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On the economic determinants of optimal stock-bond portfolios: international evidence*

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Abstract

Using a modified DCC-MIDAS specification that allows the long-term correlation component to be a function of multiple explanatory variables, we show that the stock-bond correlation in the US, the UK, Germany, France, and Italy is mainly driven by inflation and interest rate expectations as well as a flight-to-safety during times of stress in financial markets. Based on the new DCC-MIDAS model, we construct stock-bond hedge portfolios and show that these portfolios outperform various benchmark portfolios in terms of portfolio risk. While optimal daily weights minimize portfolio risk, we find that portfolio turnover and trading costs can be substantially reduced when switching to optimal monthly weights.

Keywords: Stock-bond correlation, DCC, DCC-MIDAS, survey data, macro expectations, forecasting, portfolio choice, asset allocation.

JEL Classification: C32, C58, E44, E52, G11, G15, G17

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1 Introduction

Evaluating the potential benefits of explicitly modeling short- and long-term components in conditional correlations has recently become a swiftly expanding research area in financial econometrics.[1] For example, economic gains in financial applications such as portfolio choice or risk management have been documented in Colacito et al. (2011), Bauwens et al. (2013), and Bauwens and Otranto (2016).

We contribute to this growing literature by proposing a new specification for dynamic correlations that allows the long-term component to be a function of multiple low-frequency explanatory variables and, hence, to fluctuate at a lower frequency than the short-term correlation. Such a MIxed Data Sampling (MIDAS) framework is ideally suited for analyzing the low-frequency economic determinants of high-frequency conditional correlations. Our specification nests the DCC-MIDAS model of Colacito et al. (2011) in the specific case that lagged monthly realized correlation is the only explanatory variable. The new model allows us to combine lagged realized correlation, RC, with other economic explanatory variables, X, and to check whether those variables have explanatory power for the long-term correlation when controlling for lagged realized correlation. We specify the long-term component as a function of the weighted lagged values of the explanatory variables, whereby – in the spirit of the RiskMetrics model – we impose exponentially decaying weights. To make the new model tractable, we estimate an individual smoothing parameter for lagged realized correlation but impose the restriction that all other explanatory variables obey the same smoothing parameter. However, for each explanatory variable we estimate the coefficient that determines the variable's effect on the correlation. Hence, at each point in time the new model allows us to decompose the long-term correlation into the contributions stemming from the individual economic determinants. We refer to the new specification as the DCC-RC-X model. Of course, there are other approaches to introduce explanatory variables into conditional correlations. For example, the conditional correlation model presented in Bauwens and Otranto (2016) assumes that conditional correlations depend on market volatility. However, they focus on a single explanatory variable and do not cover the mixed-frequency case. While their model is also applicable to a high-dimensional setting, we restrict our attention to the bivariate case.

[1] Typically, a long-term component is either introduced as a time-varying constant or as a multiplicative factor in the conditional correlation (see, for example, Colacito et al., 2011, Hafner and Linton, 2010, and Bauwens et al., 2016/2017).

For a cross-section of countries, we apply the new DCC-RC-X approach to modeling the time-varying correlation between stock and bond returns. Although for most countries this correlation is close to zero on average, it varies strongly over time. As the following quote underlines, the stock-bond correlation is of crucial importance for financial practitioners:

> "The correlation between stocks and bonds is one of the most important inputs to the asset allocation decision. However, it is difficult to estimate reliably, and can change drastically with macroeconomic conditions." Pimco (2013)

The quote also shows that practitioners are well aware of the fact that movements in the stock-bond correlation can often be traced back to changes in the economic environment. At least since Shiller and Beltratti (1992) and Campbell and Ammer (1993), there is a growing academic literature on the determinants of the comovement between stock and bond returns. More recent empirical and theoretical contributions are Connolly et al. (2005), Andersen et al. (2007), Andersson et al. (2008), Baele at al. (2010), David and Veronesi (2013), and Asgharian et al. (2015/2016), among others.

Using monthly expectations data from Consensus Economics for the April 1991 to January 2016 period, we provide international evidence on the economic determinants of the low-frequency stock-bond correlation. Our analysis covers data for the US, the UK, Germany, France, and Italy. We find that in all countries expectations regarding future CPI inflation are an important driver of the long-term stock-bond correlation. Our parameter estimates suggest that market participants expect central banks to counteract increasing inflation expectations by raising the policy rate.[2] This expectation leads to upward revisions in future expected returns which requires stock and bond prices to decline today.[3] That is, higher inflation expectations tend to increase the comovement between stocks and bonds. Similarly and by the same logic, we find that expectations of an increase in the future three-month interest rate boost the stock-bond correlation. Stress in financial markets (as measured by realized stock market volatility) is another important

[2] Engle and West (2006), Clarida and Waldman (2008), and Conrad and Lamla (2010) provide theoretical and empirical evidence for the notion that the response of financial markets to news about inflation depends on market participants' beliefs about the central bank's reaction function. If a central bank is expected to have a strong preference for low inflation, market participants increase their expectations concerning the policy rate in response to higher than expected inflation.

[3] The observation that stock market returns are negatively related to (expected) inflation goes back to Fama and Schwert (1977).

driver of the stock-bond correlation. We find that elevated levels of stock market volatility significantly reduce the stock-bond correlation in the US, the UK, Germany, and France. This observation can be rationalized by a flight-to-quality phenomenon (see Connolly et al., 2005, Bekaert et al., 2009, or Adrian et al., 2016). That is, in times of turbulent stock markets investors reduce their risk exposure by selling stocks and buying bonds which induces a negative correlation. For Italy, the stock-bond correlation appears to increase in response to heightened domestic stock market volatility. Again, this can be explained by a type of flight-to-quality. While for the other countries the explanation relies on a domestic re-balancing of stock and bond holdings, it appears that investors withdraw money from both Italian stocks and bonds and invest in safe haven countries (see also Conrad and Zumbach, 2016). Our results suggest that the long-term stock-bond correlation is mainly driven by expectations regarding future monetary policy and phases of stress in financial markets. Thus, we complement and extend previous findings by, for example, Andersson et al. (2008) and Asgharian et al. (2015) using a new model framework and considering a wider set of countries.

We then examine whether incorporating information about the economic environment in the long-term correlation of the DCC-RC-X model helps to improve asset allocation when constructing stock-bond hedge portfolios. We consider an investor who must hold stocks (bonds) and adds bonds (stocks) to reduce the portfolio risk. We compare the portfolio variance of this hedge portfolio for the different estimates of the conditional covariance matrix as implied by various DCC-RC-X models and certain benchmark models. Using the test for equal portfolio variances proposed by Engle and Colacito (2006), we show that hedge portfolios that are based on forecasts of the conditional covariance matrix from the DCC-RC-X models outperform portfolios based on simple benchmark models (such as a constant covariance matrix or the random walk model) in terms of portfolio variance. This is an important result, since simple benchmark models are often hard to beat (see DeMiguel et al., 2009). We also provide evidence that in the US, the UK, and Italy the DCC-RC-X models lead to portfolios with significantly lower variances than portfolios based on the standard DCC model when stock markets are not in turmoil. This finding is intuitively reasonable, since the long-term components of the DCC-RC-X models change smoothly with macroeconomic conditions and are most informative if conditional correlations do not change too abruptly. A nice feature of the DCC-RC-X models is that they allow us to directly link changes in optimal portfolio weights to changes in the underlying explanatory variables. For example, the negative stock-bond correlation that has been prevalent in most countries since the Great Depression can be explained by deflationary fears and the expectation of an ongoing expansionary monetary policy. Therefore, an investor who must hold stocks will also be long in bonds to hedge portfolio risk. That is, the favorable negative correlation creates hedging opportunities without the need for short selling. However, the risk of such a portfolio can dramatically increase if the correlation unexpectedly heads in a positive direction.[4] This example illustrates that it is of crucial importance to have a model that anticipates such changes in correlations. Finally, we provide a comparison of portfolios that are based on daily optimal weights with portfolios that are based on monthly optimal weights. Although the former lead to portfolios with lower risk, the latter portfolios require much less re-balancing (since monthly optimal weights are smoother) and, hence, have lower turnover. In essence, the net excess returns after trading costs are usually higher for the portfolios based on monthly optimal weights.

The remaining paper is organized as follows. Section 2 outlines the DCC-RC-X specification. Section 3 introduces the dataset. Section 4 presents our empirical results on the stock-bond correlation and the macro environment, while Section 5 presents the portfolio choice application. Section 6 provides some extensions and robustness checks. Finally, Section 7 concludes. Additional empirical results can be found in the Appendix.

2 Econometric Model

We denote the daily stock and bond returns by $r_{S,t}$ and $r_{B,t}$ and consider the bivariate vector of returns $\mathbf{r}_t = (r_{S,t}, r_{B,t})'$. We assume that expected returns $\mathbf{E}[\mathbf{r}_t|\mathcal{F}_{t-1}] = \boldsymbol{\mu} = (\mu_S, \mu_B)'$ are constant and write $\mathbf{r}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t$, where $\boldsymbol{\varepsilon}_t = (\varepsilon_{S,t}, \varepsilon_{B,t})'$. The conditional covariance matrix of the innovations $\boldsymbol{\varepsilon}_t$ is given by $\mathbf{H}_t = \mathbf{Var}[\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1}]$ and can be decom-

[4]For example, on December 14, 2015, the Financial Times article "Markets got used to monetary policy medicine" expressed concerns that the risk of stock-bond portfolios might "suddenly shoot up" in response to a positive "correlation shock" due to "central banks not being as accommodative as people wanted them to be". Similarly, on October 06, 2016, the Wall Street Journal published an article titled "Relationship between bonds and stocks gets complicated". It was argued that the correlation switched from negative to positive in September 2016 "because markets grew nervous about central-bank policy", i.e. because of the expectation of a tighter monetary policy.

posed as follows $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$, where

$$\mathbf{R}_t = \begin{pmatrix} 1 & \rho_{SB,t} \\ \rho_{SB,t} & 1 \end{pmatrix} \quad \text{and} \quad \mathbf{D}_t = \begin{pmatrix} h_{S,t}^{1/2} & 0 \\ 0 & h_{B,t}^{1/2} \end{pmatrix} \tag{1}$$

with $\rho_{SB,t}$ denoting the conditional correlation between stock and bond returns and $h_{S,t}$ and $h_{B,t}$ the conditional variances. If $\mathbf{R}_t$ is constant, the model reduces to the constant conditional correlation (CCC) model of Bollerslev (1990).

The DCC-RC-X specification: We model $h_{S,t}$ and $h_{B,t}$ as GARCH(1,1) processes with parameters $\omega_i > 0$, $\alpha_i > 0$, $\beta_i \geq 0$ and $\alpha_i + \beta_i < 1$, $i \in \{S, B\}$, and define the 'volatility-adjusted' residuals $Z_{S,t} = \varepsilon_{S,t}/\sqrt{h_{S,t}}$ and $Z_{B,t} = \varepsilon_{B,t}/\sqrt{h_{B,t}}$. Hence, the conditional stock-bond correlation can be expressed as

$$\rho_{SB,t} = \frac{\mathbf{Cov}(r_{S,t}, r_{B,t}|\mathcal{F}_{t-1})}{\sqrt{\mathbf{Var}[r_{S,t}|\mathcal{F}_{t-1}]\mathbf{Var}[r_{B,t}|\mathcal{F}_{t-1}]}} = \mathbf{E}[Z_{S,t}Z_{B,t}|\mathcal{F}_{t-1}], \tag{2}$$

i.e. in terms of the conditional correlation between the volatility-adjusted residuals. These dynamic correlations are modeled by specifying an equation for the 'quasi-correlations' in a first step and then by rescaling in a second step (see Engle, 2002). The quasi-correlations $\mathbf{Q}_t = [q_{ij,t}]_{i,j=S,B}$ are given by

$$\mathbf{Q}_t = (1 - \alpha_{SB} - \beta_{SB})\bar{\mathbf{R}}_\tau + \alpha_{SB}\boldsymbol{z}_{t-1}\boldsymbol{z}'_{t-1} + \beta_{SB}\mathbf{Q}_{t-1}, \tag{3}$$

where $\boldsymbol{z}_t = (Z_{S,t}, Z_{B,t})'$ and $\alpha_{SB} > 0$, $\beta_{SB} \geq 0$, $\alpha_{SB} + \beta_{SB} < 1$. The matrix $\bar{\mathbf{R}}_\tau$ contains the low-frequency long-term correlations, where τ denotes the lower frequency. Our model reduces to Engle's (2002) DCC specification with correlation targeting when $\bar{\mathbf{R}}_\tau$ is assumed to be constant and equal to the sample correlation matrix of the volatility-adjusted residuals. Instead, we allow the off-diagonal elements $\bar{\rho}_{SB,\tau}$ of $\bar{\mathbf{R}}_\tau$ to be driven by lagged monthly realized correlations as well as exogenous explanatory variables that are also observed at a monthly frequency. We will denote the explanatory variables by $X_{j,\tau}$, $j = 1, \ldots, J$. In this mixed frequency setting, the quasi-correlations can be written as

$$q_{SB,t} = \bar{\rho}_{SB,\tau} + \alpha_{SB}(Z_{S,t-1}Z_{B,t-1} - \bar{\rho}_{SB,\tau}) + \beta_{SB}(q_{SB,t-1} - \bar{\rho}_{SB,\tau}), \tag{4}$$

i.e. as evolving around the long-term correlation. In order to ensure that the long-term correlation $\bar{\rho}_{SB,\tau}$ is less than one in absolute value, we employ the Fisher-z transformation and specify

$$\bar{\rho}_{SB,\tau} = \frac{\exp(2m_{SB,\tau}) - 1}{\exp(2m_{SB,\tau}) + 1} \tag{5}$$

with

$$m_{SB,\tau} = \theta_{RC} \sum_{k=0}^{K_{RC}} \lambda_{RC}^k RC_{\tau-1-k} + \theta_1 \sum_{k=0}^{K_1} \lambda_1^k X_{1,\tau-1-k} + \ldots + \theta_J \sum_{k=0}^{K_J} \lambda_J^k X_{J,\tau-1-k} \quad (6)$$

$$= m_{RC,\tau} + m_{1,\tau} + \ldots + m_{J,\tau}. \quad (7)$$

In equation (6), RC_τ stands for the monthly realized correlation between the volatility-adjusted residuals

$$RC_\tau = \frac{\sum_{t=N_{\tau-1}+1}^{N_\tau} Z_{S,t} Z_{B,t}}{\sqrt{\sum_{t=N_{\tau-1}+1}^{N_\tau} Z_{S,t}^2 \sum_{t=N_{\tau-1}+1}^{N_\tau} Z_{B,t}^2}}, \quad (8)$$

where $N_\tau = \sum_{i=1}^{\tau} N^{(i)}$ with $N^{(i)}$ denoting the number of days within month i and $N_0 = 0$. When no explanatory variable $X_{j,\tau}$ is included, the model basically coincides with the DCC-MIDAS of Colacito et al. (2011).[5] Conrad et al. (2014) also employ a variant of equation (6) but impose the restriction that $\theta_{RC} = 0$ and $J = 1$, i.e. they consider a single explanatory variable only. On the contrary, we are explicitly interested in modeling the long-term correlation as a function of multiple explanatory variables while at the same time controlling for the effect of the lagged RC_τ. This will reveal whether macro conditions contain information that is complementary to the information included in lagged RC_τ. However, as discussed in Conrad and Loch (2015) for the case of a GARCH-MIDAS model, estimating individual weighting schemes for several variables at the same time is difficult. We therefore impose the following restriction: we estimate the parameter $0 < \lambda_{RC} < 1$, but impose the constraint that all $X_{j,\tau}$ variables share the same smoothing parameter, i.e. $\lambda_1 = \ldots = \lambda_J = \lambda$. This is a sensible restriction, since estimates with $J = 1$ for the different variables suggested that the same λ applies to all explanatory variables. Based on a grid search, we found $\lambda = 0.96$ to be the best choice in terms of information criteria.[6] In this way, equation (6) is parsimoniously specified and can be thought of as an 'Exponential Smoother' in the spirit of the RiskMetrics model. In addition, we choose $K_{RC} = K_1 = \ldots = K_J = 48$ lags, i.e. we employ four MIDAS lag years.[7] Note that despite these assumptions, equation (6) still involves $J + 2$ parameters that have to be

[5]Their long-term component uses a Beta weighting scheme and, in the absence of other explanatory variables than RC_τ, does not require a Fisher-z transformation.

