of Switzerland. Accordingly, the multivariate Q–statistics do not reject the null hypothesis of no serial correlation in the standardised residuals at any conventional level in all cases. Hence, the estimated bivariate models seem to be well specified.

Furthermore, while the conditional mean equations are built as VAR models, they are replaced by VECM specifications in cases where stock and prices are cointegrated on the basis of the results in Section [4.1.](#page-15-1) Accordingly, we model the conditional mean equations within a VECM framework in the US, Canada and Japan. 11 The corresponding results indicate that the long-run relationship between stock and bond markets breaks down with the first downgrade of the US sovereign debt credit rating in history (see η_{ii} coefficients). By contrast, stock market prices start to adjust toward the long-run equilibrium with bond prices after August 2011 in Canada. Finally, in Japan, stock prices adjust toward the long-run equilibrium with bond prices prior to 2013; however, they start to diverge from their long-run relationship at the beginning of 2013.

Pre-crisis

Starting with the pre-crisis period, the results point mainly to the existence of positive return spillovers between stock and bond market returns in both directions in selected economies, as summarised in Table [1.](#page-17-0) We document that the spillovers from bond to stock markets are stronger than spillovers in the opposite direction in all economies; nonetheless, more economies exhibit return spillover effects from stock to bond markets in this period. Against this backdrop, we find positive bidirectional return spillovers between stock and bond markets in the Netherlands, Portugal, the UK and Canada. Moreover, financial markets exhibit positive return spillovers from stock to bond markets in Austria, Belgium, France, Ireland, Italy, Spain, Denmark and the US, but negative ones in Australia and Japan, prior to the subprime mortgage crisis. Finally, we are not able to find any clear evidence for return spillovers between both financial markets in Finland, Germany, Greece, Norway, Sweden and Switzerland in this period.

Subprime mortgage crisis

The spillover dynamics between stock and bond markets start to change with the first signs of the global financial turmoil. For example, the pre-crisis bidirectional return spillovers between the two variables exhibit a remarkable positive shift during the subprime mortgage crisis in the UK. Further, a positive spillover effect from bond to stock markets becomes evident in the US. Similarly, Finland also experiences a positive spillover effect from stock to bond markets, whereas the positive pre-crisis return spillover effects from stock to bond markets in the Netherlands and Portugal get stronger. By contrast, the negative pre-crisis return spillover effects from stock to bond markets turn to positive

¹¹Similarly, we also modelled the conditional mean equations in the US, Canada and Japan allowing for three shifts during the crisis periods in the cointegrating relationship as in the spillover coefficients. However, the results remained mainly unchanged. The related estimation results are available from the authors upon request.

	AT	ΒE	FI	FR	DE	$_{\rm GR}$	IE	IT	NL	PΤ	SP	DK	NO.	SE	CH	UK	US	CA	JP	AU
$\psi_{sb,i}$									0.0768 (0.04)	0.1048 (0.04)						0.1453 (0.05)		0.0651 (0.03)		
$\psi^{d1}_{sb,i}$																0.3149 (0.18)	0.2618 (0.11)			
$\psi^{d2}_{sb,i}$					0.5617 (0.30)					0.4186 (0.25)		-0.5883 (0.34)			0.4635 (0.26)	0.5608 (0.21)			1.7926 (0.62)	
$\psi_{sb,i}^{d3}$					0.1530	0.0413				-0.1311						-0.1193	-0.0661			
	0.0160	0.0144		0.0101	(0.07)	(0.02)	0.0182	0.0190	0.0064	(0.05) 0.0142	0.0198	0.0117				(0.06)	(0.04)		-0.0069	-0.0214
$\psi_{bs,i}$	(0.00)	(0.00)		(0.00)			(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)							(0.00)	(0.01)
$\psi^{d1}_{bs,i}$			0.0244 (0.01)						0.0213 (0.01)	0.0303 (0.01)		-0.0533 (0.01)				0.0280 (0.01)			0.0211 (0.01)	0.0434 (0.02)
$\psi^{d2}_{bs,i}$							0.0214 (0.01)					-0.0250 (0.01)	-0.0407 (0.02)						0.0111 (0.01)	0.0810 (0.04)
$\psi^{d3}_{bs,i}$		0.0277	0.0220	0.0183	0.0158	0.0929			0.0173	0.0458			-0.0172			0.0237			0.0140	0.0361
LogL	–7735.69	(0.01) -7362.52	(0.01) -8741.97	(0.01) -8148.36	(0.01) -8113.52	(0.02) 1770.33	-8581.19	-8511.63	(0.01) -7556.44	(0.02) -8892.98	-8760.61	-7674.29	(0.01) -7862.10	-8222.09	-6379.35	(0.01) -7537.31	-8439.24	-7202.53	(0.00) -6167.41	(0.02) -7997.95
Q(5)	19.00	18.4610	18.98 [0.52]	25.03 [0.20]	19.01 [0.52]	22.02	15.57 [0.74]	27.50	17.03	24.64 [0.22]	21.91 [0.35]	12.40	18.14	17.25	26.27 [0.16]	27.52 [0.12]	26.68 [0.14]	23.72 [0.26]	12.31	22.63
$Q^2(5)$	[0.52] 19.15 [0.45]	[0.56] 26.0467 $[0.13]$	26.18 [0.13]	26.19 [0.13]	25.78 [0.14]	[0.34] 25.34 [0.15]	21.26 $[0.32]$	[0.12] 23.10 $[0.23]$	[0.65] 26.29 [0.12]	19.01 [0.46]	26.79 [0.11]	[0.90] 21.92 [0.29]	[0.58] 20.46 [0.37]	[0.64] 23.95 [0.20]	16.99 [0.59]	22.58 [0.26]	27.13 [0.10]	16.37 [0.63]	$[0.91]$ 22.90 $[0.24]$	[0.31] 21.06 [0.33]

Table 1: Results of the bivariate VAR-UEDCC-AGARCH estimations: Return Spillover Coefficients

In all return spillover coefficients, $i = 1$ unless it is stated otherwise. For Germany, $i = 2$ is used for $\psi_{bs,i}$ and $\psi_{bs,i}^{dl}$ for $l = 1, 2, 3$. For Greece, $i = 2$ for all $\psi_{sb,i}^{dl}$ with $l = 1, 2, 3$. In Spain, $\psi_{bs,2} = -0.0082$ in addition to the reported coefficients. Finally, $i = 2$ for all return spillover coefficients in Switzerland. Overall, we exclude the insignificant coefficients from the mean equations. Hence, we omit the usual annotation to show the significance level of the

coefficients for brevity in this table. For exact significance levels of each coefficient, see Tables A.11[–A.30](#page-40-1)[.](#page-59-1)

in Australia and Japan. On the other hand, Danish financial markets exhibit a negative spillover effect from stock to bond markets during the first crisis stage.

Peak of the global financial crisis

The time-variation in the return dynamics between stocks and bonds continues with the peak of the global financial crisis. More specifically, Denmark experiences bidirectional negative return spillovers between these markets during this period. In the meantime, a negative spillover effect from stock to bond markets arises in Norway. While the positive return spillovers in Germany, Portugal, Switzerland and the UK get stronger from bond to stock markets, the spillover effect in the opposite direction exhibits a positive shift in Ireland and Australia. Finally, a positive bidirectional return spillover effect is found in Japan.

Euro area sovereign debt crisis

The euro area debt crisis period further shows different dynamics between the two returns under consideration. Specifically, we find evidence for bidirectional return spillovers in Germany, Greece, Portugal and the UK. Thereof, the spillover effects are positive in both directions in Germany and Greece, whereas the spillover effects from bond to stock markets are negative in Portugal and the UK. The stronger positive spillover effects in Germany and Greece are also consistent with the characteristics of the financial markets in each country. While it underpins the joint collapse of stock and bond markets in Greece, the stronger positive spillover effect in Germany points to the robustness of its financial markets during the euro area debt crisis. Moreover, we find negative spillover coefficients for the US and Norway. While the negative spillover coefficient weakens the initially positive spillover effect from bond to stock markets in the US, it results in a negative spillover in the reverse direction in Norway. Finally, the positive spillovers from stock to bond markets become stronger in Belgium, Finland, France, the Netherlands, Japan and Australia.

Overall, our results suggest the existence of time-varying return spillovers between stock and bond markets in selected economies through the most recent financial turmoil. Figure [2](#page-20-0) illustrates the return spillover coefficients in each stage of the financial crisis. A graphical inspection indicates that the spillover effect from bond to stock markets is less frequent than in the other direction. While the slightly positive spillover effect from bond to stock markets gets stronger during the first two stages of the global financial turmoil, it gets weaker during the euro area debt crisis. By contrast, the right panel shows that the spillover effect - despite its smaller magnitude - from stock to bond markets gets stronger and more intense during the euro area debt crisis. Last but not least, a pure comparison of the absolute size of the return spillover coefficients has to be interpreted cautiously bearing in mind that it does not take into account that stock returns are much more volatile than those of bonds.

4.3 Volatility spillover results

After presenting the return dynamic linkages between stock and bond markets in the previous section, we now take a closer look at the volatility linkages between the two

	AT	BE	FI	${\rm FR}$	DE	GR	IE	$\rm IT$	NL	$\mathcal{P}\mathcal{T}$	SP	DK	N _O	SE	CH	UK	US	CA	JP	AU
α_{sb}							0.0189 (0.01)				0.0702 (0.03)									
α_{sb}^{d1}	0.3845 (0.11)			0.6674 (0.32)			0.6440 (0.29)		0.4988 (0.26)											
α_{sb}^{d2}							0.6742 (0.37)								0.3379 (0.15)		0.2870 (0.13)			0.6305 (0.15)
α_{sb}^{d3}																				
β_{sb}	-0.0973 (0.05)	0.2009 (0.08)		0.3595 (0.09)	0.5635 (0.01)			0.1351 (0.04)	0.6065 (0.16)	0.0386 (0.02)		0.6286 (0.19)		0.2495 (0.10)		0.3432 (0.09)	0.0791 (0.03)		0.2095 (0.08)	
β^{d1}_{sb}				-0.6221 (0.29)	-0.2774 (0.08)				-0.6153 (0.22)				0.2728 (0.12)							
β_{sb}^{d2}																				-0.4502 (0.13)
β_{sb}^{d3}	0.1614 (0.04)		-0.0585 (0.03)		-0.2136 (0.04)	0.0123 (0.01)			-0.2174 (0.07)	-0.0255 (0.02)		-0.2967 (0.12)	-0.1294 (0.04)	-0.1656 (0.05)		-0.1494 (0.04)	-0.0430 (0.01)	-0.0361 (0.01)		
α_{bs}					0.0002 (0.00)			0.0004 (0.00)							0.0002 (0.00)		0.0010 (0.00)			
α^{d1}_{bs}	0.0004 (0.00)			0.0004 (0.00)	0.0009 (0.00)				0.0005 (0.00)		0.0015 (0.00)				0.0008 (0.00)	0.0049 (0.00)	0.0088 (0.00)	0.0009 (0.00)		
α_{bs}^{d2}			0.0005 (0.00)			0.0023 (0.00)			0.0003 (0.00)						0.0018 (0.00)					0.0014 (0.00)
α_{bs}^{d3}	0.0005 (0.00)	0.0015 (0.00)	0.0004 (0.00)	0.0003 (0.00)	0.0007 (0.00)			0.0020 (0.00)	0.0010 (0.00)						0.0030 (0.00)	0.0008 (0.00)	0.0034 (0.00)			
β_{bs}		0.0008 (0.00)					0.0005 (0.00)		0.0003 (0.00)	0.0005 (0.00)	0.0005 (0.00)	0.0005 (0.00)							0.0003 (0.00)	
β_{bs}^{d1}											-0.0013 (0.00)					-0.0044 (0.00)	-0.0065 (0.00)			
β_{bs}^{d2}														0.0007 (0.00)		0.0005 (0.00)			-0.0003 (0.00)	
β_{bs}^{d3}						0.0324 (0.01)	0.0028 (0.00)				0.0028 (0.00)	0.0006 (0.00)			-0.0024 (0.00)		-0.0031 (0.00)		-0.0004 (0.00)	
α^{DCC}	0.0402 (0.01)	0.0472 (0.01)	0.0449 (0.01)	0.0461 (0.00)	0.0433 (0.01)	0.0196 (0.00)	0.0160 (0.01)	0.0431 (0.01)	0.0435 (0.01)	0.0208 (0.01)	0.0340 (0.01)	0.0359 (0.01)	0.0176 (0.01)	0.0280 (0.01)	0.0322 (0.01)	0.0368 (0.01)	0.0467 (0.00)	0.0301 (0.01)	0.0259 (0.01)	0.0359 (0.01)
β^{DCC}	0.9417 (0.01)	0.9369 (0.01)	0.9399 (0.02)	0.9413 (0.00)	0.9486 (0.01)	0.9804 (0.00)	0.9828 (0.01)	0.9538 (0.01)	0.9453 (0.01)	0.9787 (0.01)	0.9628 (0.02)	0.9421 (0.01)	0.9703 (0.03)	0.9629 (0.01)	0.9511 (0.01)	0.9511 (0.02)	0.9446 (0.01)	0.9603 (0.01)	0.9684 (0.01)	0.9557 (0.01)

Table 2: Results of the bivariate VAR-UEDCC-AGARCH estimations: Volatility Transmission Coefficients

Notes: Subscripts s and b refer to stock and bond market returns' equation, respectively. The subscripts ss (bb) denote coefficients referring to stock and bond market returns' own past, while sb (bs) denotes the spillover coefficients. Moreover, the superscript dl for $l = 1, 2, 3$ stands for the shifts in spillover coefficients in related crisis periods. The α^{DCC} and β^{DCC} coefficients are the related parameters of the dynamic conditional correlation Q as specified in equation (5). [He](#page-14-0)teroscedasticity-robust standard errors are ^given in parentheses.

 Overall, we exclude the insignificant coefficients from the variance equations. Hence, we omit the usual annotation to show the significance level of thecoefficients for brevity in this table. For exact significance levels of each coefficient, see Tables A.1[1–A.3](#page-40-1)[0.](#page-59-1)

Figure 2: Return Spillover Coefficients: All countries

Notes: The graphs plot the return spillover coefficients of all countries over the period 1999:1:1−2015:9:30. Accordingly, the black, light grey, dark grey and grey bars represent the spillover coefficients during the pre-crisis period, subprime mortgage crisis, the peak of the global financial crisis and the euro area sovereign debt crisis, respectively. While the left panel shows the spillover coefficients from bond to stock markets, the right panel illustrates the spillover effect in the opposite direction.

financial variables across the crisis periods.

Table [2](#page-19-0) summarises the estimated results of the return shock and volatility spillovers, as well as the dynamic correlation for all countries. The coefficient estimates of the full bivariate UEDCC-AGARCH models are reported in the right panel of Tables [A.11–](#page-40-0)[A.30](#page-59-0) in [A](#page-34-1)ppendix A (the insignificant parameters are dropped). The multivariate Q -statistics for the squared standardised residuals indicate that the multivariate models are able to capture the variance dynamics properly in all cases. Our results also appear to fulfil the non-negativity conditions of [Conrad and Karanasos](#page-31-7) [\(2010\)](#page-31-7) and the stationarity condition of [Engle](#page-32-5) [\(2002\)](#page-32-5) (α^{DCC} and β^{DCC} are positive and significant and their sum is less than one in all cases). In comparison with the earlier studies on the linkages between stock and bond market returns, we also consider volatility spillovers, captured by the β_{ij} coefficients for $i, j = s, b, s \neq b$, in addition to return shock spillover parameters, modelled with the α_{ij} for $i, j = s, b, s \neq b$, in our bivariate models. Furthermore, we allow the spillover coefficients to shift in times of financial crisis, that is, the superscript d for $l = 1, 2, 3$ denotes the shifts in spillover coefficients in related crisis periods, as discussed earlier.

Overall, the results of the variance equations indicate that stock and bond market returns exhibit strong conditional heteroscedasticity as the ARCH- and GARCH-parameters are positive and highly significant in almost all cases. In addition, γ_{ss} coefficients capturing the asymmetric response of stock market volatility to its past return shocks are positive and highly significant in all cases. These asymmetric characteristics of stock market returns are in line with the previous literature and confirm mostly the stylised facts of stock returns. Unlike the asymmetric properties of stock returns, previous studies did not pay much attention to asymmetries in the bond market returns. Yet, our results show that the γ_{bb} coefficient, which captures the asymmetric response of bond market volatility to its own past return shocks, is positive and highly significant for a large number of bond markets in the euro area. These asymmetric characteristics of bond market returns may be an outcome of the recent financial turmoil and the subsequent economic and political uncertainties in the euro area.

Pre-crisis

The results point to weak return shock spillovers between the stock and bond markets across the selected economies. We only document positive return shock spillover effects from bond to stock markets in Ireland and Spain, and from stock to bond markets in Germany, Italy, Switzerland and the US during the pre-crisis period. By contrast, we find positive bidirectional volatility spillovers between stock and bond markets in Belgium, the Netherlands, Portugal, Denmark and Japan. On the other hand, unidirectional positive volatility spillovers from bond to stock markets are evident for France, Germany, Italy, Sweden, the UK and the US, whereas the Austrian financial markets experience a negative spillover effect in the opposite direction during the pre-crisis period. Last but not least, the positive return shock spillovers from bond to stock markets encounter the opposite effect via volatility spillovers in Ireland and Spain.

Subprime mortgage crisis

The results suggest that positive bidirectional return shock spillovers become evident between both domestic financial markets in Austria, France and the Netherlands. Moreover, both pre-crisis positive return shock spillovers in Germany and Ireland get stronger in related directions during the first stage of the financial crisis. In addition, financial markets in Spain, Switzerland, the UK, the US and Canada start to exhibit positive return shock spillovers from stock to bond markets. We also document that the volatility spillovers turn negative in France, Germany and the Netherlands from bond to stock markets, and in Spain, the UK and the US from stock to bond markets during this period.

Peak of the global financial crisis

During the peak of the global financial crisis, we find bidirectional positive return shock spillovers for Australia, whereas this positive spillover effect is offset by a strong negative volatility spillover effect from bond to stock markets. Moreover, we document positive unidirectional return shock spillovers from bond to stock returns in Ireland, Switzerland and the US, and in the reverse direction in Belgium, Greece, the Netherlands and Switzerland. Finally, financial markets in Sweden and the UK exhibit positive volatility spillovers from stock to bond returns, whereas Japanese financial markets experience negative ones in the same direction during the period.

Euro area sovereign debt crisis

Against the background of the source of uncertainty, the return shock and volatility spillovers dominate the euro area financial markets during the recent sovereign debt crisis. While the positive univariate return shock spillovers from stock to bond markets become stronger in euro area economies such as Austria, Belgium, Finland, France, Germany, Italy and the Netherlands, as well as in Switzerland, the UK and the US, we do not find any clear return shock spillover in the other direction. However, this is compensated by the mainly significant volatility spillover coefficients in many countries. We document positive volatility spillovers from bond to stock markets in Austria and Greece, whereas the volatility spillovers in the same direction are negative for Finland, Germany, the Netherlands, Portugal, as well as for non-euro area economies such as Denmark, Norway, Sweden, the UK, the US and Canada. Considering the volatility spillovers from stock to bond markets, we find a positive spillover effect in Greece, Ireland, Spain and Denmark, as well as a negative effect for the Swiss, Japanese and US financial markets.

Figure 3: Volatility Spillover Coefficients: All countries

Notes: The graphs plot the return shock and volatility spillover coefficients of all countries over the period 1999:1:1−2015:9:30. Moreover, the black, light grey, dark grey and grey bars represent the spillover coefficients during the pre-crisis period, subprime mortgage crisis, the peak of the global financial crisis and the euro area sovereign debt crisis, respectively. While the upper figures show the return shock spillover coefficients (left: from bond to stock; right: from stock to bond markets), the bottom figures illustrate the volatility spillover coefficients (left: from bond to stock; right: from stock to bond markets).

Overall, our findings provide evidence that both return shock and volatility spillover effects are subject to considerable shifts during the financial crises. As Figure [3](#page-22-0) illustrates, our extended model appears to be able to capture the time-variation in the volatility transmission properly. Against this backdrop, both return shock and volatility spillovers from bond to stock markets are stronger than in the opposite direction. Moreover, the return shock spillovers in both directions (upper panels) get stronger during the first two stages of the recent financial turmoil. While we do not find any significant return shock spillover from bond to stock markets, the same spillover effect in the opposite direction remains stronger than its pre-crisis counterpart during the sovereign debt crisis in the euro area. On the other hand, the positive pre-crisis volatility spillovers from bond to stock markets (bottom left panel) become mostly negative during the first two phases of the financial crisis, while it turns positive but weaker than its pre-crisis values during the sovereign debt crisis in the euro area. By contrast, the volatility spillovers from stock to bond markets (bottom right panel) remain stronger than the pre-crisis levels for many countries during the last years of our sample. In a broad sense, these stronger return shock and volatility spillover effects from bond to stock markets are also consistent with the previous studies such as [Scruggs and Glabadanidis](#page-33-3) [\(2003\)](#page-33-3) and [Kim et al.](#page-33-1) [\(2006\)](#page-33-1) which, however, only focus on the return shock spillovers. In fact, especially for the period covering the euro area debt crisis, the return shock spillovers from bond to stock markets remain absent, whereas our results provide strong evidence for a (negative) volatility spillover effect during this period. Therefore, studies disregarding the volatility spillovers - which may have important implications for investors and policy-makers, especially in times of financial crisis - may fail to detect any lagged linkages between volatilities of both financial markets.

4.4 Dynamic conditional correlations

Figure [4](#page-24-0) illustrates the evolution of the dynamic conditional correlations between stock and bond markets, along with the corresponding correlations obtained from the baseline model in order to pinpoint the importance of the lagged volatility linkages on the correlation dynamics.

As evident from these figures, the dynamic correlations of our model (black line) show an increasingly negative stock-bond return correlation in euro area financial markets during the first years of the common currency area. This is consistent with previous studies, such as [Cappiello et al.](#page-31-4) [\(2006\)](#page-31-4) and [Kim et al.](#page-33-1) [\(2006\)](#page-33-1), confirming the segmentation of stock and bond markets at national levels in the euro area. However, these correlations start to follow different patterns across euro area financial markets with the emergence of the global financial crisis. Such correlations start to increase rapidly in financially weak euro area economies, especially after the collapse of Lehman Brothers in late 2008. The correlations rise to 80% in Greece, Italy, Ireland, Portugal and Spain during the peak of the euro area sovereign debt crisis pointing to a joint collapse of the national stock and bond markets. By contrast, they remain mainly negative in core EMU economies during the recent global financial turmoil. However, they spike in almost all European economies during the second half of 2013 reflecting financial market uncertainty associated with the future of the euro area. By contrast, they remain mainly in the negative territory in developed economies outside continental Europe, such as the US, Canada, Japan and Australia, during the recent financial turmoil.