[6]Asgharian et al. (2016) estimate a DCC-MIDAS model for the US stock-bond correlation including one variable at a time. Their parameter estimates imply that the optimal weighting scheme is almost flat. Our choice of $\lambda = 0.96$ is in line with their finding and ensures that the weights are slowly declining.

[7]We checked empirically that choosing 48 as a truncation lag is innocuous. Including more than 48 lags does not change any of our results.

estimated. In the empirical application, each explanatory variable $X_{j,\tau}$ is standardized so that the order of magnitude of the θ_j's is comparable. The θ_j parameters determine the impact of each variable on the long-term correlation and, in particular, the sign of the marginal effect. We refer to the specification with RC_τ and additional explanatory variables as DCC-RC-X and to the specification with $J = 0$ as DCC-RC.

Finally, the short-term correlation is obtained by rescaling:

$$\rho_{SB,t} = \frac{q_{SB,t}}{\sqrt{q_{SS,t}q_{BB,t}}} \tag{9}$$

Model estimation: Following Engle (2002) and Colacito et al. (2011), we estimate the DCC-MIDAS model in two steps. In a first step, we estimate univariate GARCH models for the stock and bond returns. Then, in a second step, we construct the volatility-adjusted residuals and estimate the parameters in the long- and short-term correlation components. That is, we sequentially maximize the first and the second term of the following log quasi-likelihood function

$$\mathcal{L} = -\sum_{t=1}^{T}\left(2\log(2\pi) + 2\log(|\mathbf{D}_t|) + \boldsymbol{\varepsilon}_t'\mathbf{D}_t^{-2}\boldsymbol{\varepsilon}_t\right) - \sum_{t=1}^{T}\left(\log(|\mathbf{R}_t|) + \boldsymbol{z}_t'\mathbf{R}_t^{-1}\boldsymbol{z}_t - \boldsymbol{z}_t'\boldsymbol{z}_t\right) \tag{10}$$

For further details on the two-step maximization, see Engle (2008).

Correlation ratios: In order to quantify the overall relevance of the long-term component as a determinant of the conditional correlation, we calculate the following correlation ratio (CR_1)

$$CR_1 = \frac{\mathbf{Var}[\bar{\rho}_{SB,\tau}]}{\mathbf{Var}[\rho_{SB,\tau}]}, \tag{11}$$

where $\rho_{SB,\tau} = 1/N^{(\tau)}\sum_{t=N_{\tau-1}+1}^{N_\tau}\rho_{SB,t}$. That is, CR_1 measures how much of the variability in the monthly conditional correlation can be attributed to changes in the long-term correlation. Equation (7) has the nice property that it provides a direct decomposition of the long-term correlation into the contributions, $m_{j,\tau}$, of the individual explanatory variables. We use this property to compute a second correlation ratio (CR_2)

$$CR_2 = \frac{\mathbf{Var}[m_{1,\tau} + \ldots + m_{J,\tau}]}{\mathbf{Var}[m_{SB,\tau}]}, \tag{12}$$

which measures how much of the total variation in $m_{SB,\tau}$ is due to changes in the explanatory variables. Hence, CR_2 portrays how relevant the explanatory variables are once one controls for the lagged realized correlation.

Correlation news impact function: The additional flexibility that is provided by the DCC-RC-X in comparison to the nested DCC can be illustrated by means of the correlation news impact function (CNIF), see Kroner and Ng (1998) and Engle (2008). The correlation news impact function shows how correlations are updated in response to news by expressing the correlation in $t+1$ as a function of the standardized shocks in t and prior information. The CNIF of the DCC-RC-X can be written as

$$\begin{aligned} CNIF_{t+1} &= f(Z_{S,t}, Z_{B,t}|\bar{\rho}_{SB,\tau}, q_{SS,t}, q_{BB,t}, q_{SB,t}) \\ &= \frac{(1-\alpha_{SB}-\beta_{SB})\bar{\rho}_{SB,\tau} + \alpha_{SB} Z_{S,t} Z_{B,t} + \beta_{SB} q_{SB,t}}{\sqrt{(1-\alpha_{SB}-\beta_{SB}+\alpha_{SB} Z_{S,t}^2 + \beta_{SB} q_{SS,t})(1-\alpha_{SB}-\beta_{SB}+\alpha_{SB} Z_{B,t}^2 + \beta_{SB} q_{BB,t})}} \end{aligned} \quad (13)$$

Clearly, the CNIF of the DCC is nested by restricting $\bar{\rho}_{SB,\tau} = \bar{\rho}_{SB}$. In principle, the CNIF can be represented in a three-dimensional plot as a correlation news impact *surface*. Since our specification is symmetric in both shocks, we prefer to present two-dimensional plots where either both shocks have the same sign and $Z_{B,t} = Z_{S,t}$ or have opposite signs and $Z_{B,t} = -Z_{S,t}$. Note that even if there is no shock, i.e. $Z_{S,t} = Z_{B,t} = 0$, there is an adjustment towards $\bar{\rho}_{SB,\tau}$ due to mean-reversion. For simplicity, consider the case where in addition $q_{SS,t} = q_{BB,t} = 1$ so that $\rho_{SB,t} = q_{SB,t}$. Then, we obtain

$$CNIF_{t+1} = \left(1 - \frac{\beta_{SB}}{1-\alpha_{SB}}\right)\bar{\rho}_{SB,\tau} + \frac{\beta_{SB}}{1-\alpha_{SB}}\rho_{SB,t}, \quad (14)$$

which shows that (in the absence of shocks) the CNIF is a weighted average of the long-term and the short-term correlation with $0 < \beta_{SB}/(1-\alpha_{SB}) < 1$ by construction. Thus, the adjustment towards $\bar{\rho}_{SB,\tau}$ is stronger the lower α_{SB} and β_{SB} are.

Figure 1 shows the CNIF of equation (13) for a situation in which $\rho_{SB,t} = 0.1$. The blue line represents a CNIF with $\bar{\rho}_{SB,\tau} = 0.3$ and the red line a CNIF with $\bar{\rho}_{SB,\tau} = -0.18$. The left (right) panel considers the case $Z_{B,t} = Z_{S,t}$ ($Z_{B,t} = -Z_{S,t}$). When $Z_{S,t} = Z_{B,t} = 0$, in both panels the blue (red) line is above (below) $\rho_{SB,t} = 0.1$ due to mean-reversion. Further, when $Z_{S,t}$ is increasing this leads to upward (downward) adjustments in the CNIF in the left (right) panel which simply reflects that shocks of the same (opposite) sign tend to increase (decrease) correlations. Finally, note that the difference in the two CNIFs is decreasing in the size of the shocks. Figure 1 nicely illustrates that in the DCC-RC-X the adjustment of the conditional correlation in response to news depends on the *current stance* of the long-term component. In sharp contrast, the long-term component is assumed to be constant in the DCC. It also helps us to understand under which circumstances the DCC-RC-X and the DCC will respond differently to shocks. If, for simplicity, we assume that both models have the same α_{SB} and β_{SB} parameters and also the same current short-term correlation $\rho_{SB,t}$, then Figure 1 can be interpreted as showing the CNIFs of a DCC with $\bar{\rho}_{SB} = -0.18$ and a DCC-RC-X with $\bar{\rho}_{SB,\tau} = 0.3$. Thus, the figure suggests that the differences in the updating of the correlations in response to news will be the strongest when shocks are small (and $|\bar{\rho}_{SB,\tau} - \bar{\rho}_{SB}|$ is large).

3 Data

We focus on the US and four major European countries, i.e. the United Kingdom (UK), Germany (GER), France (FR), and Italy (IT). For each country, we combine daily stock and bond returns with monthly macroeconomic expectations data and realized stock market volatility. Our data covers the period from April 1991 to January 2016 and includes around 6300 daily (the actual number of daily observations varies across countries due to different public holidays) and 298 monthly observations.

Stock and bond market data: The left panels of Figure 2 show the evolution of the stock and bond prices over the full sample period. For each country, we consider daily log-returns on MSCI stock prices and 10-year government bond prices.[8] Summary statistics for the daily stock and bond returns as well as their correlation for a rolling window of 22-days can be found in Panel A of Table 1, and for monthly realized stock and bond market volatilities, defined as the square root of the sum of squared daily returns, in Panel B. For all countries but Italy, the average annualized stock returns are higher than average annualized bond returns but at the same time stock volatility is at least twice as high as bond volatility. For all countries, the average 22-days rolling window correlation is close to zero. However, the minimum and maximum correlations over the sample period are roughly between ± 0.9, i.e. the correlations fluctuate heavily over time. The right panels of Figure 2 illustrate this behavior by plotting the 22-days rolling window correlations and, in addition, the much smoother 252-days rolling window correlations.

[8] The respective Tickers for the stock prices are: *MSUSAM$, MSUTDKL, MSGERML, MSFRNCL, MSITALL*. The respective Tickers for the 10-year government bond prices are: *BMUS10Y, BMUK10Y, BMBD10Y, BMFR10Y, BMIT10Y*.

Macro expectations data: We employ monthly expectations data for CPI inflation, GDP growth, and the three-month interest rate (I3M) from Consensus Economics.[9] For inflation and GDP growth, each month the forecasters provide expectations for this year's and next year's realizations, i.e. *fixed event* forecasts. We follow Dovern et al. (2012) and construct one-year-ahead *fixed horizon* predictions by first taking the average of the this year, $\bar{X}_{\tau,this}$, and the next year, $\bar{X}_{\tau,next}$, fixed event forecasts over the cross-section of forecasters, where τ refers to the month in which the prediction is produced. Fixed horizon one-year ahead predictions are then obtained as

$$X_\tau = \frac{k}{12}\bar{X}_{\tau,this} + \frac{12-k}{12}\bar{X}_{\tau,next},$$

where $k = 1, \ldots, 12$ refers to the number of remaining months in the year. The three-month interest rate predictions are directly for a fixed horizon of twelve months and, hence, we simply average over the forecasters. Panel C of Table 1 presents the summary statistics for the expectations data and Figure 3 provides an impression of the evolution of the expectations data over time and across countries. It also shows the monthly realized volatilities in the five stock markets.[10]

For each country, Table 2 provides an overview of the correlation between the expectations data, monthly realized stock market volatility (RV) and the monthly realized stock-bond correlation. In particular, the table reveals a strong correlation between inflation and interest rate expectations. Similarly, expectations on GDP growth have a sizable positive correlation with the three-month interest rate. This can be viewed as evidence that forecasters believe in central banks following a Taylor type policy rule, so that higher inflation and/or growth expectations are aligned with higher short-term interest rate expectations due to the expected monetary policy response.[11] The negative correlation between GDP growth and RV is in line with the counter-cyclical behavior of stock volatility documented, for example, in Schwert (1989) or, more recently, Paye (2012) and

[9]In contrast to the Fed's and the ECB's quarterly Survey of Professional Forecasters (SPF), Consensus Economics expectations are available for a range of countries and on a monthly basis, which substantially increases the number of usable observations. To be more specific, survey participants are asked to provide their forecasts in the first week of each month. The forecasts are then released in the second week of the month.

[10]For the DCC-RC-X model estimation, we standardize the explanatory variables by subtracting their means and dividing by their standard deviations. Since realized volatility is heavily skewed, we standardize it by subtracting its *median* and dividing by its standard deviation.

[11]For empirical evidence on the consistency of survey expectations with the Taylor rule see Dräger et al. (2016).

Conrad and Loch (2015). Finally, the table gives a first indication on how the stock-bond correlation is related to the economic environment. For all countries but Italy we find a strong positive correlation with expectations on inflation and the three-month interest rate, a weaker positive correlation with expected GDP growth, and a strong negative correlation with RV. The correlation pattern differs for Italy, where we find a negative correlation with expected GDP growth and a slightly positive correlation with RV instead. Also, the correlations with inflation and interest rate expectations are comparably low.

4 Long-term stock-bond correlation and the macro environment

4.1 GARCH parameter estimates

First, we very briefly present the parameter estimates for the GARCH(1,1) models for stocks and bonds in Tables 3. The parameter estimates for α_i and β_i are highly significant and take the usual values. As expected, both stock and bond returns have considerable volatility persistence as measured by $\alpha_i + \beta_i$ being close to one. Interestingly, for all countries but Italy the α_i (β_i) estimates are higher in the stock (bond) than on the bond (stock) market which suggests that stock markets are more responsive to news than bond markets. Finally, for all countries the unconditional variance, $\sigma_i^2 = \omega_i/(1 - \alpha_i - \beta_i)$, that is implied by the parameter estimates is higher in the stock than in the bond market.