Figure [4](#page-24-0) also highlights the differences between the dynamic correlations obtained from the baseline and extended models by a pairwise comparison for each country.[12](#page-2-0) Overall, the dynamic correlations obtained from the extended model seem to exhibit more erratic movements than those obtained from the baseline model, which is also consistent with our estimation results. This implies that the lagged volatility transmission has a remarkable impact on the correlation structure. In general, both dynamic correlations are supposed to have the same form in the absence of spillover effects. Accordingly, the dynamic correlations tend to move together when the spillovers are weak, whereas stronger spillover effects between both financial variables lead to remarkable deviations of the correlations obtained from the baseline and extended models. For example, the positive volatility spillover effect in the pre-crisis period is offset by a negative spillover effect in Portugal during the euro area debt crisis. This is reflected by the different correlations in the precrisis period in Figure [4,](#page-24-0) while this difference is absent from the negative spillovers and both correlations seem to have similar dynamics during the sovereign debt crisis in the

¹²The model selection is also supported by statistical as well as economic arguments. First, our timevarying spillover coefficients are highly significant for all stock and bond markets considered in this study. This is also backed by a statistical model comparison based on the likelihood ratios or information criteria. The estimation results of the initial DCC-model of [Engle](#page-32-5) [\(2002\)](#page-32-5) are not reported in this paper for brevity, but are available from the authors upon request.

Figure 4: DCC comparison between stock and bond returns

Notes: The graphs plot the dynamic conditional correlations obtained from the baseline (grey line) and extended (black line) models between domestic stock and bond market returns for selected economies over the period 1999:1:1−2015:9:30.

Figure ⁴ (continued): DCC comparison between stock and bond returns

Notes: The graphs plot the dynamic conditional correlations obtained from the baseline (grey line) and extended (black line) models between domestic stock and bond market returns for selected economies over the period 1999:1:1−2015:9:30.

euro area. Against this backdrop, the lagged volatility transmission seems to also have important practical implications for investors, volatility traders and risk managers.

4.5 Economic implications of volatility spillovers

This subsection aims to emphasise the economic implications of time-varying volatility spillovers for investors and risk managers. Earlier studies, such as [Kroner and Sultan](#page-33-9) [\(1993\)](#page-33-9), [Kroner and Ng](#page-33-10) [\(1998\)](#page-33-10) and [Ewing and Malik](#page-32-15) [\(2005\)](#page-32-15) show that the choice of the variance model has important implications for risk-minimising portfolio weights as well as the hedge ratios. [Kroner and Sultan](#page-33-9) [\(1993\)](#page-33-9) argue that the risk-minimising hedge ratio is time-varying and hence suggest using a GARCH framework for estimating the covariance matrix. Moreover, [Kroner and Ng](#page-33-10) [\(1998\)](#page-33-10) show that different multivariate volatility models can lead to different estimations for the risk-minimising portfolio weights and hedge ratios. Similarly, [Ewing and Malik](#page-32-15) [\(2005\)](#page-32-15) highlight the importance of volatility shifts in portfolio management. Against this background, this paper emphasises the relevance of timevarying volatility spillovers in the estimation of the portfolio weights (and hedge ratios) of the considered assets in the multivariate volatility framework. To this end, we compare the relative performance of the portfolio constructed with the weights obtained from the VAR (VECM) UEDCC-AGARCH model (extended portfolio) to that of the portfolio in which the risk-minimising portfolio weights are calculated with the baseline DCC-GARCH framework (baseline portfolio) in terms of average portfolio returns, volatility and information ratios.

Similar to the related studies, we first consider the problem of calculating the optimal asset holdings of the fully invested portfolio under the no-shorting constraint. Against this backdrop, the equation for risk-minimising portfolio weights takes the following form for equities

$$
w_{s,t} = \frac{h_{bb,t} - h_{sb,t}}{h_{ss,t} - 2 * h_{sb,t} + h_{bb,t}}
$$
\n(7)

with the optimal portfolio holdings of stocks considering the no-shorting constraint being

$$
w_{s,t}^{*} = \begin{cases} 0 & \text{if } w_{s,t} < 0\\ w_{s,t} & \text{if } 0 \le w_{s,t} \le 1\\ 1 & \text{if } w_{s,t} > 1. \end{cases}
$$
 (8)

Accordingly, $w_{b,t}^* = 1 - w_{s,t}^*$ corresponds to the optimal portfolio weights of the bond holdings. After calculating the risk-minimising portfolio weights of stocks and bonds obtained from the extended and baseline frameworks, we use these weights to construct the extended and baseline portfolios, which consist of domestic stocks and 10-year government bonds for all countries considered in this study. Then, we calculate the daily portfolio returns, their standard deviations and the information ratios of the constructed portfolios and compare their performances accordingly. Table [3](#page-28-0) summarises the results of the portfolio performance comparison over different periods and for various country groups.[13](#page-2-0)

In Table [3,](#page-28-0) the top and bottom panels present the differences in average daily returns and information ratios, while the positive numbers point to a better performance of the extended portfolio relative to the baseline portfolio in terms of more returns/lower losses and better information ratios.^{[14](#page-2-0)} Moreover, the volatility differences of both portfolios are reported in the middle panel in which negative values point to a better performance in the sense of lower standard deviation of the extended portfolio compared to that of the baseline one. The numbers in brackets tell in how many cases (out of the total number of countries considered in each group) the portfolio based on weights obtained from the extended GARCH framework performed better than based on those from the baseline portfolio.

Overall, the extended portfolio generated on average slightly lower returns than the portfolio based on the baseline DCC framework and worse information ratios over the full sample; however, it provided better returns and information ratios in 7 out of 20 countries considered in this empirical analysis. Considering different country groups, our portfolio performed better in some peripheral euro area members as well as developed countries in the rest of the world in terms of average returns. Moreover, it generated more returns than the baseline portfolio in 16 out of 20 countries during the subprime mortgage crisis, while it was beaten by the baseline portfolio in the other two crisis stages. However, the aim of constructing a risk-minimising portfolio is to build a minimum variance portfolio rather than generating more excess returns, and thus the focus has been shifted from average daily returns to portfolio volatilities. As such, the daily returns of the extended portfolio were less volatile than those of the baseline portfolio in 18 out of the 20 countries over the full sample period. Moreover, this mainly remained unchanged in most countries over the course of the most recent global financial crisis. In summary, our results suggest that considering the time-variation in the return and volatility spillovers in a multivariate volatility modelling framework leads to lower portfolio volatility, on average.

5 Conclusion

In this paper, we analyse the time-varying dynamic linkages between stock and bond market returns and volatilities for twenty advanced economies over the period January 1999 to September 2015. In particular, we examine how return and volatility spillovers between both financial variables have been affected by the different stages of the most recent financial crisis. Our contributions to the existing literature are threefold: (i) Our

¹³SMC, GFC and EDC stand for the subprime mortgage crisis, the peak of the global financial crisis and the euro area sovereign debt crisis, respectively. Peripheral EMU: Belgium, Greece, Ireland, Italy, Portugal and Spain; Core EMU: Austria, Finland, France, Germany and the Netherlands; Non-EMU-Europe: Denmark, Norway, Sweden, Switzerland and the UK; RoW: Australia, Canada, Japan and the US. The results of a country-by-county portfolio performance comparison are not reported here for brevity, but are available from the authors upon request.

¹⁴The information ratio is a measure for the risk-adjusted returns of a portfolio compared to a benchmark. It is defined as the excess returns (portfolio returns minus benchmark returns) divided by its standard deviation (excess returns and its standard deviation are also referred to as active return and tracking error, respectively). The information ratio takes the following form: $IR = (R_p - R_b)/\sqrt{Var(R_p - R_b)}$ where R_p and R_b are the realised returns of the extended and baseline portfolios, respectively, and $\sqrt{Var(R_p - R_b)}$ is the standard deviation of the excess returns.

	All countries	Peripheral EMU	Core $\mathop{\rm EMU}\nolimits$	Non-EMU- EU	Row
		Average Daily Return Differences $\times 10^{-3}$			
	-0.00200	0.00111	-0.00490	-0.00527	0.00107
FullSample	(7/20)	(3/6)	(1/5)	(1/5)	(2/4)
PreCrisis	-0.00195	0.00349	-0.00613	-0.00654	0.00086
	(8/20)	(4/6)	(1/5)	(1/5)	(2/4)
SMC	0.02257	0.01936	0.03188	0.01945	0.01964
	(16/20)	(5/6)	(5/5)	(4/5)	(2/4)
GFC	-0.03716	-0.04345	-0.04711	-0.06006	0.01333
	(1/20)	(0/6)	(0/5)	(0/5)	(1/4)
EDC	-0.00324	-0.00120	-0.00600	-0.00324	-0.00284
	(8/20)	(3/6)	(1/5)	(2/5)	(2/4)
		Average Standard Deviation Differences $\times 10^{-3}$			
FullSample	-0.02841	-0.10420	-0.01047	-0.01043	0.04037
	(18/20)	(6/6)	(5/5)	(4/5)	(3/4)
PreCrisis	0.00802	0.00899	-0.00132	-0.00298	0.03199
	(12/20)	(4/6)	(2/5)	(4/5)	(2/4)
SMC	-0.01258	-0.01610	-0.03005	-0.01770	0.02095
	(15/20)	(4/6)	(4/5)	(4/5)	(3/4)
GFC	-0.03978	-0.03754	-0.03844	-0.02615	-0.06185
	(15/20)	(6/6)	(4/5)	(3/5)	(2/4)
EDC	-0.04580	-0.17331	-0.01546	-0.01568	0.06989
	(17/20)	(6/6)	(5/5)	(4/5)	(2/4)
Information Ratios					
FullSample	-0.0073	0.0034	-0.0155	-0.0153	-0.0033
	(7/20)	(3/6)	(1/5)	(1/5)	(2/4)
PreCrisis	-0.0093	0.0060	-0.0198	-0.0248	0.0002
	(8/20)	(4/6)	(1/5)	(1/5)	(2/4)
SMC	0.0597	0.0512	0.0991	0.0604	0.0223
	(16/20)	(5/6)	(5/5)	(4/5)	(2/4)
GFC	-0.0838	-0.0858	-0.1149	-0.0977	-0.0247
	(1/20)	(0/6)	(0/5)	(0/5)	(1/4)
EDC	-0.0077	0.0037	-0.0196	-0.0085	-0.0090
	(8/20)	(3/6)	(1/5)	(2/5)	(2/4)

Table 3: Portfolio Performance Comparison

Notes: This table reports a summary of the relative performance of the extended to baseline portfolio. The portfolios are compared in terms of their average daily returns, standard deviations and information ratios over the different crisis stages as well as the full sample. Accordingly, the differences between average daily portfolio returns and standard deviations are reported in percentage points for all countries and various country groups. While positive numbers report a better performance (relatively more returns or fewer losses) in terms of returns and information ratios, the negative numbers in the middle panel point to better performance in the sense of less volatility compared to the baseline portfolio. The numbers in brackets refer to in how many cases out of the total number of countries considered in each group the portfolio based on the extended GARCH framework performed better than the baseline portfolio.

adopted bivariate VAR (VECM) UEDCC-AGARCH model enables us to model volatility spillovers directly via linkages between lagged conditional variances of stock and bond returns, (ii) We examine how return and volatility spillovers between both financial variables have been affected by the different stages of the most recent financial crisis, and (iii) Our bivariate model is also flexible enough to capture possible negative volatility spillovers between both financial variables. Hence, a thorough empirical analysis of the dependence between stock and bond returns is conducted during the period under investigation.