4.2 DCC and DCC-RC parameter estimates

For each country, the first two lines in Table 4 present the parameter estimates for the DCC and DCC-RC models. We base the models on the standardized residuals from the GARCH estimates from the previous section.[12]

The parameter estimates of α_{SB} and β_{SB} imply that the conditional correlations in the DCC-RC model are markedly less persistent than in the DCC model. This effect

[12]Alternatively, we could employ an asymmetric GARCH model or a GARCH-MIDAS model as, for example, in Conrad et al. (2014) in the first step. However, as a result the volatility-adjusted residuals would depend on the selection of the best volatility model which might vary across stock/bond markets and, more importantly, across countries. We prefer to rely on simple GARCH models with the same specification across all countries, which ensures that our comparison of model performance is solely driven by differences in the specification of conditional correlations.

provides support for the notion that the explicit modeling of a time-varying long-term correlation takes out persistence from the short-term correlation (see also Colacito et al., 2011, and Bauwens et al., 2016). The θ_{RC} estimates in the DCC-RC models are positive and highly significant for all countries. That is, the current long-term stock-bond correlation is positively related to the lagged monthly realized stock-bond correlations. The λ_{RC} estimates imply that the optimal weights on the lagged RC vanish after about one year. According to the AIC and BIC criteria, the DCC-RC is clearly preferred to the DCC in all countries. Finally, the last column of Table 4 presents the CR_1 correlation ratios for the DCC-RC models. Between 80% (France) and 92% (Italy) of monthly conditional correlations can be explained by changes in past RC.

Figure 4 shows the estimated short- and long-term components. Roughly speaking, for all countries but Italy, the correlations have been positive from the beginning of the sample in 1995, then became negative during the 1998 default of Russian bonds, came back into the positive territory again, but turned and stayed mainly negative since the beginning of the 2000s. The most negative correlations are observed during and in the aftermath of the collapse of the dot-com bubble and during the financial crisis and Great Recession. For Italy, the correlation behaves similarly until 2008/9 but then becomes and stays positive until the end of the sample period.

4.3 DCC-RC-X parameter estimates

In a next step, we add macroeconomic variables as additional predictors of the long-term correlation. Since inflation expectations and three-month interest rate expectations are highly correlated (see Table 2), we include one or the other in order to avoid a multi-collinearity problem. Table 4 shows that the specifications which additionally include the macro expectations lead to further improvements in the model fit. For example, for the US we find that inflation expectations as well as short-term interest rate expectations are highly significant.[13] Also, lagged RV is found to be significant. In addition, we include the first principle component of inflation and interest rate expectations as an explanatory variable. Since both variables are informative about the markets' expectation concerning future monetary policy, we refer to this variable as 'monetary policy' (MP) factor.[14] Again, MP is highly significant. When including inflation expectations and RV, the estimate of

[13] A detailed discussion of the signs of the estimated coefficients will be provided in Section 4.4.

[14] Although there is no independent monetary policy in Germany, France, and Italy, expected inflation and interest rate conditions in these countries are highly relevant for the ECB's monetary policy.

λ_{RC} drops considerably, which implies a faster decay of the weighting scheme on lagged RC values. Also, the correlation ratio CR_1 increases from 87.20% for the DCC-RC to 90.98% for the DCC-RC-RV-CPI. The value of the correlation ratio CR_2 implies that roughly 12% of the variation in the long-term correlation is due to CPI and RV. As a consequence, the AIC and BIC clearly favor this model. For the other countries, the evidence in favor of the DCC-RC-X model is markedly weaker. We find inflation to be significant in Germany and Italy, GDP growth in France and RV in Italy. Consequently, for these countries the gains in terms of increases in CR_1 compared to the DCC-RC are considerably smaller than for the US. This is also reflected in CR_2 ratios between 3.35% (Italy) and 8.88% (Germany) for the best performing model. While the AIC criterion still prefers the best macro expectation based model over the DCC-RC for all countries, the BIC – which punishes more severely than the AIC for additional parameters – prefers the pure DCC-RC for the UK, France, and Italy.

4.4 Pure DCC-X models and economic interpretation

Section 4.3 suggests that – apart from the US – the explanatory power of expected macro conditions and RV is limited when controlling for RC. Next, we reestimate all models but exclude lagged RC. This allows for a clearer picture of the underlying economic relationship between the explanatory variables and the long-term stock-bond correlation. Table 5 shows that in pure DCC-X models, expected inflation, the three-month interest rate, the monetary policy factor as well as lagged RV are important drivers of the stock-bond correlation. Obviously, this relationship is partly masked when including RC which appears to encompass most of these drivers.

First, stock market volatility has a significant and strongly negative effect in all countries but Italy. The negative sign of the effect is in line with a flight-to-quality phenomenon (see, e.g., Connolly et al., 2005, Cappiello et al., 2006, and Adrian et al., 2016). In times of turbulence in stock markets investors require a higher risk premium on stocks while expected returns for bonds decrease. Investors re-balance their portfolio risks by selling stocks and buying bonds which results in a negative stock-bond correlation.[15] We only find a significantly positive effect for Italy. This may be explained by investors who do

[15] A related explanation is that a "Value-at-Risk (VaR) shock" induced by an upsurge of stock market volatility prompts investors to sell their stock holdings due to VaR constraints and to buy less risky bonds.

not consider the government bonds of all countries as 'equally safe'. Specifically, during crisis times investors may sell Italian stocks as well as bonds and flee into the safe haven of German government bonds.[16] Hence, during phases of high RV in the Italian stock market the stock-bond correlation increases due to simultaneously falling stock and bond prices.

Second, the coefficient on expected inflation is positive in all countries. It is significant for the US, Germany, France, and Italy. The positive sign implies that an increase in expected inflation leads to a rise in the long-term stock-bond correlation. This effect can be rationalized as follows. If monetary policy follows an inflation objective, then it will react to higher expected inflation by increasing the policy rate. Anticipating this policy response, investors require higher expected returns on stocks and bonds in the future which (everything else unchanged) induces a decline of stock and bond prices today.[17] Conversely, the parameter estimates imply that declining inflation expectations lead to a decreasing stock-bond correlation that eventually becomes negative. This behavior can be rationalized by the argument of Baele et al. (2010) that deflationary fears lead to a negative stock-bond correlation because stock prices decrease in times of bad economic prospects due to the cash flow effect while at the same time bond prices increase.[18]

Third, in the US, the UK, Germany and Italy an increase in the expected interest rate is associated with a significant upswing in the stock-bond correlation. This effect is in line with the response to an increase in expected inflation as discussed above and can again be explained by the common discount rate effect (see also Yang et al., 2009, for similar

[16] Based on high-frequency data, Conrad and Zumbach (2016) provide strong evidence for this behavior during the European sovereign debt crisis. Also, Perego and Vermeulen (2016) make a similar argument for explaining why the stock-bond correlation turned positive for southern European countries during the sovereign debt crisis while it stayed negative for northern European countries.

[17] Andersen et al. (2007, p.257) find that the same news can lead to increasing or decreasing stock prices, depending on whether the cash flow or the discount effect dominates. Their estimates suggest that "the cash flow effect dominates during contractions while the discount effect dominates in expansions (due to central bank policy)". As Table 2 shows, inflation expectations are unconditionally more strongly correlated with interest rate expectations than with GDP growth. Thus, it is not surprising that the discount rate effect dominates (on average) the cash flow effect for stock returns.

[18] In contrast to our estimates, the general equilibrium model of David and Veronesi (2013) predicts that in a deflationary regime increasing inflation expectations should decrease bond prices but increase stock prices and, hence, induce a negative stock-bond return correlation. This effect materializes if for stocks the cash flow effect dominates. A recent example for such a scenario is the so-called 'Trump reflation trade'.

evidence for the US and UK).

Fourth, the monetary policy factor is significant in all countries but France and, as expected, has the same sign as inflation or interest rate expectations. That is, the expectation of a more contractive monetary policy increases the stock-bond correlation.

Fifth, in line with the findings in Andersson et al. (2008), expectations on future GDP growth are insignificant in all countries. Also, note that the CR_1 ratios for the DCC-RV-GDP model are much lower than for all other specifications. Yet, the insignificance might be due to a potentially time-varying sign of the effect of GDP growth, i.e. the sign of the effect of GDP growth might depend on the stance of expected monetary policy. To capture such an effect, we estimate a model that includes GDP growth, the monetary policy factor, and an interaction term of the two. The parameter estimates suggest that for the US, the UK, and Germany there is indeed a time-varying effect (see Table 6). The sign of the interaction term can be interpreted as follows. If monetary policy is expected to tighten (MP above average), a *decline* in GDP growth expectations leads to an increase in the stock-bond correlation. This response is in line with increasing bond and stock prices (due to the discount effect). On the other hand, if monetary policy is expected to be accommodative (MP below average), a *decline* in GDP growth expectations reduces the stock-bond correlation. In this case, lower GDP growth is good news for bonds but bad news for stocks (due to the cash flow effect).[19] Only for Italy, we directly observe a significantly negative coefficient for GDP growth.

Although, the CR_1 ratios as well as the AIC and BIC suggest that omitting RC as an explanatory variable leads to a loss in terms of model fit, the pure DCC-X models clearly reveal that expected macro conditions as well as RV are economically important drivers of the stock-bond correlation. In summary, our results suggest that the time-varying long-term stock-bond correlation is closely linked to expectations regarding future monetary policy and a flight-to-quality phenomenon during crisis times. Note that our results complement previous findings on the time-varying stock-bond correlation. In particular, our findings regarding the effects of expected inflation and stock market volatility are in line with Andersson et al. (2008) and Asgharian et al. (2016). However, Andersson et al. (2008) exclusively rely on predictive regressions, while Asgharian et al. (2016) consider US data only.

[19]This interpretation is in line with Boyd et al. (2005) who show that 'rising unemployment is good news for stocks during economic expansions and bad news during contractions' (see also Andersen et al., 2007).

4.5 Graphical decomposition of the long-term correlation

For each country, Figure 5 shows the long-term stock-bond correlation as predicted by the DCC-RV-X model from Table 5 as well as its decomposition into the individual contributions from the two explanatory variables as defined in equation (7). For example, for the US both the monetary policy factor, m_{MP}, as well as realized volatility, m_{RV}, contribute positively to the long-term stock bond correlation at the beginning of the sample period. The decline in correlation into negative territory is mainly driven by lower inflation expectations and an increase in RV after the default of Russian bonds and the Long-Term Capital Management crisis in 1998 as well as the burst of the dot-com bubble in 2001. The second and even sharper decrease in correlation occurred in 2008 and is triggered by a massive increase in volatility during the financial crisis. The fact that the correlation stays negative towards the end of the sample period is due to the strongly negative monetary policy factor. That is, the expectation of a deflationary regime and an ongoing expansive monetary policy keeps the correlation in the negative territory. The behavior of the stock-bond correlation in the UK, Germany, and France is broadly similar to the one in the US. Again, Italy is different. The model predicts a strongly negative stock-bond correlation for the 2004 to 2008 period. Then, the correlation turns positive during the financial crisis, which reflects the flight-to-quality argument from before.

5 Dynamic Hedge Portfolio

In this section, we apply the different models to a portfolio choice problem, i.e we evaluate the potential economic gains of modeling time-varying long-run correlations by implementing a dynamic asset allocation strategy. We use the in-sample (IS) period June 1995 to December 2013 and the out-of-sample (OOS) period January 2014 to January 2016. All models have been reestimated for the IS period. The corresponding parameter estimates are provided in Tables 14 to 16 in Appendix D. Portfolio evaluation is based on daily portfolio returns.

5.1 Portfolio choice problem

We consider an investor who constructs a dynamic hedge portfolio (HP). That is, the investor must hold either stocks (bonds) in his portfolio but adds bonds (stocks) to reduce the portfolio risk. For example, if the investor must hold stocks, the weights of this hedge portfolio are obtained as the solution of the minimization problem:

$$\min_{\mathbf{w}_t} \mathbf{w}_t' \mathbf{H}_t \mathbf{w}_t \qquad s.t. \qquad \mathbf{w}_t' \tilde{\boldsymbol{\mu}} = \mu_0, \tag{15}$$

where $\tilde{\boldsymbol{\mu}} = (\tilde{\mu}_S, 0)'$ is the vector of expected excess returns on stocks and bonds and $\mathbf{w}_t = (w_{S,t}, w_{B,t})'$ the vector of potfolio weights. The required excess return is assumed to be given by $\mu_0 = \tilde{\mu}_S$. The optimal weights are then given by

$$\mathbf{w}_t^{HP} = (w_{S,t}^{HP}, w_{B,t}^{HP})' = (1, -\mathbf{Cov}(r_{S,t}, r_{B,t}|\mathcal{F}_{t-1})/\mathbf{Var}(r_{B,t}|\mathcal{F}_{t-1}))'$$

and $1 - w_{S,t}^{HP} - w_{B,t}^{HP} = -w_{B,t}^{HP}$ is held in cash. Thus, in addition to holding stocks, the investor will be long/short in bonds if the covariance between stocks and bonds is negative/positive. Focusing on a hedge portfolio has the advantage that the optimal portfolio weights do not depend on expected returns (see also Section 6). For a further discussion of hedge portfolios and their applications see Engle (2008) and Engle and Colacito (2006). We impose the restriction that the investor must hold stocks (bonds) if the average return on stocks (bonds) during the IS period is higher than the average return on bonds (stocks). According to Table 1, the investor is required to hold stocks in the US, the UK, Germany, and France while she is required to hold bonds in Italy.

5.2 DCC-MIDAS models and benchmark competitors

For the empirical evaluation of the portfolio choice problem, we use the standard DCC model as well as the best DCC-(RC)-X models as identified by the AIC in Tables 15 and 16. As natural competitors, we consider the following simple, yet powerful benchmark models:

Constant covariance matrix (Const): Our first benchmark portfolio is based on the assumption of a time-invariant constant covariance matrix. This portfolio is obtained by replacing the entries of $\mathbf{H}_t$ with estimates of the unconditional variances of stocks and bonds and their unconditional covariance. Hence, the optimal portfolio weights are constant. For the IS evaluation, we estimate the entries of the covariance matrix by their sample counterparts over the full IS period. For the much shorter OOS evaluation period, we estimate these quantities by their realized counterparts during the June 2013 - December 2013 period, i.e. during the last six months of the IS period. This ensures that we use timely estimates that are representative of the market environment before the start of the OOS period.

Monthly Random Walk (RW) covariance matrix: For all days within month τ, the RW model estimates the conditional covariance matrix $\mathbf{H}_t$ by the realized covariance matrix of month $\tau - 1$. Thus, the second benchmark model will produce portfolio weights that vary at a monthly frequency.

Constant Conditional Correlation (CCC): We also consider a daily CCC model. Since the daily CCC model is based on the same estimates $\hat{h}_{S,t}$ and $\hat{h}_{B,t}$ as the DCC/DCC-(RC)-X models but assumes a constant conditional correlation, a comparison with the DCC/DCC-(RC)-X models will reveal the potential gains of employing a short-/long-term conditional correlation structure.

5.3 Daily optimal portfolio weights

We construct optimal daily portfolio weights for the DCC, the DCC-(RC)-X as well as the three benchmark models. For the DCC and DCC-(RC)-X models, the optimal daily portfolio weights, $\widehat{\mathbf{w}}_t^{HP}$, are based on the forecast $\widehat{\mathbf{H}}_{t|t-1}$, where the diagonal elements are simply the estimates of the one-day ahead conditional variances of stocks, $\hat{h}_{S,t}$, and bonds, $\hat{h}_{B,t}$, and the off-diagonal elements are given by $\hat{\rho}_{SB,t}\sqrt{\hat{h}_{S,t}\hat{h}_{B,t}}$. In case of the CCC model, the off-diagonal elements are set to $\hat{\rho}_{SB}\sqrt{\hat{h}_{S,t}\hat{h}_{B,t}}$, where $\hat{\rho}_{SB}$ is the IS correlation of the volatility-adjusted residuals. Recall that for the Const model, the optimal weights do not change at all, while for the RW model the optimal weights are changing at the monthly frequency only. Nevertheless, all models require daily re-balancing.

5.4 Monthly optimal portfolio weights

As an alternative to the daily optimal portfolio weights, we also consider optimal weights that are changing at a monthly frequency. That is, at the end of each month, we choose portfolio weights for stocks, bonds, and cash that are kept constant over the following month. A comparison of monthly and daily portfolio weights is important for a realistic evaluation, since portfolio weights that change at a daily frequency are likely to generate lower variances but might suffer from the costs associated with excessive re-balancing. First, define monthly stock and bond returns as

$$r_{S,\tau} = \sum_{k=1}^{N^{(\tau)}} r_{S,t+k} \quad \text{and} \quad r_{B,\tau} = \sum_{k=1}^{N^{(\tau)}} r_{B,t+k}, \tag{16}$$

where day t denotes the last day of month $\tau - 1$. Constructing the monthly portfolio weights requires an estimate of the monthly conditional covariance matrix $\mathbf{H}_{\tau|\tau-1}$, i.e. we need to obtain estimates of $\mathbf{Var}[r_{S,\tau}|\mathcal{F}_{\tau-1}]$, $\mathbf{Var}[r_{B,\tau}|\mathcal{F}_{\tau-1}]$ as well as $\mathbf{Cov}(r_{S,\tau}, r_{B,\tau}|\mathcal{F}_{\tau-1})$.

The forecast of the monthly conditional variance of stocks and bonds can be computed as

$$\mathbf{Var}[r_{i,\tau}|\mathcal{F}_{\tau-1}] = \sum_{k=1}^{N^{(\tau)}} h_{i,t+k|\tau-1} = N^{(\tau)}\sigma_i^2 + \frac{1-(\alpha_i+\beta_i)^{N^{(\tau)}}}{1-(\alpha_i+\beta_i)}(h_{i,t+1|\tau-1}-\sigma_i^2), \qquad (17)$$

where $h_{i,t+k|\tau-1} = \mathbf{Var}[r_{i,t+k}|\mathcal{F}_{\tau-1}] = \sigma_i^2 + (\alpha_i+\beta_i)^{k-1}(h_{i,t+1|\tau-1}-\sigma_i^2)$ and $\sigma_i^2 = \omega_i/(1-\alpha_i-\beta_i)$, $i \in \{S, B\}$. The conditional covariance can be approximated by

$$\mathbf{Cov}(r_{S,\tau}, r_{B,\tau}|\mathcal{F}_{\tau-1}) \approx \sum_{k=1}^{N^{(\tau)}} \rho_{SB,t+k|\tau-1}\sqrt{h_{S,t+k|\tau-1}h_{B,t+k|\tau-1}}, \qquad (18)$$

with

$$\rho_{SB,t+k|\tau-1} \approx \bar{\rho}_{SB,\tau} + (\alpha_{SB}+\beta_{SB})^{k-1}(\rho_{SB,t+1|\tau-1}-\bar{\rho}_{SB,\tau}). \qquad (19)$$

For more details on the derivation of equations (18) and (19) see Appendix A. Equation (19) illustrates that the forecast of the conditional correlation converges to the current value of the long-term correlation component for $k \to \infty$. However, for the monthly conditional covariance forecasts this effect is limited by the fact that the k is at most $N^{(\tau)}$ and $\alpha_{SB}+\beta_{SB}$ is typically close to one. The optimal monthly portfolio weights $\widehat{\mathbf{w}}_\tau^{HP}$ then depend on the estimate $\widehat{\mathbf{H}}_{\tau|\tau-1}$.

Table 7 evaluates how well the different models do in forecasting the ex-post realized monthly covariances over the IS period. We consider a simple Mincer-Zarnowitz regression of the realized covariance on a constant and the covariance forecast. We report the regression R^2 as well as the p-value of the F-test that the constant is zero and the slope coefficient is one. We consider forecasts from the DCC/DCC-(RC)-X models as well as from the RW and the CCC benchmark models as described above. In all countries the RW forecast achieves a higher R^2 than the CCC forecast, whereas the DCC and DCC-(RC)-X models clearly improve upon the RW forecast in terms of R^2. Among all models, the DCC-RC model achieves the highest R^2 in three out of the five countries. Note that the null hypothesis of forecast efficiency is typically rejected for the benchmark models but not for the DCC/DCC-(RC)-X models.[20]

5.5 Comparison in terms of portfolio variance

We are now interested in formally testing whether the DCC and DCC-(RC)-X models deliver portfolios with smaller variances than the benchmark models. We denote the

[20] In particular, the CCC model suffers from the constant conditional correlation assumption because realized covariances frequently change their sign during the IS period.

estimate of the conditional covariance matrix from model j by $\widehat{\mathbf{H}}_{j,t|t-1}$ and the estimate based on a certain benchmark model (BM) by $\widehat{\mathbf{H}}_{BM,t|t-1}$. Following Engle and Colacito (2006), we test for the equality of the variances of two portfolios based on $\widehat{\mathbf{H}}_{j,t|t-1}$ and $\widehat{\mathbf{H}}_{BM,t|t-1}$ by testing whether the difference

$$d_{j,BM,t} = ((\widehat{\mathbf{w}}_{j,t}^{HP})'(\mathbf{r}_t - \bar{\mathbf{r}}))^2 - ((\widehat{\mathbf{w}}_{BM,t}^{HP})'(\mathbf{r}_t - \bar{\mathbf{r}}))^2 \tag{20}$$

is different from zero by means of a Diebold-Mariano (1995) type test. We employ the portfolio variance as our criterion for comparing the different models, because – as shown in Engle and Colacito (2006) – the portfolio variance is minimized when using the true conditional covariance matrix.

Suppose that portfolio standard deviations based on $\widehat{\mathbf{H}}_{j,t|t-1}$ and $\widehat{\mathbf{H}}_{BM,t|t-1}$ are given by $\hat{\sigma}_{P,j}$ and $\hat{\sigma}_{P,BM}$. We can quantify the gain/loss (G/L) from using the covariance matrix $\widehat{\mathbf{H}}_{j,t|t-1}$ instead of $\widehat{\mathbf{H}}_{BM,t|t-1}$ as follows: if we are willing to accept $\hat{\sigma}_{P,BM}$ units of risk and base our portfolio on $\widehat{\mathbf{H}}_{j,t|t-1}$, then we can require an excess return of $\mu_0 \hat{\sigma}_{P,BM}/\hat{\sigma}_{P,j}$. Hence, we end up with an increase/decrease of the required excess return by

$$G/L_{j,BM} = 100 \cdot (\hat{\sigma}_{P,BM} - \hat{\sigma}_{P,j})/\hat{\sigma}_{P,j}\%. \tag{21}$$

5.6 Empirical evaluation of portfolio variances

5.6.1 Comparison with benchmark models

We first discuss the IS results. Table 8 shows the results for daily and monthly portfolios. In all countries, the DCC and DCC-(RC)-X models significantly reduce the portfolio variance in comparison to the three benchmark models. For example, for the US the gain of building a portfolio with daily changing weights based on the covariance matrix from the DCC-RC-RV-CPI model instead of using the constant covariance matrix is 5.78%. That is, an investor with required (yearly) return of 10% could increase the required return to 10.578% while taking the same risk as before. As expected, gains are generally the strongest with respect to the portfolio based on the constant covariance matrix, followed by the portfolio based on the CCC and then the RW.[21] Also, in all countries the gains are higher for portfolios with daily changing weights than for the ones with monthly weights.

For the OOS period, we obtain quite similar results. As Table 9 shows, in all countries the DCC and DCC-(RC)-X based portfolios still improve upon the portfolios based on

[21] The finding that the gains against the CCC are higher than against the RW is in line with the observation that the R^2 values for the CCC in the MZ-regressions are lower than those for the RW.

the constant covariance matrix. Similarly, for all countries but Italy, we find that the DCC/DCC-(RC)-X based portfolios improve upon the CCC model. With the exception of Germany and France, the models also compare favorably with the RW model. The fact that we loose some significance compared to the IS period, may be simply due to the much shorter OOS period that comprises 530 daily observations only. Obviously, using only two years of OOS observations, it becomes more difficult to discriminate between the models. The results for Germany, France, and Italy are also likely to be influenced by the unusual market environment due to the ECB's quantitative easing (QE) program. In response to QE, bond prices strongly increased in Germany, France and Italy with annualized bond returns above 8%.

In summary, the DCC as well as the DCC-(RC)-X models clearly lead to significantly lower portfolio variances than the benchmark models, which translates into economically sizable increases in required returns that can be realized without taking more risk.

5.6.2 Comparison with DCC model

Tables 8 and 9 also show that the DCC-(RC)-X models achieve slightly higher gains than the DCC model. Of course, the DCC is a much harder competitor. Direct Engle and Colacito (2006) tests against the DCC suggest that the DCC-(RC)-X models still achieve positive gains, but these gains are almost always insignificant (results not reported). However, this result might be explained by the fact that relative model performance varies over time. First, in times of financial turmoil in the stock market, the quality of the GARCH forecasts of daily and monthly volatility can be expected to deteriorate drastically (see Stürmer, 2016). Since the covariance forecasts use these volatility forecasts as inputs, we can expect that all models do not perform well in times of crisis, which implies that it becomes harder to differentiate between models. Second, since the daily conditional correlations from the various DCC-(RC)-X models and the nested DCC models are almost identical (e.g. the correlation between $\rho_{SB,t}$ based on the DCC and the DCC-RV-CPI is 0.99 for the US), we can only expect to see differences in the performance if the two respond differently to shocks. As discussed in Section 2, this is the case if shocks are small. Since we find the level of monthly RV to be positively related to the size of the shocks, we can only expect the DCC-X models to perform differently from the DCC if RV is not extreme.[22] We therefore consider Engle and Colacito (2006) tests as in equation (20) but distinguish between a 'normal' and a 'high' volatility regime. A high volatility regime is defined as RV being above the 70th percentile of its historical distribution.

Table 10 reveals some very interesting findings for the IS period. For both daily and monthly weights, portfolios based on the DCC-(RC)-X models have significantly lower variances than the DCC based portfolios during 'normal' volatility regimes in the US, the UK, and Italy. The (significant) gains range from 0.34 to 0.72 percent and are, as expected, somewhat below the gains that can be achieved against the simple benchmark models.[23] During phases of high volatility in the stock market, the gains/losses are insignificant. The finding that the DCC-(RC)-X models improve upon the DCC when volatility is normal is reasonable, since the long-term components are intended to capture smoothly time-varying macro and financial conditions and, hence, should improve covariance forecasts in stable environments but not when financial volatility upsurges unexpectedly. Table 10 provides somewhat weaker evidence for the OOS period, where significant gains are realized in the US and, to some extent, the UK, France, and Italy.

Most importantly, the DCC-(RC)-X models provide an economic rationale for why optimal portfolio weights vary over time. Figures 6 and 7 show the optimal bond (stock) weights for the IS and OOS period. For example, for the US, the UK, Germany, and France the optimal bond weight is negative during the first three years of the IS period. The negative weight can be explained by a strongly positive monetary policy factor, i.e. contractive monetary policy, which leads to a positive stock-bond correlation. On the other hand, the weight on bonds is large and positive when RV is high, i.e. during the burst of the dot-com bubble as well as during the financial crisis. Finally, the sharp decrease in the weight on bonds in 2013 reflects heightened bond market volatility during the taper tandrum episode. Since the stock-bond correlation was mainly negative during recent years, the optimal hedge portfolios for the US, the UK, Germany, and France are mostly long in bonds.

[22]More precisely, we find that the level of monthly RV is positively related to $\sum_{k=1}^{N^{(\tau)}} |Z_{S,t+k} Z_{B,t+k}|$, by which we measure the "monthly absolute shock product". Intuitively, if this measure is low, mean-reversion dominates when updating correlations and, hence, DCC-(RC)-X and DCC might potentially update in different directions. On the other hand, if this measure is large, DCC-(RC)-X and DCC will have very similar updates.

[23]Note that these gains are similar to the below 1% gains of the DCC-MIDAS compared to the DCC that Colacito et al. (2011) report on average for two-dimensional portfolios of stock indices from the G7 countries.

5.7 Portfolio risk, portfolio turnover, net excess returns and Sharpe ratios

Next, we descriptively compare the characteristics of the portfolios based on daily/monthly weights constructed from the DCC and the DCC-(RC)-X models. First, we consider the IS period. As Table 12 shows, in all countries the hedge portfolios achieve a lower portfolio risk than when purely investing in the stock (bond) market. For example, the annualized volatility of the US stock market is 19.88%, while the hedge portfolio based on daily weights from the DCC-RC model reduces risk to 18.17%. When the same model is employed but with monthly weights, the portfolio risk slightly increases to 18.38%. Whether we consider daily or monthly portfolio weights, it is always one of the DCC-X based portfolios that is the portfolio with the lowest risk. This confirms our findings from Section 5.6.

Although our main criterion for portfolio choice is portfolio risk, we also provide summary information on portfolio returns and Sharpe ratios. In order to make a realistic comparison between the returns on the portfolios based on daily/monthly weights, transaction costs should be taken into account. This will punish models that generate 'too much trading'. For calculating transaction costs, we first have to quantify the portfolio turnover. We define the total portfolio turnover from day $t-1$ to day t as

$$TO_t = \sum_{i \in \{S,B\}} \left| w_{i,t} - w_{i,t-1} \frac{1 + r_{i,t-1}}{1 + w_{S,t-1} r_{S,t-1} + w_{B,t-1} r_{B,t-1} + (1 - w_{S,t-1} - w_{B,t-1}) r_f} \right|, \tag{22}$$

where r_f denotes the risk-free rate.[24] For example, Table 12 shows that for the US the portfolio based on daily weights from the DCC-RC model has an average daily turnover of 18.45%. This turnover sharply decreases to only 4.75% when the same model is used to construct the portfolio but with monthly weights. Using monthly weights thus substantially reduces portfolio turnover and, hence, trading costs. Interestingly, the low persistence of the conditional correlation in the DCC-RC(-X) models (as measured by $\alpha_{SB} + \beta_{SB}$, see Table 5), causes the DCC-RC(-X) to be the model with the highest/lowest turnover when considering daily/monthly portfolios. This is because the higher weight, $(1 - \alpha_{SB} - \beta_{SB})$, that is attached to the long-term component creates an additional source of variation for the daily conditional covariance forecasts but smoothes the monthly fore-

[24]For simplicity, we assume that the risk-free rate is equal to zero.

casts. Hence, the optimal daily/monthly portfolio weights based on the DCC-RC-X become more/less variable than the weights based on the DCC and DCC-X. Note that the comparably low turnover for the Italian portfolios can be rationalized by the observation that the investor must hold bonds in Italy. Since bonds are less volatile than stocks, keeping the weight on bonds equal to one requires only little re-balancing.