The results suggest that mean, shock and volatility spillovers between stock and bond returns exhibit a substantial time-variation over the recent financial crisis. In particular, the results show that the return and shock spillovers are mostly running from stocks to bonds; such spillovers are time-varying over the different stages of the recent crisis. Regarding volatility spillovers, they are mostly running from bond returns to those of stock and are also time-varying, especially during the European sovereign debt crisis, but not during the other stages of the recent crisis and the pre-crisis period. These findings are broadly consistent with previous studies (e.g., [Scruggs and Glabadanidis](#page-33-3) [\(2003\)](#page-33-3), [Kim et al.](#page-33-1) [\(2006\)](#page-33-1), among others), even though such studies only focus on return shock spillovers. By contrast, we also include the volatility transmission mechanism into our variance equations in addition to return shock spillovers. For instance, while the return shock spillover coefficients remain insignificant, the volatility spillover coefficients are highly significant during the euro area debt crisis. This also highlights the importance of the lagged volatility structure for a proper volatility transmission modelling between financial markets.

The results reflect cross-country differences in terms of policies and to what extent they have been affected by the different stages of the recent financial crisis. Moreover, our findings have important practical implications. They suggest limited diversification opportunities for investors within national economies during the European sovereign debt crisis, since the two financial assets are shown to be strongly interlinked during such period. However, the portfolio performance comparison results suggest that the portfolio volatility can be reduced considering the time-varying return and volatility spillovers in calculating the risk-minimising weights of the selected assets in the portfolio despite limited diversification opportunities within national financial markets.

This paper can be considered as an initial step to incorporate the time-varying volatility transmission mechanism in examining linkages between financial markets. In this regard, our study can also be extended in various ways. While this study documents significant time-variation in the volatility transmission, the determinants of these shifts in the transmission are not closely studied here. It may be an interesting extension to examine the main driving forces behind the time-varying volatility transmission and the structural channels of the transmission mechanism. On the other hand, we define the same crisis periods for all countries under investigation in order to observe the possible changes in the transmission mechanism. While this approach finds strong evidence for time-varying volatility linkages between the national stock and bond markets, the crisis periods can also be estimated for each country endogenously. This will certainly shed light on the country-specific factors influencing the volatility linkages between the domestic financial markets. Moreover, changes in the spillover coefficients are assumed to be known and set ex-post in this study. However, the changes in return and volatility spillover coefficients may be captured in real-time implementation by allowing for time-varying parameters e.g. obtained by estimating the model in rolling windows. Despite these limitations, this paper is able to pinpoint the importance of the time-varying volatility transmission on the linkages between stock and bond returns appropriately. Hence, the remaining open questions are left for further research.

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A Appendix

Statistics	Variable	Germany	France	NetherlandAustria		Finland	Belgium
	$r_{s,t}$	0.151	0.003	-0.006	0.016	0.007	-0.001
Mean	$r_{b,t}$	0.008	0.008	0.008	0.009	0.007	0.008
Std. Dev.	$r_{s,t}$	1.152	1.473	1.455	1.406	1.846	1.267
	$r_{b,t}$	0.349	0.354	0.336	0.337	0.328	0.358
Skewness	$r_{s,t}$	-0.021	-0.001	-0.105	-0.214	-0.355	0.025
	$r_{b,t}$	-0.175	-0.177	-0.216	-0.284	-0.145	-0.199
Ex. Kurtosis	$r_{s,t}$	4.322	4.739	6.284	7.626	7.267	5.924
	$r_{b,t}$	1.867	2.818	1.503	2.282	1.506	4.409
JB	$r_{s,t}$	$3402.***$	4089.***	7197.***	10659.***	9694.***	6390.***
	$r_{b,t}$	$657.9***$	1468.***	$445.2***$	$1006.***$	$428.0***$	3568.***
LB(10)	$r_{s,t}$	$22.99**$	$56.49***$	$67.70***$	$29.64***$	$21.65***$	$52.06***$
	$r_{b,t}$	$38.38***$	$27.25***$	$32.97***$	$59.39***$	$24.85***$	$126.51***$
$LB^2(10)$	$r_{s,t}$	$2240.***$	$2112.***$	3527.***	$4181.***$	$508.4***$	$2761.***$
	$r_{b,t}$	$409.9***$	$672.1***$	$358.4***$	684.8***	$413.6***$	2941.***

Table A.1: Descriptive Statistics - core EMU members

Notes: This table reports descriptive statistics of stock and bond returns for selected economies, denoted by $r_{s,t}$ and $r_{b,t}$, respectively. JB is the Jarque–Bera test for normality. $LB(p)$ and $LB²(p)$ are [Ljung and](#page-33-11) [Box](#page-33-11) [\(1978\)](#page-33-11) tests for the p^{th} order serial correlation on returns $r_{i,t}$ and squared returns $r_{i,t}^2$ for $i = s, b$, respectively.

 $*,**$ and $***$ denote statistical significance at 10%, 5% and 1% levels, respectively.

Statistics	Variable	Greece	Italy	Ireland	Portugal	Spain
Mean	$r_{s,t}$	-0.036	-0.012	0.005	-0.018	-0.001
	$r_{b,t}$	-0.010	0.008	0.007	0.008	0.009
Std. Dev.	$r_{s,t}$	1.909	1.514	1.372	1.194	1.485
	$r_{b,t}$	1.645	0.442	0.518	0.722	0.449
Skewness	$r_{s,t}$	-0.211	-0.081	-0.572	-0.193	0.069
	$r_{b,t}$	1.072	0.653	0.456	-0.606	0.904
Ex. Kurtosis	$r_{s,t}$	5.897	4.343	7.833	31.82	5.006
	$r_{b,t}$	122.2	19.48	31.82	50.72	16.010
JB	$r_{s,t}$	6362.***	3437.***	11406.***	$6850.***$	4567.***
	$r_{b,t}$	2680125.***	69361.***	184417.***	468467.***	47258.***
LB(10)	$r_{s,t}$	$40.17***$	$46.59***$	$35.15***$	$46.39***$	$30.79***$
	$r_{b,t}$	$304.8***$	$94.16***$	$231.6***$	$229.5***$	$215.1***$
$LB^2(10)$	$r_{s,t}$	$532.1***$	1868.***	2860.***	$1328.***$	$1465.****$
	$r_{b,t}$	$704.6***$	$522.7***$	885.6***	$387.4***$	$320.3***$

Table A.2: Descriptive Statistics - peripheral EMU members

Notes: See Table [A.1.](#page-34-0)

Statistics	Variable	Sweden	Norway	Denmark	Switzerland	UK
Mean	$r_{s,t}$	0.016	0.037	0.033	0.004	0.001
	$r_{b,t}$	0.005	0.007	0.007	0.005	0.006
Std. Dev.	$r_{s,t}$	1.514	1.376	1.266	1.189	1.208
	$r_{b,t}$	0.339	0.348	0.347	0.291	0.386
Skewness	$r_{s,t}$	0.055	-0.623	-0.240	-0.176	-0.160
	$r_{b,t}$	-0.172	-0.138	-0.082	0.059	-0.014
Ex. Kurtosis	$r_{s,t}$	3.492	6.523	5.633	6.924	6.136
	$r_{b,t}$	2.827	3.721	3.948	5.767	1.811
JB	$r_{s,t}$	$2222.***$	8027.***	5819.***	8750.***	6873.***
	$r_{b,t}$	$1477.****$	$2534.***$	2842.***	$6057.***$	597.4***
LB(10)	$r_{s,t}$	$29.90***$	$20.53**$	$36.38***$	$72.14***$	81.99***
	$r_{b,t}$	$58.52***$	93.86***	$56.17***$	$26.28***$	$34.62***$
$LB^2(10)$	$r_{s,t}$	$1640.***$	4386.***	2762.***	$2831.***$	3067.***
	$r_{b,t}$	$242.9***$	$467.9***$	$334.5***$	$155.5***$	$422.5***$

Table A.3: Descriptive Statistics - non-EMU Europe

Notes: See Table A.1.

Table A.4: Descriptive Statistics - non-EMU developed countries

Statistics	Variable	US	Canada	Japan	Australia
	$r_{s,t}$	0.010	0.016	0.006	0.014
Mean	$r_{b,t}$	0.005	0.008	0.006	0.004
Std. Dev.	$r_{s,t}$	1.241	1.122	1.357	0.989
	$r_{b,t}$	0.483	0.369	0.255	0.497
Skewness	$r_{s,t}$	-0.178	-0.656	-0.367	-0.493
	$r_{b,t}$	-0.061	-0.163	-0.559	-0.081
Ex. Kurtosis	$r_{s,t}$	8.122	9.396	6.315	5.941
	$r_{b,t}$	2.579	1.074	6.717	2.682
JB	$r_{s,t}$	12031.***	16387.***	7356.***	6603.***
	$r_{b,t}$	$1214.***$	$229.5***$	8442.***	1314.***
LB(10)	$r_{s,t}$	$52.14***$	$53.75***$	$20.55**$	14.59
	$r_{b,t}$	$16.75*$	12.10	$15.95*$	$39.51***$
$LB^2(10)$	$r_{s,t}$	$3412.***$	$3515.***$	2892.***	$3025.***$
	$r_{b,t}$	$402.4***$	288.4	1807.***	$381.6***$

Notes: See Table A.1.

Country	s_t on b_t	b_t on s_t
Germany	$-2.093(5)$	$-1.398(5)$
France	$-1.785(10)$	0.690(10)
Netherlands	$-1.775(8)$	0.410(4)
Austria	$-1.486(2)$	0.274(5)
Finland	$-2.140(7)$	0.059(4)
Belgium	$-1.809(10)$	0.241(5)
Greece	$-1.168(10)$	$-1.580(10)$
Italy	$-1.850(6)$	$-0.688(12)$
Ireland	$-1.634(8)$	$-1.372(3)$
Portugal	$-1.419(9)$	$-0.742(12)$
Spain	$-2.001(5)$	$-0.001(8)$
Sweden	$-2.047(6)$	$-1.390(7)$
Norway	$-2.397(1)$	$-1.771(10)$
Denmark	$-2.233(8)$	$-2.216(8)$
Switzerland	$-1.748(7)$	$-0.269(7)$
UK	$-2.304(8)$	$-0.750(6)$
US	$-1.662(5)$	$-1.688(2)$
Canada	$-2.410(6)$	$-1.744(5)$
Japan	$-1.339(6)$	$-0.387(11)$
Australia	$-2.177(3)$	0.274(5)

Table A.5: Results of the Engle and Granger cointegration tests between stock and bond prices

Notes: This table reports the results of the Engle and Granger cointegration tests between the log of stock prices (s_t) and the log of bond prices (b_t) . The pairwise Engle and Granger tests are conducted by regressing s_t on b_t and vice versa for each of the selected economies. The lag order is chosen by considering the AIC and given in parenthesis. The 1%, 5%, and 10% critical values from the MacKinnon (1991) for the augmented Dickey−Fuller test statistic are −3.89, −3.33, and −3.04, respectively.