Next, we can calculate the portfolio excess return net of transaction costs as

$$r_{P,t} = w_{S,t} r_{S,t} + w_{B,t} r_{B,t} + (1 - w_{S,t} - w_{B,t}) r_f - r_f - c \cdot TO_t, \tag{23}$$

where $c \cdot TO_t$ represents proportional transaction costs. Following Bollerslev et al. (2016), we impose $c = 0.02$. Table 12 reports *annualized* net excess returns. Note that for all countries but Italy, the realized excess returns of the various hedge portfolios are above realized returns of the country's stock (bond) market. For example, for the US the annualized average realized return in the stock market was 6.78%, while the daily portfolio based on the DCC achieved a return of 9.46%. Since the stock-bond correlation was negative during most of our IS period in the US, the investor was long in bonds for most of the time. US bonds had a positive return and so the optimal hedge portfolio resulted in an excess return higher than the return on the US stock market.[25] For all countries (except Italy) and all models, we find that the net excess returns of the portfolios based on monthly weights are higher than the net excess returns of the portfolios based on daily weights. Since the monthly weights are more stable, they simply require less re-balancing and, hence, are cheaper to implement. Among the different portfolios, the one based on monthly DCC weights results in the highest net excess return (again except for Italy).

Finally, the last column presents the portfolio Sharpe ratios. Although the daily portfolios have lower risk, the figures clearly indicate that the portfolios based on monthly weights achieve higher Sharpe ratios. For all countries but Italy, the DCC based portfolios lead to the highest Sharpe ratios. Note that this finding does not contradict the results from the Engle and Colacito (2006) tests. As discussed for Engle and Colacito (2006), a comparison in terms of empirical Sharpe ratios does not necessarily lead to the selection of the model that minimizes the portfolio variance.

Table 13 shows that for the OOS period the results are slightly different. In all countries, the portfolio with the lowest variance is based on one of the DCC-(RC)-X

[25] Obviously, this result also depends on the assumption that $r_f = 0$. Since the investor is long in bonds on average, she has to borrow money at the risk-free rate. If this rate is non-zero, this will reduce her excess return.

models. While the pattern with respect to portfolio turnover is the same as IS, now the highest net excess return and the highest Sharpe ratio are obtained for a DCC-RV-MP/CPI based portfolio in the US, UK, Germany, and France.[26] That is, during our OOS period the MP/CPI factor appears to be highly relevant. Our results therefore suggest that the DCC-(RC)-X models may improve upon the simple DCC in certain environments in which the influence of monetary policy is strong.

In summary, IS and OOS we always find the minimal portfolio risk for one of the DCC-(RC)-X models. While IS the highest Sharpe ratios are observed for the DCC model, OOS the DCC-RV-MP/CPI model is clearly preferred.

6 Extensions and Robustness

6.1 A global financial stress factor

Monthly realized stock market volatilities are highly correlated across countries (see Table 17). This illustrates that stress in financial markets is very much globally synchronized and suggests that there might be a single global financial stress factor driving the flight-to-quality phenomenon. Given the prominent role played by the US stock market, we consider RV in the US stock market as a direct and simple proxy for this global risk factor. Alternatively, we use the VIX index, which reflects the stock market's expectation of volatility during the following month and is widely considered as the 'fear gauge'. For example, Adrian et al. (2016) argue that expected returns on bonds tend to fall and expected returns on stocks to rise when the VIX is above its median, which coincides with periods of flight-to-safety. We reestimate the DCC-MIDAS models from Table 5 by replacing the local RV with the US RV or the VIX (see Table 18). We find that US RV significantly drives the long-term stock-bond correlation in the UK, Germany, and France, but not in Italy. However, with the exception of France, including US RV instead of the domestic RV leads to a decline in the CR_1 ratio and, hence, the model fit. The decline is most dramatic in Italy, implying that the Italian stock-bond correlation is driven by domestic rather than global factors. We find the same results when including the VIX.

[26]For the UK, we observe negative net excess returns and negative Sharpe ratios. This is because the investor is forced to hold stocks, although during the OOS period UK stocks have a negative average return.

6.2 Monthly DCC

We also evaluated the one-step ahead forecast from a DCC model that is directly estimated for monthly data. Considering a monthly DCC is interesting, since it allows for a comparison of the *direct* one-month ahead covariance forecast with the *iterated* one as described by equation (18). We find that the monthly DCC leads to considerably lower gain/loss ratios that are insignificant or even significantly negative when compared to the RW model. Our results clearly suggest that portfolios based on monthly changing weights using iterative forecasts from the daily DCC perform much better than portfolios based on monthly weights from the monthly DCC. This finding is in line with Kole et al. (2015) who study forecasting Value-at-Risk (VaR) under temporal aggregation. In particular, they find that the ten-day VaR forecasts of daily models based on an iterated procedure are more accurate than forecasts based on models that are directly estimated at the 10-day frequency.

6.3 Alternative portfolios

As a robustness check, we consider different alternatives to the hedge portfolio in Section 5. Our findings are broadly confirmed and detailed results are available upon request.

Optimal risky portfolio (ORP): For the ORP, we need to specify the assumed excess returns for stocks and bonds in order to obtain the portfolio weights. They are obtained as the solution of the minimization problem in (15) with $\tilde{\boldsymbol{\mu}} = \boldsymbol{\mu} - r_f\mathbf{1}$ denoting the vector of assumed excess returns and $\mathbf{1}$ a bivariate vector of ones. Again, we impose $r_f = 0$. For both the IS as well as the OOS period, we set the assumed returns equal to the realized excess returns during the IS period. Finally, we set the required return equal to the realized stock return in each country. The portfolio evaluation based on the ORP yields very similar results to those in Section 5.

Short selling constraint: The solution for the weights of the ORP allows for short selling of stocks or bonds. However, we verified that all our results are unaffected when imposing a short selling constraint.

Minimum variance portfolio (MVP): If stocks and bonds are assumed to have the same expected excess return $\tilde{\mu}_S = \tilde{\mu}_B = \tilde{\mu}$, then $\tilde{\boldsymbol{\mu}} = \tilde{\mu}\mathbf{1}$ and we can show that the optimal portfolio is a combination of the MVP and cash. If, in addition, $\mu_0 = \tilde{\mu}$, then the investor will only hold the MVP and no cash. Again, the empirical results are such that essentially all our conclusions remain unchanged.

6.4 Corrected DCC

As an alternative to the DCC model given by equation (3), we also implemented a specification in the spirit of the 'corrected' DCC model of Aielli (2013). Note that for this model the recursion given by equation (19) holds exactly. We found all our results to be robust with respect to this modification. Detailed results are available upon request.

7 Conclusions

We suggest a modified version of the DCC-MIDAS specification of Colacito et al. (2011) that allows us to model the long-term stock-bond correlation as a function of both lagged realized correlations and additional explanatory variables. Our findings suggest that expectations regarding future monetary policy and a flight-to-quality phenomenon are the main drivers of the correlation. The relative importance of these factors varies over time and across countries. In particular, the special role played by Italy appears interesting from a European policy perspective. Further, models that enable us to anticipate changes in the long-term stock-bond correlation are highly relevant from a portfolio choice and risk management perspective. We show that stock-bond hedge portfolios that are based on forecasts of the conditional covariance matrix from the DCC-(RC)-X models have significantly lower portfolio risk than portfolios based on simple benchmark models. In addition, the DCC-(RC)-X models tend to improve upon the simple DCC in terms of portfolio variance when stock markets are not in turmoil. Since changes of the long-term correlation in the DCC-(RC)-X models reflect smooth movements in the macro environment, they are most informative during times of tranquility in the stock market. Most importantly, knowing the macro determinants of changes in the long-term correlations provides a clear economic rationale for why portfolio weights change over time. Finally, we find that portfolio turnover can be substantially reduced by switching from daily to monthly optimal weights. Monthly weights are more stable and often result in higher net excess returns after trading costs.

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A Construction of Monthly Covariance Forecasts

We define monthly stock and bond returns as

$$r_{S,\tau} = \sum_{k=1}^{N^{(\tau)}} r_{S,t+k} \quad \text{and} \quad r_{B,\tau} = \sum_{k=1}^{N^{(\tau)}} r_{B,t+k},$$

where day t denotes the last day of month $\tau - 1$. The covariance between monthly stock and bond returns can be written as

$$\begin{aligned}
\mathbf{Cov}(r_{S,\tau}, r_{B,\tau}|\mathcal{F}_{\tau-1}) &= \sum_{k=1}^{N^{(\tau)}} \mathbf{Cov}(r_{S,t+k}, r_{B,t+k}|\mathcal{F}_{\tau-1}) && (24)\\
&= \sum_{k=1}^{N^{(\tau)}} \mathbf{E}(Z_{S,t+k} Z_{B,t+k} \sqrt{h_{S,t+k} h_{B,t+k}}|\mathcal{F}_{\tau-1}) && (25)\\
&\approx \sum_{k=1}^{N^{(\tau)}} \mathbf{E}(Z_{S,t+k} Z_{B,t+k}|\mathcal{F}_{\tau-1}) \sqrt{h_{S,t+k|\tau-1} h_{B,t+k|\tau-1}} && (26)\\
&= \sum_{k=1}^{N^{(\tau)}} \rho_{SB,t+k|\tau-1} \sqrt{h_{S,t+k|\tau-1} h_{B,t+k|\tau-1}} && (27)
\end{aligned}$$

where the first line follows because $r_{S,t+k}$ and $r_{B,t+j}$ are uncorrelated for $k \neq j$ and the approximation in equation (26) is based on a first order Taylor series expansion of $\mathbf{E}(Z_{S,t+k} Z_{B,t+k} \sqrt{h_{S,t+k} h_{B,t+k}}|\mathcal{F}_{\tau-1})$ as in Engle (2008, equation (9.10)).

Next, we need to derive an expression for $\rho_{SB,t+k|\tau-1}$. Again, as in Engle (2008), we use the approximation $\rho_{SB,t+k|\tau-1} = \mathbf{E}[Z_{S,t+k-1} Z_{B,t+k-1}|\mathcal{F}_{\tau-1}] \approx \mathbf{E}[q_{SB,t+k}|\mathcal{F}_{\tau-1}]$. Engle and Sheppard (2005) show that this approximation works well if the diagonal elements of $\mathbf{Q}_t$ are close to one and k is large. Finally, we apply the approximation to equation (4) and obtain

$$\begin{aligned}
\rho_{SB,t+k|\tau-1} &\approx \bar{\rho}_{SB,\tau} + (\alpha_{SB} + \beta_{SB})(\rho_{SB,t+k-1|\tau-1} - \bar{\rho}_{SB,\tau}) && (28)\\
&= \bar{\rho}_{SB,\tau} + (\alpha_{SB} + \beta_{SB})^{k-1}(\rho_{SB,t+1|\tau-1} - \bar{\rho}_{SB,\tau}). && (29)
\end{aligned}$$

B Tables

Table 1: Descriptive statistics

		Apr 1991 - Jan 2016			June 1995 - Dec 2013			Jan 2014 - Jan 2016		
Country	Variable	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Panel A: Daily return data										
US	Stocks	6257	6.74	1.14	4679	6.78	1.25	523	2.01	0.89
	Bonds	6257	1.50	0.47	4679	1.06	0.48	523	4.42	0.41
	RC RW(22)	6236	-0.08	0.46	4679	-0.15	0.44	523	-0.38	0.29
UK	Stocks	6277	3.50	1.11	4697	3.67	1.19	526	-5.57	0.95
	Bonds	6277	2.57	0.41	4697	2.04	0.39	526	6.59	0.41
	RC RW(22)	6256	-0.08	0.44	4697	-0.17	0.40	526	-0.30	0.29
GER	Stocks	6283	5.03	1.41	4712	5.68	1.51	525	-1.05	1.28
	Bonds	6283	2.75	0.34	4712	2.18	0.35	525	8.14	0.37
	RC RW(22)	6262	-0.08	0.48	4712	-0.19	0.45	525	-0.28	0.30
FRA	Stocks	6301	4.56	1.36	4728	4.78	1.43	531	2.21	1.22
	Bonds	6301	2.97	0.36	4728	2.40	0.35	531	9.12	0.38
	RC RW(22)	6279	-0.05	0.44	4728	-0.16	0.40	531	-0.15	0.28
IT	Stocks	6287	1.80	1.48	4710	1.02	1.49	526	-1.09	1.57
	Bonds	6287	3.59	0.47	4710	3.33	0.44	526	10.95	0.47
	RC RW(22)	6266	0.11	0.42	4710	0.03	0.43	526	0.34	0.30
Panel B: Monthly realized volatility										
US	Stocks	298	15.56	2.70	223	17.17	2.90	25	13.04	1.56
	Bonds	298	7.00	0.71	223	7.28	0.74	25	6.30	0.53
UK	Stocks	298	15.54	2.46	223	16.50	2.67	25	13.76	1.82
	Bonds	298	6.12	0.64	223	5.97	0.56	25	6.31	0.43
GER	Stocks	298	19.70	3.08	223	21.17	3.28	25	19.23	1.89
	Bonds	298	5.13	0.55	223	5.24	0.51	25	5.48	0.61
FRA	Stocks	298	19.38	2.75	223	20.41	2.99	25	18.23	1.96
	Bonds	298	5.44	0.59	223	5.32	0.55	25	5.76	0.52
IT	Stocks	298	21.29	2.90	223	21.03	3.14	25	23.90	2.09
	Bonds	298	6.50	1.08	223	6.05	1.04	25	7.13	0.74
Panel C: Monthly expectation data										
US	CPI	298	2.38	0.78	223	2.28	0.68	25	1.41	0.47
	I3M	298	3.24	2.05	223	3.17	2.04	25	0.78	0.36
	GDP	298	2.58	0.99	223	2.57	1.09	25	2.72	0.22
UK	CPI	298	2.78	0.75	223	2.66	0.65	25	2.26	0.50
	I3M	298	4.60	2.55	223	4.33	2.11	25	1.02	0.16
	GDP	298	1.95	1.07	223	1.92	1.10	25	2.60	0.15
GER	CPI	298	1.85	0.79	223	1.61	0.43	25	1.19	0.35
	I3M	298	3.29	2.11	223	2.93	1.29	25	0.12	0.14
	GDP	298	1.52	1.04	223	1.54	1.07	25	1.80	0.19
FRA	CPI	298	1.66	0.61	223	1.56	0.40	25	0.78	0.29
	I3M	298	3.31	2.20	223	2.90	1.35	25	0.11	0.11
	GDP	298	1.68	0.97	223	1.72	1.02	25	1.08	0.26
IT	CPI	298	2.50	1.35	223	2.18	0.72	25	0.60	0.28
	I3M	298	4.28	3.47	223	3.41	2.11	25	0.11	0.11
	GDP	298	1.19	1.12	223	1.13	1.23	25	0.76	0.29

Notes: The reported statistics include the number of observations, the mean, and standard deviation (SD). The mean is annualized for the daily returns and monthly realized volatility. The full data covers the sample period from April 1991 to January 2016 and includes 6277 (US), 6257 (UK), 6283 (GER), 6301 (FR), 6287 (IT) daily and 298 monthly observations. In the portfolio choice application in Section 5, we consider the in-sample June 1995 to December 2013 period and the out-of-sample January 2014 to January 2016 period.

Table 2: Country-wise correlations

Country	Variable	CPI	$I3M$	GDP	RV	$RCorr$
US						
	CPI	1.00				
	$I3M$	0.66	1.00			
	GDP	0.30	0.27	1.00		
	RV	-0.25	-0.15	-0.40	1.00	
	$RCorr$	0.45	0.60	0.18	-0.39	1.00
UK						
	CPI	1.00				
	$I3M$	0.29	1.00			
	GDP	0.02	0.23	1.00		
	RV	-0.12	-0.11	-0.33	1.00	
	$RCorr$	0.19	0.58	0.23	-0.39	1.00
GER						
	CPI	1.00				
	$I3M$	0.76	1.00			
	GDP	0.04	0.19	1.00		
	RV	-0.29	-0.13	-0.10	1.00	
	$RCorr$	0.46	0.50	0.09	-0.41	1.00
FRA						
	CPI	1.00				
	$I3M$	0.74	1.00			
	GDP	0.16	0.49	1.00		
	RV	-0.12	-0.08	-0.10	1.00	
	$RCorr$	0.35	0.45	0.18	-0.40	1.00
IT						
	CPI	1.00				
	$I3M$	0.92	1.00			
	GDP	0.31	0.50	1.00		
	RV	-0.09	-0.24	-0.10	1.00	
	$RCorr$	0.21	0.14	-0.12	0.06	1.00

Notes: Country-wise correlations of the macroeconomic expectations, monthly realized stock market volatility and the monthly realized correlations, $RCorr$, of stock and bond returns over the full April 1991 to January 2016 sample period.

Table 3: GARCH(1,1) model estimations

Country	μ	ω	α	β	BIC	AIC
Panel A: Stocks						
US	0.0515*** (0.0102)	0.0125*** (0.0034)	0.0828*** (0.0116)	0.9071*** (0.0127)	2.6844	2.6801
UK	0.0379*** (0.0102)	0.0137*** (0.0034)	0.0926*** (0.0119)	0.8968*** (0.0130)	2.6991	2.6948
GER	0.0559*** (0.0136)	0.0290*** (0.0092)	0.0847*** (0.0107)	0.8996*** (0.0105)	3.1928	3.1885
FRA	0.0472*** (0.0140)	0.0288*** (0.0090)	0.0815*** (0.0108)	0.9020*** (0.0135)	3.1783	3.1740
IT	0.0369** (0.0144)	0.0183*** (0.0054)	0.0794*** (0.0116)	0.9149*** (0.0119)	3.3706	3.3663
Panel B: Bonds						
US	0.0081 (0.0052)	0.0020*** (0.0006)	0.0419*** (0.0057)	0.9490*** (0.0070)	1.2005	1.1962
UK	0.0107** (0.0046)	0.0015*** (0.0005)	0.0424*** (0.0076)	0.9493*** (0.0093)	0.9358	0.9315
GER	0.0139*** (0.0038)	0.0009*** (0.0003)	0.0437*** (0.0065)	0.9489*** (0.0077)	0.5767	0.5725
FRA	0.0136*** (0.0041)	0.0016*** (0.0005)	0.0444*** (0.0065)	0.9431*** (0.0095)	0.6952	0.6909
IT	0.0171*** (0.0043)	0.0012** (0.0005)	0.0805*** (0.0147)	0.9185*** (0.0141)	0.9516	0.9473

Notes: The table reports country-wise estimation results for the GARCH(1,1) model estimation over the full April 1991 - January 2016 sample. The numbers in parentheses are Bollerslev-Wooldridge (1992) robust standard errors. ***, **, * indicate significance at the 1%, 5%, and 10% level. BIC is the Bayesian information criterion and AIC is the Akaike information criterion.

Table 4: DCC and DCC-RC-MIDAS-X model estimations

Model	α_{SB}	β_{SB}	λ_{RC}	θ_{RC}	θ_{RV}	θ_X	BIC	AIC	CR_1	CR_2
US-DCC	0.0406^{***}	0.9532^{***}					3.7372	3.7347		
	(0.0077)	(0.0097)								
US-DCC-RC	0.0655^{***}	0.8522^{***}	0.6051^{***}	0.3722^{**}			3.7285	3.7235	87.20	
	(0.0145)	(0.0532)	(0.1838)	(0.1674)						
US-DCC-RC-RV-CPI	0.0647^{***}	0.8442^{***}	0.4180^{***}	0.4042^{***}	-0.0035	0.0086^{***}	**3.7252**	**3.7177**	**90.98**	**11.86**
	(0.0143)	(0.0489)	(0.1449)	(0.0966)	(0.0029)	(0.0027)				
US-DCC-RC-RV-I3M	0.0646^{***}	0.8456^{***}	0.4103^{***}	0.4165^{***}	-0.0061^{**}	0.0040^{***}	3.7272	3.7197	89.81	9.59
	(0.0139)	(0.0473)	(0.1385)	(0.0937)	(0.0031)	(0.0015)				
US-DCC-RC-RV-MP	0.0646^{***}	0.8447^{***}	0.4016^{***}	0.4126^{***}	-0.0054^{*}	0.0042^{***}	3.7262	3.7186	90.51	11.35
	(0.0141)	(0.0478)	(0.1391)	(0.0930)	(0.0030)	(0.0014)				
US-DCC-RC-RV-GDP	0.0650^{***}	0.8494^{***}	0.5337^{***}	0.3935^{***}	-0.0034	0.0015	3.7304	3.7229	87.66	2.09
	(0.0141)	(0.0489)	(0.1615)	(0.1265)	(0.0032)	(0.0023)				
UK-DCC	0.0324^{***}	0.9628^{***}					3.7114	3.7089		
	(0.0071)	(0.0089)								
UK-DCC-RC	0.0467^{***}	0.8978^{***}	0.8174^{***}	0.1801^{**}			**3.6999**	3.6949	89.16	
	(0.0076)	(0.0233)	(0.0826)	(0.0799)						
UK-DCC-RC-RV-CPI	0.0463^{***}	0.8994^{***}	0.8306^{***}	0.1671^{**}	0.0010	0.0034	3.7023	3.6948	89.86	1.18
	(0.0077)	(0.0237)	(0.0818)	(0.0799)	(0.0032)	(0.0028)				
UK-DCC-RC-RV-I3M	0.0469^{***}	0.8967^{***}	0.7991^{***}	0.1887^{**}	-0.0007	0.0009	3.7031	3.6956	89.28	0.34
	(0.0076)	(0.0235)	(0.1094)	(0.0871)	(0.0034)	(0.0026)				
UK-DCC-RC-RV-MP	0.0468^{***}	0.8964^{***}	0.7512^{***}	0.1930^{***}	-0.0018	0.0060	3.7017	**3.6942**	**90.60**	**6.53**
	(0.0077)	(0.0219)	(0.1044)	(0.0722)	(0.0032)	(0.0039)				
UK-DCC-RC-RV-GDP	0.0463^{***}	0.8996^{***}	0.8405^{***}	0.1611	-0.0005	-0.0016	3.7030	3.6955	88.69	0.36
	(0.0076)	(0.0252)	(0.1061)	(0.1015)	(0.0035)	(0.0031)				
GER-DCC	0.0396^{***}	0.9559^{***}					3.6553	3.6528		
	(0.0082)	(0.0097)								
GER-DCC-RC	0.0515^{***}	0.9120^{***}	0.8908^{***}	0.1136^{**}			3.6407	3.6357	87.42	
	(0.0074)	(0.0179)	(0.0514)	(0.0520)						
GER-DCC-RC-RV-CPI	0.0502^{***}	0.9115^{***}	0.8531^{***}	0.1269^{**}	0.0041	0.0138^{***}	**3.6396**	**3.6321**	**88.42**	**8.88**
	(0.0074)	(0.0174)	(0.0678)	(0.0617)	(0.0043)	(0.0051)				
GER-DCC-RC-RV-I3M	0.0515^{***}	0.9118^{***}	0.8772^{***}	0.1155	-0.0023	0.0021	3.6438	3.6363	86.36	1.04
	(0.0075)	(0.0200)	(0.1176)	(0.0940)	(0.0046)	(0.0066)				
GER-DCC-RC-RV-MP	0.0513^{***}	0.9106^{***}	0.8324^{***}	0.1362^{*}	-0.0017	0.0064	3.6422	3.6347	86.39	7.19
	(0.0074)	(0.0185)	(0.1043)	(0.0790)	(0.0039)	(0.0042)				
GER-DCC-RC-RV-GDP	0.0508^{***}	0.9138^{***}	0.9172^{***}	0.0894^{*}	-0.0011	-0.0038	3.6434	3.6359	87.18	1.37
	(0.0075)	(0.0174)	(0.0480)	(0.0518)	(0.0048)	(0.0035)				
FRA-DCC	0.0373^{***}	0.9548^{***}					3.7571	3.7547		
	(0.0080)	(0.0103)								
FRA-DCC-RC	0.0469^{***}	0.9157^{***}	0.8933^{***}	0.1013^{***}			**3.7503**	3.7453	80.02	
	(0.0080)	(0.0208)	(0.0381)	(0.0363)						
FRA-DCC-RC-RV-CPI	0.0456^{***}	0.9176^{***}	0.9009^{***}	0.0849^{**}	-0.0001	0.0062	3.7517	3.7442	81.06	5.04
	(0.0078)	(0.0199)	(0.0399)	(0.0377)	(0.0042)	(0.0041)				
FRA-DCC-RC-RV-I3M	0.0467^{***}	0.9169^{***}	0.9113^{***}	0.0855^{**}	-0.0014	-0.0021	3.7532	3.7457	80.16	1.06
	(0.0081)	(0.0207)	(0.0494)	(0.0431)	(0.0043)	(0.0043)				
FRA-DCC-RC-RV-MP	0.0467^{***}	0.9160^{***}	0.8876^{***}	0.0971^{**}	-0.0017	0.0016	3.7532	3.7458	79.17	1.28
	(0.0080)	(0.0211)	(0.0516)	(0.0443)	(0.0041)	(0.0033)				
FRA-DCC-RC-RV-GDP	0.0458^{***}	0.9178^{***}	0.9407^{***}	0.0633^{*}	-0.0014	-0.0050^{*}	3.7516	**3.7441**	**82.34**	**8.07**
	(0.0080)	(0.0198)	(0.0364)	(0.0344)	(0.0045)	(0.0029)				
IT-DCC	0.0257^{**}	0.9717^{***}					3.6417	3.6392		
	(0.0103)	(0.0119)								
IT-DCC-RC	0.0528^{***}	0.8696^{***}	0.7431^{***}	0.2579^{***}			**3.6308**	3.6258	91.76	
	(0.0103)	(0.0423)	(0.0620)	(0.0617)						
IT-DCC-RC-RV-CPI	0.0503^{***}	0.8743^{***}	0.7390^{***}	0.2352^{***}	0.0059^{**}	0.0036^{*}	3.6315	**3.6240**	**92.46**	**3.35**
	(0.0101)	(0.0419)	(0.0659)	(0.0623)	(0.0029)	(0.0021)				
IT-DCC-RC-RV-I3M	0.0511^{***}	0.8728^{***}	0.7419^{***}	0.2450^{***}	0.0045	0.0014	3.6327	3.6252	91.89	1.48
	(0.0101)	(0.0419)	(0.0625)	(0.0613)	(0.0029)	(0.0017)				
IT-DCC-RC-RV-MP	0.0507^{***}	0.8737^{***}	0.7403^{***}	0.2419^{***}	0.0051^{*}	0.0016	3.6323	3.6248	92.14	2.15
	(0.0101)	(0.0418)	(0.0635)	(0.0615)	(0.0029)	(0.0013)				
IT-DCC-RC-RV-GDP	0.0524^{***}	0.8671^{***}	0.7523^{***}	0.2349^{***}	0.0027	-0.0014	3.6326	3.6251	91.85	1.45
	(0.0103)	(0.0435)	(0.0666)	(0.0646)	(0.0028)	(0.0015)				

Notes: The table reports country-wise estimation results for the DCC, DCC-RC, and DCC-RC-RV-X model estimations based on standardized residuals from the GARCH(1,1) models in Table 3. The correlation ratios CR1/CR2 are calculated according to equation (11/12). For each country, the lowest AIC/BIC and highest CR1/CR2 are shown in bold. Otherwise, see the notes for Table 3.