Country	Lags	$\,r\,$	Eigenvalues	Trace test	95\% c.v.
		$r=0$	0.002	8.562	15.410
Germany	$\mathbf 5$	$r \leq 1$	0.000	0.343	3.840
	$\mathbf 5$	$r=0$	0.002	9.236	15.410
France		$r\leq 1$	0.000	0.060	3.840
Netherlands	8	$r=0$	0.003	12.466	15.410
		$r \leq 1$	0.000	1.178	3.840
	$\mathbf{1}$	$r=0$	0.001	3.923	15.410
Austria		$r \leq 1$	0.000	0.321	3.840
Finland	$1\,$	$r=0$	0.002	8.249	15.410
		$r \leq 1$	0.000	0.000	3.840
Belgium	3	$r=0$	0.003	12.866	15.410
		$r \leq 1$	0.000	0.931	3.840
Greece	11	$r=0$	0.001	3.091	15.410
		$r \leq 1$	0.000	0.215	3.840
Italy	$\,6$	$r=0$	0.002	7.478	15.410
		$r\leq 1$	0.000	0.930	3.840
Ireland	$\sqrt{6}$	$r=0$	0.001	6.395	15.410
		$r \leq 1$	0.000	0.626	3.840
Portugal	12	$r=0$	0.002	9.696	15.410
		$r\leq 1$	0.001	2.146	3.840
	$\,$ 6 $\,$	$r=0$	0.002	8.098	15.410
Spain		$r \leq 1$	0.000	0.404	3.840
Sweden	$\mathbf{1}$	$r=0$	0.002	9.646	15.410
		$r \leq 1$	0.000	0.008	3.840
Norway	$\boldsymbol{6}$	$r=0$	0.003	11.609	15.410
		$r\leq 1$	0.000	0.000	3.840
Denmark	$\boldsymbol{6}$	$r=0$	0.002	10.251	15.410
		$r \leq 1$	0.000	0.197	3.840
Switzerland	7	$r=0$	0.002	8.337	15.410
		$r \leq 1$	0.000	0.191	3.840
UK	$\overline{9}$	$r=0$	0.003	11.191	15.410
		$r \leq 1$	0.000	0.214	3.840
US	8	$r=0$	0.002	7.377	15.410
		$r \leq 1$	0.000	0.256	3.840
Canada	$\bf 5$	$r=0$	0.002	7.099	15.410
		$r \leq 1$	0.000	0.086	3.840
Japan	$\overline{0}$	$r=0$	0.001	4.289	15.410
		$r \leq 1$	0.000	0.859	3.840
Australia	3	$r=0$	0.001	6.206	15.410
		$r \leq 1$	0.000	0.334	3.840

Table A.6: Results of the Johansen (1995) cointegration tests between stock and bond prices

Notes: This table reports the results of the Johansen cointegration tests between the log of stock prices and the log of bond prices. The trace test column consists of the Johansen trace test statistics for each country's stock and bond prices. r is the cointegrating rank. The lag length is selected using the Akaike Information Criterion (AIC). 33

Regression	Model	Germany	France	Netherlands	Austria	Finland	Belgium
s_t on b_t	C	$-2.963(0)$	$-2.626(8)$	$-2.837(8)$	$-3.076(1)$	$-3.155(0)$	$-2.592(3)$
		[2001:08:27]	[2001:10:10]	[2002:08:07]	[2004:05:06]	[2001:07:25]	[2008:10:24]
	C/T	$-3.698(12)$	$-2.588(8)$	$-2.836(10)$	$-3.341(1)$	$-3.18(0)$	$-3.178(3)$
		[2001:10:09]	[2001:10:10]	[2002:08:08]	[2008:07:29]	[2001:07:18]	[2008:08:28]
	C/S	$-3.809(3)$	$-3.04(5)$	$-3.374(11)$	$-3.118(8)$	$-3.299(12)$	$-2.779(2)$
		[2004:12:08]	[2004:03:15]	[2004:11:25]	[2006:05:24]	[2003:07:03]	[2004:03:05]
b_t on s_t	C	$-2.913(6)$	$-2.562(2)$	$-2.889(6)$	$-3.193(12)$	$-3.033(5)$	$-2.814(2)$
		[2011:10:03]	[2012:06:08]	[2012:06:11]	[2011:10:27]	[2011:11:16]	[2012:06:08]
	C/T	$-4.543(1)$	$-4.431(1)$	$-4.69(1)$	$-4.287(9)$	$-4.369(4)$	$-4.194(1)$
		[2006:03:20]	[2006:03:10]	[2006:03:16]	[2007:02:27]	[2006:03:17]	[2006:05:12]
	C/S	$-3.88(2)$	$-3.463(6)$	$-3.988(12)$	$-3.548(1)$	$-3.764(1)$	$-3.677(10)$
		[2008:07:17]	[2008:09:16]	[2008:09:02]	[2011:06:29]	[2011:06:01]	[2008:09:04]

Table A.7: Results of the Gregory and Hansen cointegration tests between stock and bond prices: core EMU members

Notes: This table reports the results of the Gregory and Hansen cointegration tests between the log of stock prices (s_t) and the log of bond prices (b_t) . The pairwise Gregory and Hansen tests are conducted by regressing s_t on b_t and vice versa for each of the selected economies. The lag order is chosen by considering the AIC and given in parenthesis. The critical values for each specification are taken from Gregory and Hansen (1996).

Notes: See Table A.7.

Regression	Model	Sweden	Norway	Denmark	Switzerland	UK.
s_t on b_t	C	$-3.084(8)$	$-3.361(1)$	$-2.673(1)$	$-2.528(6)$	$-2.907(8)$
		[2001:10:03]	[2005:04:26]	[2013:02:18]	[2012:12:19]	[2001:10:03]
	C/T	$-3.328(0)$	$-2.894(0)$	$-2.413(11)$	$-2.987(5)$	$-3.832(7)$
		[2001:07:26]	[2005:07:06]	[2008:07:31]	[2012:04:30]	[2001:10:02]
	C/S	$-3.177(0)$	$-3.358(1)$	$-2.887(1)$	$-3.02(5)$	$-3.383(4)$
		[2001:07:23]	[2005:04:14]	[2003:06:19]	[2005:02:14]	[2009:09:24]
b_t on s_t	$\rm C$	$-2.931(1)$	$-3.042(2)$	$-3.292(1)$	$-2.944(2)$	$-3.839(1)$
		[2002:04:08]	[2011:06:22]	[2009:01:02]	[2011:08:22]	[2011:06:28]
	C/T	$-4.342(1)$	$-3.901(2)$	$-4.346(11)$	$-4.028(2)$	$-4.821(1)$
		[2006:03:23]	[2006:08:14]	[2011:09:28]	[2006:02:28]	[2011:06:28]
	C/S	$-3.348(1)$	$-3.24(1)$	$-3.428(1)$	$-3.446(2)$	$-4.126(1)$
		[2008:05:19]	[2008:08:20]	[2008:07:18]	[2010:04:07]	[2010:04:07]

Table A.9: Results of the Gregory and Hansen cointegration tests between stock and bond prices: non-EMU European economies

Notes: See Table A.7.

Notes: See Table A.7.

	Mean Equation						Variance Equation		
μ_s	$0.0469***$	$\psi_{sb,1}$		ω_s	$0.0415***$	α_{sb}		α_{bs}	
	(0.01)				(0.01)				
μ_b	0.0067	$\psi^{d1}_{sb,1}$		ω_b	$0.0013^{***}\,$	α_{sb}^{d1}	$0.3845^{\ast\ast\ast}$	α_{bs}^{d1}	$0.0004**$
	(0.00) $0.0662***$				(0.00)		(0.11)		(0.00)
$\psi_{ss,1}$	(0.01)	$\psi^{d2}_{sb,1}$		α_{ss}	$0.0176**$ (0.01)	α_{sb}^{d2}		α_{bs}^{d2}	
$\psi_{bb,1}$	$0.0628***$	$\psi_{sb,1}^{d3}$		α_{bb}	$0.0292***$	α_{sb}^{d3}		α_{bs}^{d3}	$0.0005***$
	(0.02)				(0.01)				(0.00)
		$\psi_{bs,1}$	$0.0160***$	β_{ss}	$0.8963***$	β_{sb}	$-0.0973**$	β_{bs}	
			(0.00)		(0.01)		(0.05)		
		$\psi^{d1}_{bs,1}$		β_{bb}	$0.9469***$	β^{d1}_{sb}		β^{d1}_{bs}	
					(0.01)				
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1133***$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	
		$\psi_{bs,1}^{d3}$		γ_{bb}	$0.0165*$	β^{d3}_{sb}	$0.1614***$	β_{bs}^{d3}	
					(0.01)		(0.04)		
				α^{DCC}	$0.0402***$				
					(0.01)				
				β^{DCC}	$0.9417***$				
					(0.01)				
LogL	-7735.69								
Q(5)	19.00 [0.52]								
$Q^2(5)$	19.15								
	[0.45]								

Table A.11: Results of the bivariate VAR-UEDCC-AGARCH estimation: Austria

∗∗∗ Significant at 1%

	Mean Equation			Variance Equation						
μ_s	$0.0201*$	$\psi_{sb,1}$		ω_s	$0.0107**$	α_{sb}		α_{bs}		
μ_b	(0.01) 0.0061	$\psi^{d1}_{sb,1}$		ω_b	(0.00) $0.0021**$	α_{sb}^{d1}		α_{bs}^{d1}		
$\psi_{ss,1}$	(0.00) $0.0429^{\ast\ast\ast}$ (0.01)	$\psi^{d2}_{sb,1}$		α_{ss}	(0.00)	α_{sb}^{d2}		α_{bs}^{d2}		
$\psi_{bb,1}$	$0.0884***$ (0.02)	$\psi_{sb,1}^{d3}$		α_{bb}	$0.0270***$ (0.01)	α_{sb}^{d3}		α_{bs}^{d3}	$0.0015**$ (0.00)	
		$\psi_{bs,1}$	$0.0144***$ (0.00)	β_{ss}	$0.8878***$ (0.01)	β_{sb}	$0.2009^{***}\,$ (0.08)	β_{bs}	$0.0008***$ (0.00)	
		$\psi^{d1}_{bs,1}$		β_{bb}	$0.9214***$ (0.02)	β^{d1}_{sb}		β^{d1}_{bs}		
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1716***$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}		
		$\psi_{bs,1}^{d3}$	$0.0277***$	γ_{bb}	$0.0343***$	β^{d3}_{sb}		β_{bs}^{d3}		
			(0.01)	α^{DCC}	(0.01) $0.0472***$					
				β^{DCC}	(0.01) $0.9369***$ (0.01)					
LogL	-7362.52									
Q(5)	18.46									
	[0.56]									
$Q^2(5)$	26.05 [0.13]									

Table A.12: Results of the bivariate VAR-UEDCC-AGARCH estimation: Belgium

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	$0.0499***$	$\psi_{sb,1}$		ω_s	$0.0105**$	α_{sb}		α_{bs}	
μ_b	(0.02) 0.0062 (0.00)	$\psi^{d1}_{sb,1}$		ω_b	(0.00) $0.0011**$ (0.00)	α_{sb}^{d1}		α_{bs}^{d1}	
$\psi_{ss,1}$	$0.0332**$ (0.01)	$\psi^{d2}_{sb,1}$		α_{ss}	$0.0239***$ (0.01)	α_{sb}^{d2}		α_{bs}^{d2}	$0.0005*$ (0.00)
$\psi_{bb,1}$	$0.0552***$ (0.01)	$\psi_{sb,1}^{d3}$		α_{bb}	$0.0366***$ (0.01)	α_{sb}^{d3}		α_{bs}^{d3}	$0.0004*$ (0.00)
		$\psi_{bs,1}$		β_{ss}	$0.9544***$ (0.01)	β_{sb}		β_{bs}	
		$\psi^{d1}_{bs,1}$	$0.0244**$ (0.01)	β_{bb}	$0.9506***$ (0.01)	β^{d1}_{sb}		β^{d1}_{bs}	
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.0381***$ (0.01)	β^{d2}_{sb}		β_{bs}^{d2}	
		$\psi_{bs,1}^{d3}$	$0.0220***$ (0.01)	γ_{bb}		β^{d3}_{sb}	-0.0585^{\ast} (0.03)	β_{bs}^{d3}	
				α^{DCC}	$0.0449***$				
				β^{DCC}	(0.01) $0.9399***$ (0.02)				
LogL	-8741.97								
Q(5)	18.98								
	[0.52]								
$Q^2(5)$	26.18 [0.13]								