Table 5: DCC-MIDAS-RV-X model estimations

Model	α_{SB}	β_{SB}	θ_{RV}	θ_X	BIC	AIC	CR_1
US-DCC-RV-CPI	0.0455*** (0.0090)	0.9374*** (0.0142)	−0.0115** (0.0050)	0.0199*** (0.0050)	**3.7295**	**3.7244**	**71.87**
US-DCC-RV-I3M	0.0456*** (0.0088)	0.9379*** (0.0140)	−0.0176*** (0.0045)	0.0097*** (0.0027)	3.7316	3.7266	64.49
US-DCC-RV-MP	0.0458*** (0.0089)	0.9368*** (0.0143)	−0.0153*** (0.0045)	0.0098*** (0.0024)	3.7304	3.7253	68.97
US-DCC-RV-GDP	0.0426*** (0.0082)	0.9474*** (0.0115)	−0.0175*** (0.0064)	0.0040 (0.0070)	3.7367	3.7317	38.65
UK-DCC-RV-CPI	0.0343*** (0.0077)	0.9582*** (0.0110)	−0.0144** (0.0069)	0.0092 (0.0071)	3.7126	3.7076	40.07
UK-DCC-RV-I3M	0.0382*** (0.0083)	0.9480*** (0.0139)	−0.0156*** (0.0044)	0.0091*** (0.0033)	3.7104	3.7054	60.85
UK-DCC-RV-MP	0.0397*** (0.0085)	0.9408*** (0.0154)	−0.0113*** (0.0040)	0.0189*** (0.0044)	**3.7054**	**3.7004**	**80.98**
UK-DCC-RV-GDP	0.0349*** (0.0078)	0.9574*** (0.0111)	−0.0148** (0.0072)	0.0030 (0.0060)	3.7134	3.7083	33.74
GER-DCC-RV-CPI	0.0440*** (0.0079)	0.9435*** (0.0109)	−0.0022 (0.0072)	0.0334*** (0.0090)	3.6452	3.6402	**73.01**
GER-DCC-RV-I3M	0.0463*** (0.0076)	0.9399*** (0.0108)	−0.0192*** (0.0047)	0.0163*** (0.0052)	3.6478	3.6428	64.87
GER-DCC-RV-MP	0.0459*** (0.0075)	0.9393*** (0.0108)	−0.0122** (0.0051)	0.0183*** (0.0047)	**3.6451**	**3.6401**	71.91
GER-DCC-RV-GDP	0.0444*** (0.0081)	0.9461*** (0.0110)	−0.0203*** (0.0065)	0.0102 (0.0064)	3.6526	3.6476	41.56
FRA-DCC-RV-CPI	0.0396*** (0.0079)	0.9472*** (0.0112)	−0.0121** (0.0053)	0.0129* (0.0073)	**3.7562**	**3.7512**	**49.30**
FRA-DCC-RV-I3M	0.0407*** (0.0077)	0.9462*** (0.0109)	−0.0163*** (0.0047)	0.0060 (0.0050)	3.7576	3.7526	39.52
FRA-DCC-RV-MP	0.0405*** (0.0077)	0.9460*** (0.0110)	−0.0141*** (0.0049)	0.0079 (0.0049)	3.7566	3.7516	46.32
FRA-DCC-RV-GDP	0.0404*** (0.0077)	0.9476*** (0.0108)	−0.0172*** (0.0049)	0.0012 (0.0037)	3.7586	3.7536	32.56
IT-DCC-RV-CPI	0.0277** (0.0120)	0.9666*** (0.0152)	0.0250*** (0.0071)	0.0172*** (0.0065)	**3.6399**	**3.6349**	**64.38**
IT-DCC-RV-I3M	0.0264** (0.0111)	0.9695*** (0.0133)	0.0245*** (0.0091)	0.0103* (0.0063)	3.6421	3.6371	49.78
IT-DCC-RV-MP	0.0269** (0.0114)	0.9685*** (0.0140)	0.0250*** (0.0082)	0.0096** (0.0046)	3.6412	3.6362	56.72
IT-DCC-RV-GDP	0.0261** (0.0113)	0.9702*** (0.0136)	0.0164 (0.0107)	−0.0024 (0.0069)	3.6435	3.6385	26.31

Notes: The table reports country-wise estimation results for the DCC-RV-X model based on standardized residuals from the GARCH(1,1) models in Table 3. Otherwise, see the notes for Table 3.

Table 6: DCC-MIDAS-X model estimations: GDP interaction

Model	θ_{GDP}	θ_{MP}	$\theta_{GDP \cdot MP}$	BIC	AIC	CR_1
US-DCC-GDP-MP	−0.0102 (0.0086)	0.0125*** (0.0033)	−0.0086** (0.0038)	3.7339	3.7276	56.19
UK-DCC-GDP-MP	−0.0084 (0.0063)	0.0273*** (0.0066)	−0.0062* (0.0032)	3.7080	3.7017	64.50
GER-DCC-GDP-MP	−0.0105 (0.0066)	0.0161*** (0.0048)	−0.0175*** (0.0057)	3.6445	3.6382	65.11
FRA-DCC-GDP-MP	−0.0058 (0.0071)	0.0151** (0.0070)	−0.0021 (0.0066)	3.7602	3.7540	27.75
IT-DCC-GDP-MP	−0.0148*** (0.0049)	0.0123*** (0.0039)	0.0099*** (0.0035)	3.6372	3.6310	86.70

Notes: The table reports country-wise estimation results for the DCC-X model based on standardized residuals from the GARCH(1,1) models in Table 3. We consider a DCC-MIDAS-X model that includes lags of GDP, MP as well as the interaction $GDP \cdot MP$, and report estimates of the respective θ_X parameters. Otherwise, see the notes for Table 3.

Table 7: Monthly Mincer-Zarnowitz Regressions

Model	R^2	p-value
US-RW	28.02	0.00
US-CCC	27.24	0.00
US-DCC	37.94	0.17
US-DCC-RC	**39.52**	0.25
US-DCC-RC-RV-CPI	38.87	0.58
US-DCC-RV-CPI	37.03	0.52
UK-RW	43.67	0.00
UK-CCC	27.43	0.00
UK-DCC	46.38	0.33
UK-DCC-RC	**47.74**	0.93
UK-DCC-RC-RV-MP	46.89	0.88
UK-DCC-RV-MP	45.50	0.90
GER-RW	53.08	0.00
GER-CCC	31.01	0.00
GER-DCC	**54.84**	0.73
GER-DCC-RC	54.81	0.43
GER-DCC-RC-RV-MP	53.80	0.24
GER-DCC-RV-MP	53.08	0.16
FRA-RW	37.73	0.00
FRA-CCC	17.89	0.01
FRA-DCC	**42.24**	0.98
FRA-DCC-RC	**42.24**	0.98
FRA-DCC-RC-RV-CPI	42.01	0.70
FRA-DCC-RV-CPI	40.95	0.79
IT-RW	34.14	0.00
IT-CCC	24.55	0.00
IT-DCC	44.46	0.04
IT-DCC-RC	46.63	0.13
IT-DCC-RC-RV-CPI	**47.19**	0.13
IT-DCC-RV-CPI	44.18	0.08

Notes: We evaluate the monthly covariance forecasts via a Mincer-Zarnowitz Regression of the realized covariance on a constant and the covariance forecast. We report the regression R^2 percentage value as well as the p-value of the F-test that the constant is zero and the slope coefficient is one. For each country, the highest R^2 value is shown in bold. The estimates are based on the full June 1995 to December 2013 in-sample period.

Table 8: Portfolio evaluation: in-sample gain/loss

	optimal daily weights			optimal monthly weights		
Model / Benchmark	Const	RW	CCC	Const	RW	CCC
US-DCC	5.47***	3.51***	4.86***	4.27***	2.33***	4.04***
US-DCC-RC	5.66***	3.70***	5.05***	4.48***	2.54***	4.25***
US-DCC-RC-RV-CPI	**5.78*****	**3.81*****	**5.17*****	**4.55*****	**2.61*****	**4.32*****
US-DCC-RV-CPI	5.63***	3.67***	5.02***	4.36***	2.42***	4.13***
UK-DCC	6.57***	3.45***	4.94***	5.01***	1.94***	4.05***
UK-DCC-RC	**6.59*****	**3.47*****	**4.96*****	**5.25*****	**2.17*****	**4.28*****
UK-DCC-RC-RV-MP	6.58***	3.46***	4.95***	5.17***	2.09***	4.21***
UK-DCC-RV-MP	6.56***	3.45***	4.93***	4.93***	1.86***	3.96***
GER-DCC	7.06***	3.80***	5.77***	6.21***	2.97***	5.37***
GER-DCC-RC	**7.38*****	**4.11*****	**6.09*****	**6.30*****	**3.06*****	**5.46*****
GER-DCC-RC-RV-MP	7.32***	4.05***	6.03***	6.13***	2.89***	5.29***
GER-DCC-RV-MP	7.15***	3.89***	5.86***	5.96***	2.73***	5.13***
FRA-DCC	7.03***	3.60***	5.28***	5.56***	2.18***	4.41***
FRA-DCC-RC	7.00***	3.57***	5.26***	5.68***	2.30**	4.53***
FRA-DCC-RC-RV-CPI	**7.09*****	**3.66*****	**5.34*****	**5.72*****	**2.33****	**4.57*****
FRA-DCC-RV-CPI	7.08***	3.64***	5.33***	5.50***	2.12***	4.35***
IT-DCC	10.74***	6.22***	10.16***	8.47***	4.04**	8.13***
IT-DCC-RC	11.85***	7.29***	11.27***	9.46***	4.99**	9.11***
IT-DCC-RC-RV-CPI	**11.92*****	**7.36*****	**11.34*****	**9.64*****	**5.16****	**9.29*****
IT-DCC-RV-CPI	10.94***	6.42***	10.37***	8.64***	4.21**	8.30***

Notes: We reestimate all models for the in-sample period June 1995 to December 2013. We then construct hedge portfolios based on forecasts of the covariance matrix, see Section 5 for details. We compare the portfolios based on forecasts from the DCC/DCC-(RC)-X models to benchmark portfolios based on forecasts from the constant covariance matrix (Const), the random walk (RW) covariance matrix, and the constant conditional correlation (CCC) model in terms of the portfolio variance.
The table reports the gain/loss $G/L_{j,BM} = 100 \cdot (\hat{\sigma}_{P,BM} - \hat{\sigma}_{P,j})/\hat{\sigma}_{P,j}\%$ based on the portfolio standard deviations $\hat{\sigma}_{P,j}$, resp. $\hat{\sigma}_{P,BM}$, from the DCC/DCC-(RC)-X, resp. the benchmark models. We test for the equality of the portfolio variances by testing whether the difference in equation (20) is different from zero by means of a Diebold-Mariano test. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. For each country, the highest/lowest significant gain/loss value is shown in bold. Portfolio evaluation is based on daily returns over the full in-sample period.

Table 9: Portfolio evaluation: out-of-sample gain/loss

	optimal daily weights			optimal monthly weights		
Model / Benchmark	Const	RW	CCC	Const	RW	CCC
US-DCC	11.27***	3.21**	10.31***	9.77***	1.81**	8.81***
US-DCC-RC	12.12***	3.99***	11.15***	9.92***	1.96**	8.96***
US-DCC-RC-RV-CPI	**12.36*****	**4.22*****	**11.39*****	10.36***	2.37**	9.40***
US-DCC-RV-CPI	11.85***	3.74**	10.88***	**10.39*****	**2.39*****	**9.43*****
UK-DCC	12.14***	3.33*	11.88***	11.32***	2.58**	11.08***
UK-DCC-RC	12.42***	3.59*	12.17***	11.25***	2.51	11.00***
UK-DCC-RC-RV-MP	**12.72*****	**3.87***	**12.47*****	11.79***	3.01*	11.55***
UK-DCC-RV-MP	12.70***	3.84*	12.44***	**12.27*****	**3.45*****	**12.02*****
GER-DCC	7.19**	1.79	6.61**	6.01**	0.68	5.39**
GER-DCC-RC	**8.01*****	**2.57***	**7.43*****	**6.86*****	1.48	**6.23*****
GER-DCC-RC-RV-MP	7.78**	2.35	7.20**	6.45*	1.09	5.82*
GER-DCC-RV-MP	7.52**	2.11	6.95**	6.63*	1.26	6.00*
FRA-DCC	6.34**	0.34	4.72*	6.48**	0.47	4.72**
FRA-DCC-RC	6.54**	0.53	4.92**	6.76***	0.74	5.00**
FRA-DCC-RC-RV-CPI	**6.55****	0.54	**4.93***	**6.58****	0.57	**4.82***
FRA-DCC-RV-CPI	6.46**	0.46	4.84*	6.64**	0.63	4.88*
IT-DCC	10.38***	5.39***	1.74	7.35**	2.49*	0.69
IT-DCC-RC	10.58***	5.58***	1.92	7.59***	2.73*	0.92
IT-DCC-RC-RV-CPI	**10.61*****	**5.61*****	**1.96**	**7.87*****	**2.99****	1.18
IT-DCC-RV-CPI	10.22***	5.23***	1.59	7.58**	2.72*	0.91

Notes: Portfolio evaluation in terms of portfolio variance over the out-of-sample period January 2014 - January 2016. Otherwise, see the notes for Table 8.

Table 10: Portfolio evaluation against the DCC model: in-sample gain/loss

	optimal daily weights		optimal monthly weights	
	volatility regime		volatility regime	
Model	normal	high	normal	high
US-DCC-RC	0.35**	0.11	0.37*	0.13
US-DCC-RC-RV-CPI	**0.44****	0.24	0.65**	0.12
US-DCC-RV-CPI	0.36**	0.07	**0.72*****	−0.18
UK-DCC-RC	0.41***	−0.17	0.49***	0.11
UK-DCC-RC-RV-MP	**0.44*****	−0.20	**0.53****	−0.02
UK-DCC-RV-MP	0.34**	−0.16	0.47*	−0.33
GER-DCC-RC	0.22	0.34	0.27	0.00
GER-DCC-RC-RV-MP	0.17	0.29	0.13	−0.16
GER-DCC-RV-MP	0.10	0.09	0.15	−0.40
FRA-DCC-RC	0.06	−0.07	0.16	0.09
FRA-DCC-RC-RV-CPI	0.11	0.04	0.21	0.12
FRA-DCC-RV-CPI	0.09	0.02	0.20	−0.19
IT-DCC-RC	0.39**	1.58	0.36**	1.39
IT-DCC-RC-RV-CPI	**0.45****	1.64	**0.45****	1.61
IT-DCC-RV-CPI	0.16	0.22	0.21	0.11

Notes: We compare the portfolios based on forecasts from the DCC-MIDAS models to a benchmark portfolio based on forecasts from the DCC model in terms of the portfolio variance. Portfolio evaluation is based on daily returns over the in-sample period. We now distinguish between a *normal* and *high* volatility regime. The normal (high) volatility regime is defined as realized volatility being below (above) the 70th percentile of its historical distribution. Otherwise, see the notes for Tabel 8.

Table 11: Portfolio evaluation against the DCC model: out-of-sample gain/loss

	optimal daily weights		optimal monthly weights	
	volatility regime		volatility regime	
Model	normal	high	normal	high
US-DCC-RC	0.63*	0.88	1.07**	−0.59
US-DCC-RC-RV-CPI	**0.76****	1.15	**1.31****	−0.09
US-DCC-RV-CPI	0.73***	0.34	1.11**	0.12
UK-DCC-RC	0.86	−0.17	**1.61****	−1.29
UK-DCC-RC-RV-MP	0.50	0.53	0.81	0.10
UK-DCC-RV-MP	0.54	0.45	0.72	0.93
GER-DCC-RC	0.57	0.97	0.53	1.09
GER-DCC-RC-RV-MP	−0.20	1.37	−0.71	1.64
GER-DCC-RV-MP	−0.42	1.13	−0.69	2.03
FRA-DCC-RC	0.94	−0.51	**1.37***	−0.80
FRA-DCC-RC-RV-CPI	0.48	−0.13	0.39	−0.28
FRA-DCC-RV-CPI	0.05	0.15	0.09	0.18
IT-DCC-RC	0.08	0.41	0.37	−0.10
IT-DCC-RC-RV-CPI	−0.20	**1.19***	−0.13	1.93
IT-DCC-RV-CPI	−0.93*	1.80	−1.38*	**4.17***

Notes: We compare the portfolios based on forecasts from the DCC-MIDAS models to a benchmark portfolio based on forecasts from the DCC model in terms of the portfolio variance. Portfolio evaluation is based on daily returns over the out-of-sample period. Otherwise, see the notes for Table 10.