Table A.13: Results of the bivariate VAR-UEDCC-AGARCH estimation: Finland

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	0.0142	$\psi_{sb,1}$		ω_s	0.0076	α_{sb}		α_{bs}	
μ_b	(0.01) $0.0071*$	$\psi^{d1}_{sb,1}$		ω_b	(0.01) $0.0011***$	α_{sb}^{d1}	$0.6674**$	α_{bs}^{d1}	$0.0004*$
$\psi_{ss,1}$	(0.00) $-0.0402^{***}\psi_{sb,1}^{d2}$			α_{ss}	(0.00)	α_{sb}^{d2}	(0.32)	α_{bs}^{d2}	(0.00)
$\psi_{bb,1}$	(0.01) $0.0548***$ (0.01)	$\psi_{sb,1}^{d3}$		α_{bb}	$0.0379***$ (0.01)	α_{sb}^{d3}		α_{bs}^{d3}	$0.0003***$ (0.00)
		$\psi_{bs,1}$	$0.0101**$ (0.00)	β_{ss}	$0.8925***$ (0.01)	β_{sb}	$0.3595***$ (0.09)	β_{bs}	
		$\psi^{d1}_{bs,1}$		β_{bb}	$0.9515***$ (0.01)	β^{d1}_{sb}	$-0.6221**$ (0.29)	β_{bs}^{d1}	
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1581***$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	
		$\psi_{bs,1}^{d3}$	$0.0183***$ (0.01)	γ_{bb}		β^{d3}_{sb}		β_{bs}^{d3}	
				α^{DCC}	$0.0461***$				
				β^{DCC}	(0.00) $0.9413***$ (0.00)				
LogL	-8148.36								
Q(5)	$25.03\,$								
	[0.20]								
$Q^2(5)$	26.19 [0.13]								

Table A.14: Results of the bivariate VAR-UEDCC-AGARCH estimation: France

∗∗∗ Significant at 1%

	Mean Equation			Variance Equation						
μ_s	$0.0372***$ (0.01)	$\psi_{sb,1}$		ω_s	0.0057 (0.01)	α_{sb}		α_{bs}	$0.0002^{***}\,$ (0.00)	
μ_b	0.0054 (0.00)	$\psi^{d1}_{sb,1}$		ω_b	$0.0010***$ (0.00)	α_{sb}^{d1}		α^{d1}_{bs}	$0.0009**$ (0.00)	
$\psi_{ss,1}$		$\psi_{sb,1}^{d2}$	$0.5617*$ (0.30)	α_{ss}		α_{sb}^{d2}		α_{bs}^{d2}		
$\psi_{ss,2}$		$\psi_{sb,1}^{d3}$	$0.1530**$ (0.07)	α_{bb}	$0.0221***$ (0.00)	α_{sb}^{d3}		α_{bs}^{d3}	$0.0007^{***}\,$ (0.00)	
$\psi_{bb,1}$	$0.0473***$ (0.01)	$\psi_{bs,2}$		β_{ss}	$0.8879***$ (0.01)	β_{sb}	$0.5635***$ (0.01)	β_{bs}		
$\psi_{bb,2}$		$\psi^{d1}_{bs,2}$		β_{bb}	$0.9555^{\ast\ast\ast}$ (0.01)	β^{d1}_{sb}	$-0.2774***\beta_{bs}^{d1}$ (0.08)			
		$\psi^{d2}_{bs,2}$		γ_{ss}	$0.1587^{\ast\ast\ast}$ (0.01)	β^{d2}_{sb}		β_{bs}^{d2}		
		$\psi^{d3}_{bs,2}$	$0.0158^{\ast\ast}$ (0.01)	γ_{bb}	$0.0137***$ (0.00)	β^{d3}_{sb}	$-0.2136***\beta_{bs}^{d3}$ (0.04)			
				α^{DCC}	$0.0433***$ (0.01)					
				β^{DCC}	$0.9486***$ (0.01)					
LogL	-8113.52									
Q(5)	19.01									
	[0.52]									
$Q^2(5)$	25.78 [0.14]									

Table A.15: Results of the bivariate VAR-UEDCC-AGARCH estimation: Germany

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	0.0189	$\psi_{sb,2}$		ω_s	$0.0242***$	α_{sb}		α_{bs}	
μ_b	(0.02) $0.0012\,$	$\psi^{d1}_{sb,2}$		ω_b	(0.01) $0.0034***$	α_{sb}^{d1}		α_{bs}^{d1}	
$\psi_{ss,1}$	(0.01) $0.0888***$	$\psi^{d2}_{sb,2}$		α_{ss}	(0.00) $0.0523***$	α_{sb}^{d2}		α_{bs}^{d2}	$0.0023**$
$\psi_{ss,2}$	(0.01) $-0.0274**$ (0.01)	$\psi_{sb,2}^{d3}$	$0.0413**$ (0.02)	α_{bb}	(0.01) $0.1000***$ (0.03)	α_{sb}^{d3}		α_{bs}^{d3}	(0.00)
$\psi_{bb,1}$	$0.0925***$ (0.01)	$\psi_{bs,1}$		β_{ss}	$0.9099***$ (0.02)	β_{sb}		β_{bs}	
$\psi_{bb,3}$		$\psi^{d1}_{bs,1}$		β_{bb}	$0.8500^{***}\,$ (0.02)	β^{d1}_{sb}		β^{d1}_{bs}	
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.0590^{***}\,$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	
		$\psi_{bs,1}^{d3}$	$0.0929***$ (0.02)	γ_{bb}	$0.0626**$ (0.03)	β_{sb}^{d3}	0.0123^{\ast} (0.01)	β_{bs}^{d3}	$0.0324***$ (0.01)
				α^{DCC}	$0.0196***$				
				β^{DCC}	(0.00) $0.9804***$ (0.00)				
LogL	-11770.33								
Q(5)	22.02								
	[0.34]								
$Q^2(5)$	25.34 [0.15]								

Table A.16: Results of the bivariate VAR-UEDCC-AGARCH estimation: Greece

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	$0.0384***$	$\psi_{sb,1}$		ω_s	$0.0361***$	α_{sb}	$0.0189*$	α_{bs}	
	(0.01)				(0.01)		(0.01)		
μ_b	0.0017	$\psi^{d1}_{sb,1}$		ω_b	$0.0013***$	α_{sb}^{d1}	$0.6440^{\ast\ast}$	α_{bs}^{d1}	
	(0.00)				(0.00)		(0.29)		
$\psi_{ss,1}$	$0.0460***$	$\psi^{d2}_{sb,1}$		α_{ss}	$0.0326***$	α_{sb}^{d2}	$0.6742*$	α_{bs}^{d2}	
	(0.02)				(0.01)		(0.37)		
$\psi_{bb,1}$	$0.1004***$	$\psi^{d3}_{sb,1}$		α_{bb}		α_{sb}^{d3}		α_{bs}^{d3}	
	(0.02)								
		$\psi_{bs,1}$	$0.0182***$	β_{ss}	$0.8880***$	β_{sb}		β_{bs}	$0.0005***$
			(0.00)		(0.02)				(0.00)
		$\psi^{d1}_{bs,1}$		β_{bb}	$0.9387***$	β^{d1}_{sb}		β^{d1}_{bs}	
					(0.01)				
		$\psi^{d2}_{bs,1}$	$0.0214*$	γ_{ss}	$0.0934***$	β^{d2}_{sb}		β_{bs}^{d2}	
			(0.01)		(0.02)				
		$\psi_{bs,1}^{d3}$		γ_{bb}	$0.0888***$	β^{d3}_{sb}		β_{bs}^{d3}	$0.0028***$
				α^{DCC}	(0.02)				(0.00)
					0.0160				
				β^{DCC}	(0.01) $0.9828***$				
					(0.01)				
LogL	-8581.19								
Q(5)	15.57								
	[0.74]								
$Q^2(5)$	21.26								
	[0.32]								

Table A.17: Results of the bivariate VAR-UEDCC-AGARCH estimation: Ireland

∗∗∗ Significant at 1%

	Mean Equation			Variance Equation						
μ_s	0.0024	$\psi_{sb,1}$		ω_s	$0.0116***$	α_{sb}		α_{bs}	$0.0004^{***}\,$	
	(0.01)				(0.00)				(0.00)	
μ_b	0.0018	$\psi^{d1}_{sb,1}$		ω_b	$0.0013***$	α_{sb}^{d1}		α_{bs}^{d1}		
	(0.00) $-0.0435***\psi_{sb,1}^{d2}$				(0.00) $0.0094*$	α_{sb}^{d2}		α_{bs}^{d2}		
$\psi_{ss,1}$	(0.01)			α_{ss}	(0.01)					
$\psi_{ss,2}$		$\psi_{sb,1}^{d3}$		α_{bb}	$0.0147*$	α_{sb}^{d3}		α_{bs}^{d3}	$0.0020***$	
					(0.01)				(0.00)	
$\psi_{bb,1}$	$0.0758^{\ast\ast\ast}$	$\psi_{bs,1}$	$0.0190^{***}\,$	β_{ss}	$0.9132***$	β_{sb}	$0.1351***$	β_{bs}		
	(0.01)		(0.00)		(0.01)		(0.04)			
$\psi_{bb,2}$	$-0.0371^{***}\psi^{d1}_{bs,1}$ (0.01)			β_{bb}	$0.9316***$ (0.01)	β^{d1}_{sb}		β^{d1}_{bs}		
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1161***$	β^{d2}_{sb}		β_{bs}^{d2}		
					(0.02)					
		$\psi_{bs,1}^{d3}$		γ_{bb}	$0.0687^{\ast\ast\ast}$	β^{d3}_{sb}		β_{bs}^{d3}		
					(0.02)					
				α^{DCC}	$0.0431***$					
				β^{DCC}	(0.01) $0.9538***$					
					(0.01)					
LogL	-8511.63									
Q(5)	$27.50\,$									
	[0.12]									
$Q^2(5)$	23.10									
	[0.23]									

Table A.18: Results of the bivariate VAR-UEDCC-AGARCH estimation: Italy

∗∗∗ Significant at 1%

	Mean Equation			Variance Equation					
μ_s	0.0142 (0.01)	$\psi_{sb,1}$	$0.0768**$ (0.04)	ω_s	-0.0077 (0.01)	α_{sb}		α_{bs}	
μ_b	0.0046 (0.00)	$\psi^{d1}_{sb,1}$		ω_b	$0.0013***$ (0.00)	α_{sb}^{d1}	$0.4988*$ (0.26)	α_{bs}^{d1}	$0.0005**$ (0.00)
$\psi_{ss,1}$		$\psi^{d2}_{sb,1}$		α_{ss}		α_{sb}^{d2}		α_{bs}^{d2}	$0.0003*$ (0.00)
$\psi_{bb,1}$	$0.0614***$ (0.01)	$\psi_{sb,1}^{d3}$		α_{bb}	$0.0123**$ (0.01)	α_{sb}^{d3}		α_{bs}^{d3}	$0.0010***$ (0.00)
		$\psi_{bs,1}$	$0.0064*$ (0.00)	β_{ss}	$0.8850***$ (0.01)	β_{sb}	$0.6065***$ (0.16)	β_{bs}	$0.0003***$ (0.00)
		$\psi^{d1}_{bs,1}$	0.0213^{\ast} (0.01)	β_{bb}	$0.9539***$ (0.01)	β^{d1}_{sb}	$-0.6153***\beta_{bs}^{d1}$ (0.22)		
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1688***$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	
		$\psi_{bs,1}^{d3}$	$0.0173**$ (0.01)	γ_{bb}	$0.0234***$ (0.01)	β^{d3}_{sb}	$-0.2174***\beta_{bs}^{d3}$ (0.07)		
				α^{DCC}	$0.0435***$ (0.01)				
				β^{DCC}	$0.9453***$ (0.01)				
LogL	-7556.44								
Q(5)	17.03								
	[0.65]								
$Q^2(5)$	26.29 [0.12]								

Table A.19: Results of the bivariate VAR-UEDCC-AGARCH estimation: Netherlands

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	0.0165	$\psi_{sb,1}$	$0.1048***$	ω_s	$0.0137***$	α_{sb}		α_{bs}	
	(0.01)		(0.04)		(0.00)				
μ_b	0.0019	$\psi^{d1}_{sb,1}$		ω_b	0.0000	α_{sb}^{d1}		α^{d1}_{bs}	
	(0.00) $0.1023***$	$\psi^{d2}_{sb,1}$	0.4186	α_{ss}	(0.00) $0.0370^{***}\,$	α_{sb}^{d2}		α_{bs}^{d2}	
$\psi_{ss,1}$	(0.01)		(0.25)		(0.01)				
$\psi_{ss,2}$		$\psi_{sb,1}^{d3}$	$-0.1311***$	α_{bb}	$0.0388**$	α_{sb}^{d3}		α_{bs}^{d3}	
			(0.05)		(0.02)				
$\psi_{bb,1}$	$0.0593***$	$\psi_{bs,1}$	$0.0142***$	β_{ss}	$0.8968***$	β_{sb}	$0.0386**$	β_{bs}	$0.0005**$
	(0.02)		(0.01)		(0.01)		(0.02)		(0.00)
$\psi_{bb,2}$		$\psi^{d1}_{bs,1}$	0.0303^{**}	β_{bb}	$0.9401***$	β^{d1}_{sb}		β^{d1}_{bs}	
		$\psi^{d2}_{bs,1}$	(0.01)		(0.01) $0.0995***$	β^{d2}_{sb}		β_{bs}^{d2}	
				γ_{ss}	(0.02)				
		$\psi^{d3}_{bs,1}$	$0.0458***$	γ_{bb}	$0.0531***$	β_{sb}^{d3}	$-0.0255*$	β_{bs}^{d3}	
			(0.02)		(0.02)		(0.02)		
				α^{DCC}	$0.0208***$				
					(0.01)				
				β^{DCC}	$0.9787***$				
					(0.01)				
LogL Q(5)	-8892.98 24.64								
	[0.22]								
$Q^2(5)$	19.01								
	[0.46]								

Table A.20: Results of the bivariate VAR-UEDCC-AGARCH estimation: Portugal

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	0.0140	$\psi_{sb,1}$		ω_s	$0.0185***$	α_{sb}	$0.0702**$	α_{bs}	
	(0.01) 0.0029	$\psi^{d1}_{sb,1}$			(0.00) $0.0013^{***}\,$	α_{sb}^{d1}	(0.03)	α^{d1}_{bs}	$0.0015**$
μ_b	(0.01)			ω_b	(0.00)				(0.00)
$\psi_{ss,1}$		$\psi^{d2}_{sb,1}$		α_{ss}		α_{sb}^{d2}		α_{bs}^{d2}	
$\psi_{ss,2}$		$\psi^{d3}_{sb,1}$		α_{bb}		α_{sb}^{d3}		α_{bs}^{d3}	
$\psi_{bb,1}$	$0.1100^{***}\,$	$\psi_{bs,1}$	$0.0198***$	β_{ss}	$0.9179***$	β_{sb}		β_{bs}	$0.0005***$
	(0.01)		(0.00)		(0.01)				(0.00)
$\psi_{bb,2}$	$-0.0328^{\ast\ast\ast}$	$\psi_{bs,2}$	$-0.0082*$	β_{bb}	$0.9388***$	β^{d1}_{sb}		β^{d1}_{bs}	$-0.0013**$
	(0.01)		(0.00)		(0.01)				(0.00)
		$\psi^{d1}_{bs,1}$		γ_{ss}	$0.1305***$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	
		$\psi^{d2}_{bs,1}$		γ_{bb}	$0.0778^{\ast\ast\ast}$	β^{d3}_{sb}		β_{bs}^{d3}	$0.0028***$
					(0.02)				(0.00)
		$\psi_{bs,1}^{d3}$		α^{DCC}	$0.0340**$				
					(0.01)				
				β^{DCC}	$0.9628***$				
					(0.02)				
LogL	-8760.61								
Q(5)	21.91								
	[0.35]								
$Q^2(5)$	26.79								
	[0.11]								

Table A.21: Results of the bivariate VAR-UEDCC-AGARCH estimation: Spain

∗∗∗ Significant at 1%

 $\frac{4}{\pi}$ Significant at 5\%
 $\frac{5}{\pi}$ Significant at 10\% Significant at 10%

	Mean Equation						Variance Equation		
μ_s	$0.0507^{***}\,$	$\psi_{sb,1}$		ω_s	$0.0355***$	α_{sb}		α_{bs}	
μ_b	(0.01) 0.0049	$\psi^{d1}_{sb,1}$		ω_b	(0.01) $0.0002\,$	α_{sb}^{d1}		α_{bs}^{d1}	
	(0.00)				(0.00)				
$\psi_{ss,1}$	$0.0347**$	$\psi_{sb,1}^{d2}$	$-0.5883*$	α_{ss}	$0.0307***$	α_{sb}^{d2}		α_{bs}^{d2}	
	(0.02)		(0.34)		(0.01)				
$\psi_{bb,1}$	$0.0744***$	$\psi_{sb,1}^{d3}$		α_{bb}	$0.0283***$	α_{sb}^{d3}		α_{bs}^{d3}	
	(0.02)				(0.00)				
		$\psi_{bs,1}$	$0.0117***$	β_{ss}	$0.8367***$	β_{sb}	$0.6286***$	β_{bs}	$0.0005***$
			(0.00)		(0.02)		(0.19)		(0.00)
		$\psi^{d1}_{bs,1}$	$-0.0533^{\ast\ast\ast}$ (0.01)	β_{bb}	$0.9625***$ (0.00)	β^{d1}_{sb}		β^{d1}_{bs}	
		$\psi^{d2}_{bs,1}$	$-0.0250*$	γ_{ss}	$0.1278***$	β^{d2}_{sb}		β_{bs}^{d2}	
			(0.01)		(0.02)				
		$\psi^{d3}_{bs,1}$		γ_{bb}		β^{d3}_{sb}	$-0.2967**$ β_{bs}^{d3}		$0.0006^{***}\,$
							(0.12)		(0.00)
				α^{DCC}	$0.0359***$				
					(0.01)				
				β^{DCC}	$0.9421***$				
					(0.01)				
LogL	-7674.29								
Q(5)	12.40 [0.90]								
$Q^2(5)$	21.92								
	[0.29]								

Table A.22: Results of the bivariate VAR-UEDCC-AGARCH estimation: Denmark

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	$0.0668^{\ast\ast\ast}$	$\psi_{sb,1}$		ω_s	$0.0500***$	α_{sb}		α_{bs}	
μ_b	(0.01) $0.0039\,$ (0.00)	$\psi^{d1}_{sb,1}$		ω_b	(0.01) $0.0033***$ (0.00)	α_{sb}^{d1}		α_{bs}^{d1}	
$\psi_{ss,1}$		$\psi^{d2}_{sb,1}$		α_{ss}	$0.0330***$ (0.01)	α_{sb}^{d2}		α_{bs}^{d2}	
$\psi_{bb,1}$	$0.1034^{***}\,$ (0.01)	$\psi_{sb,1}^{d3}$		α_{bb}	$0.0665***$ (0.01)	α_{sb}^{d3}		α_{bs}^{d3}	
		$\psi_{bs,1}$		β_{ss}	$0.8747***$ (0.01)	β_{sb}		β_{bs}	
		$\psi^{d1}_{bs,1}$		β_{bb}	$0.9063***$ (0.02)	β_{sb}^{d1}	$0.2728**$ (0.12)	β^{d1}_{bs}	
		$\psi^{d2}_{bs,1}$	$-0.0407**$ (0.02)	γ_{ss}	$0.1142***$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	
		$\psi_{bs,1}^{d3}$	-0.0172^{\ast} (0.01)	γ_{bb}		β^{d3}_{sb}	$-0.1294***\beta_{bs}^{d3}$ (0.04)		
				α^{DCC}	0.0176				
				β^{DCC}	(0.01) $0.9703***$ (0.03)				
LogL	-7862.10								
Q(5)	18.14 [0.58]								
$Q^2(5)$	20.46 [0.37]								

Table A.23: Results of the bivariate VAR-UEDCC-AGARCH estimation: Norway

∗∗∗ Significant at 1%

	Mean Equation			Variance Equation							
μ_s	$0.0332^{***}\,$	$\psi_{sb,1}$	ω_s	$0.0111**$	α_{sb}		α_{bs}				
μ_b	(0.01) 0.0019	$\psi^{d1}_{sb,1}$	ω_b	(0.01) $0.0022***$	α_{sb}^{d1}		α^{d1}_{bs}				
$\psi_{ss,1}$	(0.00) $-0.0312^{\ast\ast}$	$\psi_{sb,1}^{d2}$	α_{ss}	(0.00)	α_{sb}^{d2}		α_{bs}^{d2}				
$\psi_{bb,1}$	(0.01) $0.0930***$	$\psi_{sb,1}^{d3}$	α_{bb}	$0.0527***$	α_{sb}^{d3}		α_{bs}^{d3}				
	(0.02)	$\psi_{bs,1}$	β_{ss}	(0.01) $0.9252***$ (0.01)	β_{sb}	$0.2495***$ (0.10)	β_{bs}				
		$\psi^{d1}_{bs,1}$	β_{bb}	$0.9279***$ (0.01)	β^{d1}_{sb}		β^{d1}_{bs}				
		$\psi^{d2}_{bs,1}$	γ_{ss}	$0.1135^{\ast\ast\ast}$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	$0.0007*$ (0.00)			
		$\psi^{d3}_{bs,1}$	γ_{bb}		β_{sb}^{d3}	$-0.1656***\beta_{bs}^{d3}$ (0.05)					
			α^{DCC}	$0.0280***$ (0.01)							
			β^{DCC}	$0.9629***$ (0.01)							
LogL	-8222.09										
Q(5)	17.25										
	[0.64]										
$Q^2(5)$	$23.95\,$ [0.20]										

Table A.24: Results of the bivariate VAR-UEDCC-AGARCH estimation: Sweden

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	$0.0197*$	$\psi_{sb,2}$		ω_s	$0.0310***$	α_{sb}		α_{bs}	$0.0002**$
	(0.01)				(0.00)				(0.00)
μ_b	0.0049	$\psi^{d1}_{sb,2}$		ω_b	$0.0016***$	α_{sb}^{d1}		α_{bs}^{d1}	$0.0008**$
$\psi_{ss,1}$	(0.00)	$\psi_{sb,2}^{d2}$	$0.4635*$	α_{ss}	(0.00) $0.0217*$	α_{sb}^{d2}	$0.3379**$	α_{bs}^{d2}	(0.00) $0.0018^{\ast\ast}$
			(0.26)		(0.01)		(0.15)		(0.00)
$\psi_{ss,3}$	$-0.0357**$	$\psi_{sb,2}^{d3}$		α_{bb}	$0.0193^{\ast\ast}$	α_{sb}^{d3}		α_{bs}^{d3}	$0.0030***$
	(0.01)				(0.01)				(0.00)
$\psi_{bb,1}$	$0.0406***$	$\psi_{bs,2}$		β_{ss}	$0.8794***$	β_{sb}		β_{bs}	
	(0.01)				(0.01) $0.9374***$				
$\psi_{bb,3}$	$0.0302**$ (0.01)	$\psi^{d1}_{bs,2}$		β_{bb}	(0.01)	β^{d1}_{sb}		β^{d1}_{bs}	
		$\psi^{d2}_{bs,2}$		γ_{ss}	$0.1375^{\ast\ast\ast}$	β^{d2}_{sb}		β_{bs}^{d2}	
					(0.02)				
		$\psi^{d3}_{bs,2}$		γ_{bb}	$0.0305***$	β^{d3}_{sb}		β_{bs}^{d3}	$-0.0024***$
					(0.01)				(0.00)
				α^{DCC}	$0.0322***$				
				β^{DCC}	(0.01) $0.9511***$				
					(0.01)				
LogL	-6379.35								
Q(5)	26.27								
	[0.16]								
$Q^2(5)$	16.99 [0.59]								

Table A.25: Results of the bivariate VAR-UEDCC-AGARCH estimation: Switzerland

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	0.0088	$\psi_{sb,1}$	$0.1453***$	ω_s	-0.0008	α_{sb}		α_{bs}	
μ_b	(0.01) 0.0032 (0.00)	$\psi^{d1}_{sb,1}$	(0.05) $0.3149*$ (0.18)	ω_b	(0.01) $0.0007***$ (0.00)	α_{sb}^{d1}		α_{bs}^{d1}	$0.0049***$ (0.00)
$\psi_{ss,1}$	$-0.0443***\psi_{sb,1}^{d2}$ (0.01)		$0.5608***$ (0.21)	α_{ss}		α_{sb}^{d2}		α_{bs}^{d2}	
$\psi_{ss,2}$		$\psi_{sb,1}^{d3}$	$-0.1193*$ (0.06)	α_{bb}	$0.0191***$ (0.00)	α_{sb}^{d3}		α_{bs}^{d3}	$0.0008^{\ast\ast}$ (0.00)
$\psi_{bb,1}$	$0.0286**$ (0.01)	$\psi_{bs,1}$		β_{ss}	$0.8765***$ (0.01)	β_{sb}	$0.3432***$ (0.09)	β_{bs}	
$\psi_{bb,2}$	-0.0225 (0.01)	$\psi^{d1}_{bs,1}$	$0.0280**$ (0.01)	β_{bb}	$0.9736^{\ast\ast\ast}$ (0.00)	β^{d1}_{sb}		β^{d1}_{bs}	$-0.0044**$ (0.00)
		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1749***$ (0.02)	β^{d2}_{sb}		β_{bs}^{d2}	0.0005^{**} (0.00)
		$\psi_{bs,1}^{d3}$	$0.0237**$ (0.01)	γ_{bb}		β^{d3}_{sb}	$-0.1494***\beta_{bs}^{d3}$ (0.04)		
				α^{DCC}	$0.0368^{\ast\ast\ast}$				
				β^{DCC}	(0.01) $0.9511***$ (0.02)				
LogL	-7537.31								
Q(5)	27.52 [0.12]								
$Q^2(5)$	22.58 [0.26]								

Table A.26: Results of the bivariate VAR-UEDCC-AGARCH estimation: United Kingdom

^{***} Significant at 1%
** Significant at 5%

 $\frac{•}{•}$ Significant at 5\%

Significant at 10%

	Mean Equation						Variance Equation		
μ_s	$0.0300***$	$\psi_{sb,1}$		ω_s	$0.0144***$	α_{sb}		α_{bs}	$0.0010***$
μ_b	(0.01) 0.0042	$\psi^{d1}_{sb,1}$	$0.2618**$	ω_b	(0.00) $0.0015***$	α_{sb}^{d1}		α_{bs}^{d1}	(0.00) $0.0088**$
$\psi_{ss,1}$	(0.01) $-0.0479***\psi_{sb,1}^{d2}$ (0.01)		(0.11)	α_{ss}	(0.00)	α_{sb}^{d2}	$0.2870**$ (0.13)	α_{bs}^{d2}	(0.00)
$\psi_{bb,1}$		$\psi_{sb,1}^{d3}$	$-0.0661*$ (0.04)	α_{bb}	$0.0272***$ (0.00)	α_{sb}^{d3}		α_{bs}^{d3}	$0.0034^{***}\,$ (0.00)
η_{ss}	$-0.1303**$ (0.05)	$\psi_{bs,1}$		β_{ss}	$0.8958***$ (0.01)	β_{sb}	$0.0791^{\ast\ast\ast}$ (0.03)	β_{bs}	
η_{ss}^*		$\psi^{d1}_{bs,1}$		β_{bb}	$0.9590***$ (0.00)	β^{d1}_{sb}		β_{bs}^{d1}	$-0.0065*$ (0.00)
η_{bb}		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1530***$ (0.01)	β^{d2}_{sb}		β_{bs}^{d2}	
η^*_{bb}		$\psi^{d3}_{bs,1}$		γ_{bb}		β^{d3}_{sb}	$-0.0430***\beta_{bs}^{d3}$ (0.01)		$-0.0031***$ (0.00)
				α^{DCC}	$0.0467***$				
				β DCC	(0.00) $0.9446***$ (0.01)				
LogL	-8439.24								
Q(5)	26.68 [0.14]								
$Q^2(5)$	27.13 [0.10]								

Table A.27: Results of the bivariate VECM-UEDCC-AGARCH estimation: United States

^{***} Significant at 1%
** Significant at 5%

 $\frac{•}{•}$ Significant at 5\%

Significant at 10%

	Mean Equation			Variance Equation					
μ_s	$0.0361^{\ast\ast\ast}$	$\psi_{sb,1}$	$0.0651**$	ω_s	$0.0122***$	α_{sb}	α_{bs}		
μ_b	(0.01) 0.0040 (0.00)	$\psi^{d1}_{sb,1}$	(0.03)	ω_b	(0.00) $0.0016^{\ast\ast\ast}$ (0.00)	α_{sb}^{d1}	α_{bs}^{d1}	$0.0009**$ (0.00)	
$\psi_{ss,1}$	$0.0476***$ (0.02)	$\psi^{d2}_{sb,1}$		α_{ss}		α_{sb}^{d2}	α_{bs}^{d2}		
$\psi_{bb,1}$		$\psi_{sb,1}^{d3}$		α_{bb}	$0.0392***$ (0.01)	α_{sb}^{d3}	α_{bs}^{d3}		
η_{ss}		$\psi_{bs,1}$		β_{ss}	$0.9351***$ (0.01)	β_{sb}	β_{bs}		
η_{ss}^*	$-0.3803^{\ast\ast}$ (0.18)	$\psi^{d1}_{bs,1}$		β_{bb}	$0.9489^{\ast\ast\ast}$ (0.01)	β^{d1}_{sb}	β^{d1}_{bs}		
η_{bb}		$\psi^{d2}_{bs,1}$		γ_{ss}	$0.1003***$ (0.01)	β^{d2}_{sb}	β_{bs}^{d2}		
η^*_{bb}		$\psi^{d3}_{bs,1}$		γ_{bb}		β_{sb}^{d3}	$-0.0361***\beta_{bs}^{d3}$ (0.01)		
				α^{DCC}	$0.0301***$ (0.01)				
				β^{DCC}	$0.9603***$ (0.01)				
LogL	-7202.53								
Q(5)	23.72								
	[0.26]								
$Q^2(5)$	16.37 [0.63]								

Table A.28: Results of the bivariate VECM-UEDCC-AGARCH estimation: Canada

∗∗∗ Significant at 1%

	Mean Equation						Variance Equation		
μ_s	0.0023	$\psi_{sb,1}$		ω_s	$0.0466***$	α_{sb}		α_{bs}	
μ_b	(0.02) $0.0090***$	$\psi^{d1}_{sb,1}$		ω_b	(0.01) $0.0005***$	α_{sb}^{d1}		α_{bs}^{d1}	
$\psi_{ss,1}$	(0.00) $0.0516***$	$\psi^{d2}_{sb,1}$	$1.7926^{\ast\ast\ast}$	α_{ss}	(0.00) $0.0241***$	α_{sb}^{d2}		α_{bs}^{d2}	
$\psi_{bb,1}$	(0.01)	$\psi_{sb,1}^{d3}$	(0.62)	α_{bb}	(0.00) $0.0662***$	α_{sb}^{d3}		α_{bs}^{d3}	
η_{ss}	$-0.1261*$	$\psi_{bs,1}$	$-0.0069**$	β_{ss}	(0.01) $0.8752***$	β_{sb}	$0.2095***$	β_{bs}	$0.0003**$
η_{ss}^*	(0.06) $0.1914*$	$\psi^{d1}_{bs,1}$	(0.00) $0.0211***$	β_{bb}	(0.01) $0.9053***$	β^{d1}_{sb}	(0.08)	β^{d1}_{bs}	(0.00)
η_{bb}	(0.12)	$\psi^{d2}_{bs,1}$	(0.01) 0.0111	γ_{ss}	(0.01) $0.1285***$	β^{d2}_{sb}		β_{bs}^{d2}	$-0.0003*$
η^*_{bb}		$\psi_{bs,1}^{d3}$	(0.01) $0.0140***$	γ_{bb}	(0.01) $0.0364**$	β^{d3}_{sb}		β_{bs}^{d3}	(0.00) $-0.0004***$
			(0.00)	α^{DCC}	(0.02) $0.0259***$				(0.00)
				β^{DCC}	(0.01) $0.9684***$				
LogL	-6167.41				(0.01)				
Q(5)	12.31								
$Q^2(5)$	[0.91] 22.90 [0.24]								

Table A.29: Results of the bivariate VECM-UEDCC-AGARCH estimation: Japan

∗∗∗ Significant at 1%

	Mean Equation			Variance Equation						
μ_s	$0.0255^{\ast\ast\ast}$	$\psi_{sb,1}$		ω_s	$0.0123***$	α_{sb}		α_{bs}		
μ_b	(0.01) 0.0019 (0.01)	$\psi^{d1}_{sb,1}$		ω_b	(0.00) $0.0014***$ (0.00)	α_{sb}^{d1}		α_{bs}^{d1}		
$\psi_{ss,1}$		$\psi^{d2}_{sb,1}$		α_{ss}		α_{sb}^{d2}	$0.6305***$ (0.15)	α_{bs}^{d2}	$0.0014*$ (0.00)	
$\psi_{bb,1}$	$-0.0699***\psi_{sb,1}^{d3}$ (0.01)			α_{bb}	$0.0331***$ (0.01)	α_{sb}^{d3}		α_{bs}^{d3}		
		$\psi_{bs,1}$	$-0.0214**$ (0.01)	β_{ss}	$0.9224***$ (0.01)	β_{sb}		β_{bs}		
		$\psi^{d1}_{bs,1}$	$0.0434**$ (0.02)	β_{bb}	$0.9611***$ (0.01)	β^{d1}_{sb}		β^{d1}_{bs}		
		$\psi^{d2}_{bs,1}$	$0.0810**$ (0.04)	γ_{ss}	$0.1183***$ (0.02)	β^{d2}_{sb}	$-0.4502***\beta_{bs}^{d2}$ (0.13)			
		$\psi^{d3}_{bs,1}$	$0.0361**$ (0.02)	γ_{bb}		β^{d3}_{sb}		β^{d3}_{bs}		
				α^{DCC}	$0.0359***$ (0.01)					
				β^{DCC}	$0.9557***$ (0.01)					
LogL	-7997.95									
Q(5)	$22.63\,$									
	[0.31]									
$Q^2(5)$	21.06 [0.33]									

Table A.30: Results of the bivariate VAR-UEDCC-AGARCH estimation: Australia

∗∗∗ Significant at 1%