Table 12: Portfolio statistics: in-sample

	optimal daily weights				optimal monthly weights			
Model	SD	TO	$r_{P,t}$	Sharpe	SD	TO	$r_{P,t}$	Sharpe
US Stock	19.88		6.78	0.34				
US-DCC	18.20	13.21	9.46	0.52	18.41	5.36	**9.88**	**0.54**
US-DCC-RC	18.17	18.45	8.59	0.47	18.38	4.75	9.25	0.50
US-DCC-RC-RV-CPI	**18.15**	18.16	8.27	0.46	18.36	**4.67**	8.79	0.48
US-DCC-RV-CPI	18.18	14.05	8.79	0.48	18.40	5.03	8.99	0.49
UK Stock	18.88		3.67	0.19				
UK-DCC	17.20	13.90	6.30	0.37	17.45	5.51	**6.98**	**0.40**
UK-DCC-RC	**17.19**	18.19	5.33	0.31	17.41	**4.67**	6.08	0.35
UK-DCC-RC-RV-MP	17.20	18.24	5.16	0.30	17.43	**4.67**	5.88	0.34
UK-DCC-RV-MP	17.20	15.94	5.44	0.32	17.47	5.17	6.05	0.35
GER Stock	23.95		5.68	0.24				
GER-DCC	21.43	22.73	9.16	0.43	21.60	9.32	**9.79**	**0.45**
GER-DCC-RC	**21.37**	27.80	7.97	0.37	21.59	8.11	8.67	0.40
GER-DCC-RC-RV-MP	21.38	27.49	7.79	0.36	21.62	**8.00**	8.44	0.39
GER-DCC-RV-MP	21.41	25.13	8.23	0.38	21.65	8.69	8.79	0.41
FRA Stock	22.78		4.78	0.21				
FRA-DCC	20.77	21.47	6.89	0.33	21.06	7.95	**7.07**	**0.34**
FRA-DCC-RC	20.78	25.87	6.03	0.29	21.04	6.97	6.52	0.31
FRA-DCC-RV-CPI	**20.76**	25.34	5.81	0.28	21.03	**6.91**	6.12	0.29
FRA-DCC-RV-CPI	20.77	22.19	6.49	0.31	21.07	7.71	6.54	0.31
IT Bond	7.00		3.33	0.48				
IT-DCC	6.25	1.38	**2.54**	**0.41**	6.38	0.57	2.48	0.39
IT-DCC-RC	6.19	2.20	2.38	0.38	6.32	**0.53**	2.39	0.38
IT-DCC-RC-RV-CPI	**6.18**	2.11	2.38	0.39	6.31	0.54	2.38	0.38
IT-DCC-RV-CPI	6.24	1.47	**2.54**	**0.41**	6.37	0.58	2.52	0.40

Notes: Portfolio evaluation in terms of portfolio standard deviation (SD), turnover (TO), net excess returns, $r_{P,t}$ (with transaction costs $c = 2\%$), and corresponding Sharpe ratios for the hedge portfolios over the in-sample period June 1995 to December 2013. Numbers in bold indicate the models with the lowest SD, the lowest TO, and the highest $r_{P,t}$ and Sharpe ratio. See also Section 5.

Table 13: Portfolio statistics: out-of-sample

	optimal daily weights				optimal monthly weights			
Model	SD	TO	$r_{P,t}$	Sharpe	SD	TO	$r_{P,t}$	Sharpe
US Stock	14.10		2.01	0.14				
US-DCC	12.84	12.27	4.28	0.33	13.02	4.29	6.78	0.52
US-DCC-RC	12.74	16.08	3.48	0.27	13.00	**3.39**	5.96	0.46
US-DCC-RC-RV-CPI	**12.72**	15.90	3.81	0.30	12.95	3.67	6.41	0.50
US-DCC-RV-CPI	12.78	13.04	4.23	0.33	12.94	4.10	**6.83**	**0.53**
UK Stock	15.08		-5.57	-0.37				
UK-DCC	14.03	11.84	-0.67	-0.05	14.13	4.38	-1.31	-0.09
UK-DCC-RC	13.99	15.88	-1.86	-0.13	14.14	**3.47**	-2.26	-0.16
UK-DCC-RC-RV-MP	**13.96**	16.09	-1.14	-0.08	14.07	3.92	-1.51	-0.11
UK-DCC-RV-MP	**13.96**	14.16	**-0.08**	**-0.01**	14.01	4.52	-0.65	-0.05
GER Stock	20.29		-1.05	-0.05				
GER-DCC	19.42	18.97	8.27	0.43	19.63	7.36	10.16	0.52
GER-DCC-RC	**19.27**	24.19	8.69	0.45	19.48	**6.23**	9.88	0.51
GER-DCC-RC-RV-MP	19.31	24.42	10.30	0.53	19.56	7.17	**12.23**	**0.63**
GER-DCC-RV-MP	19.36	22.04	9.90	0.51	19.52	7.70	12.15	0.62
FRA Stock	19.31		2.21	0.11				
FRA-DCC	19.07	16.57	11.18	0.59	19.05	4.67	11.33	0.59
FRA-DCC-RC	19.03	21.26	10.16	0.53	**18.99**	**3.72**	9.62	0.51
FRA-DCC-RC-RV-CPI	19.03	21.04	**11.47**	**0.60**	19.03	4.48	11.14	0.59
FRA-DCC-RV-CPI	19.05	17.51	11.28	0.59	19.02	4.76	11.21	0.59
IT Bond	7.53		10.95	1.45				
IT-DCC	6.79	1.63	10.74	1.58	6.98	0.79	**11.22**	**1.61**
IT-DCC-RC	6.78	2.60	10.42	1.54	6.96	0.76	10.83	1.55
IT-DCC-RC-RV-CPI	**6.77**	2.48	10.28	1.52	6.95	0.69	10.71	1.54
IT-DCC-RV-CPI	6.80	1.63	10.40	1.53	6.96	**0.67**	11.06	1.59

Notes: Portfolio evaluation in terms of portfolio standard deviation (SD), turnover (TO), net excess returns, $r_{P,t}$ (with transaction costs $c = 2\%$), and corresponding Sharpe ratios for the hedge portfolios over the out-of-sample period January 2014 - January 2016. See also Table 12.

C Figures

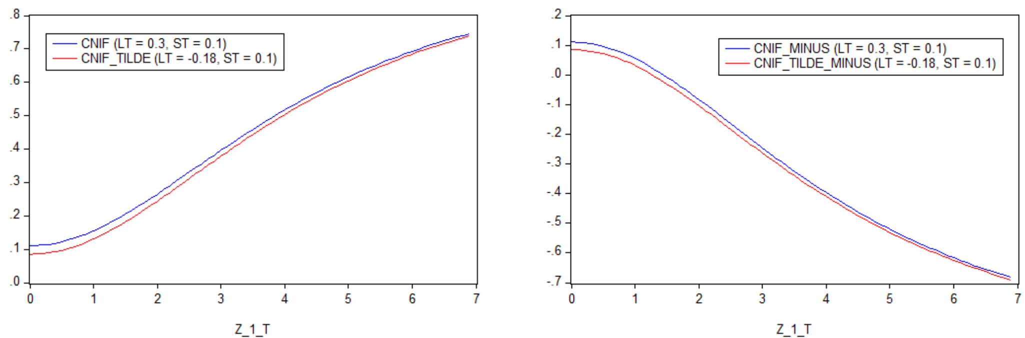

Figure 1: The figure shows the correlation news impact function, $CNIF_{t+1}$, as a function of $Z_{S,t}$ and $Z_{B,t}$, see equation (13). We choose $q_{SS,t} = q_{BB,t} = 1$ and $q_{SB,t} = 0.1$ such that $\rho_{SB,t} = 0.1$. The parameters are given by $\alpha_{SB} = 0.05$ and $\beta_{SB} = 0.9$. The left (right) panel show situations with shocks of equal sign, $Z_{B,t} = Z_{S,t}$, (opposite sign, $Z_{B,t} = -Z_{S,t}$,). The blue line represents the CNIF of a DCC-RC-X with $\bar{\rho}_{SB,\tau} = 0.3$ and the red line a CNIF with $\bar{\rho}_{SB,\tau} = -0.18$.

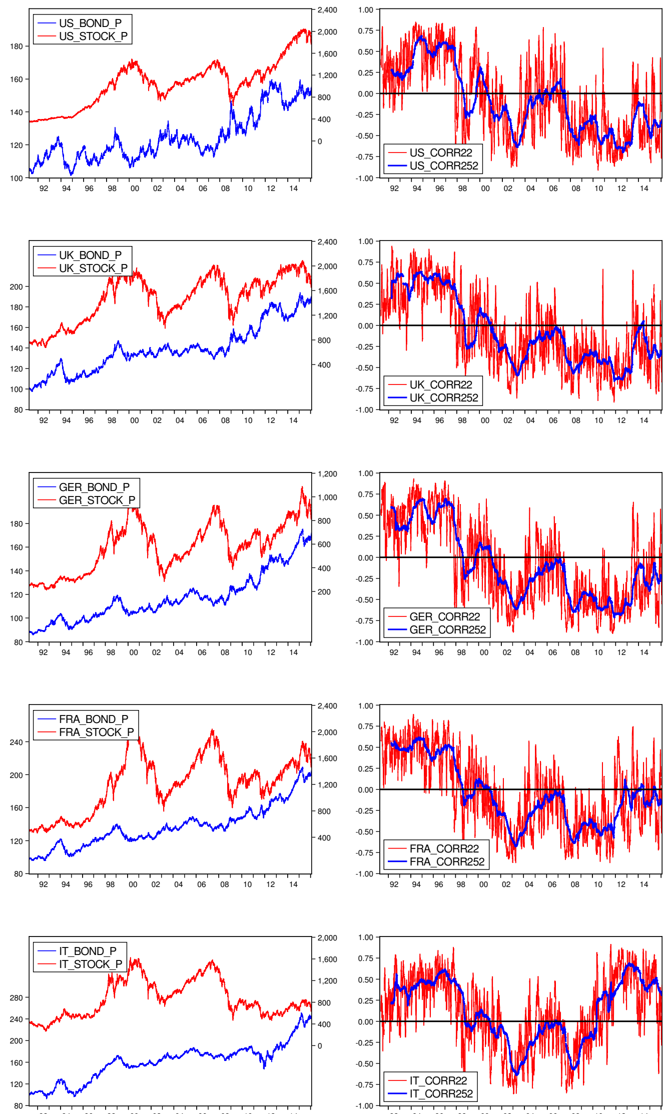

Figure 2: Country-wise daily stock and bond prices (left panels) as well as 22-days and 252-days rolling window correlations (right panels) over the full April 1991 to January 2016 sample period.

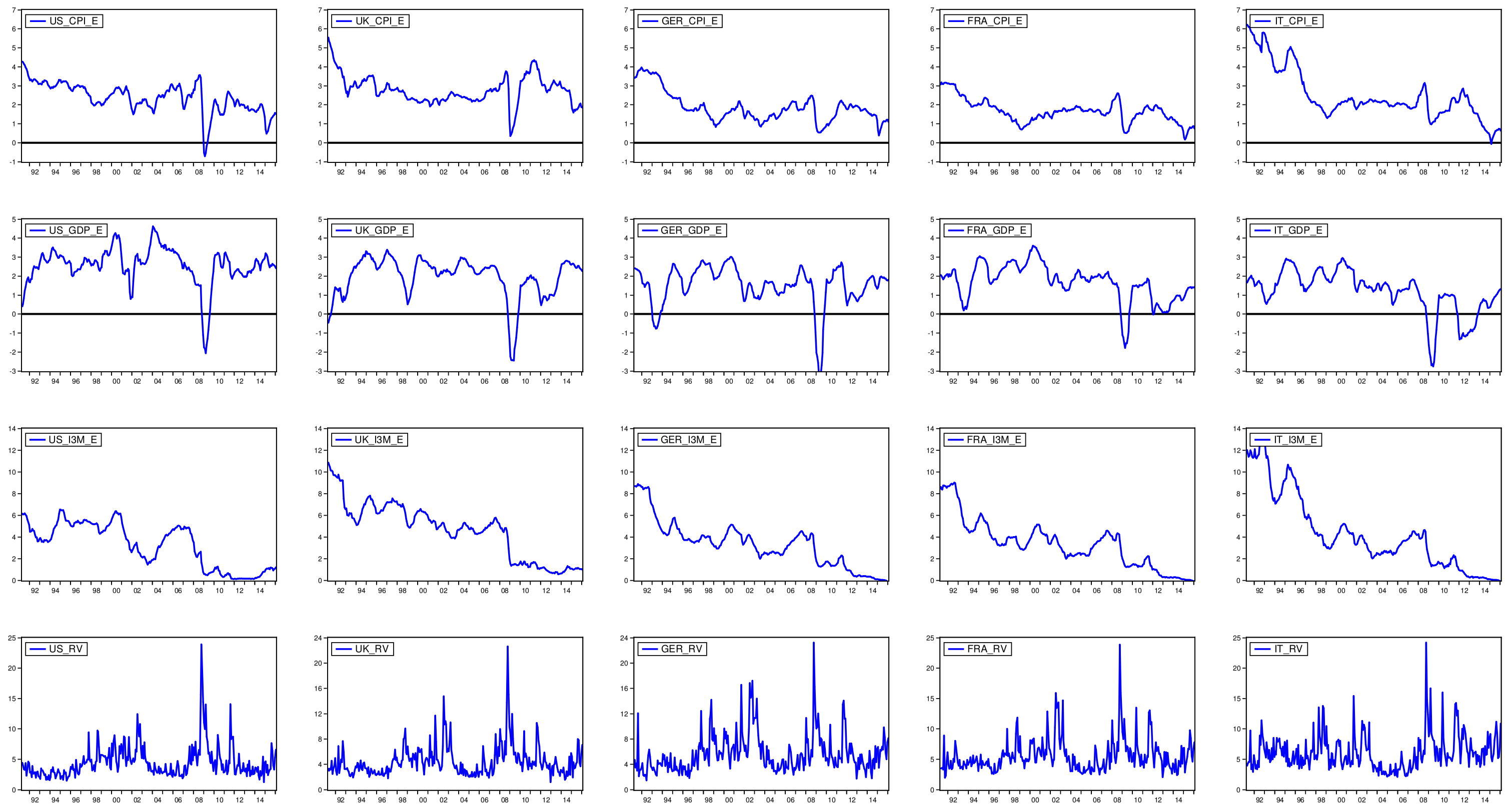

Figure 3: Country-wise monthly macroeconomic expectations data and realized stock market volatility over the full April 1991 to January 2016 sample period.

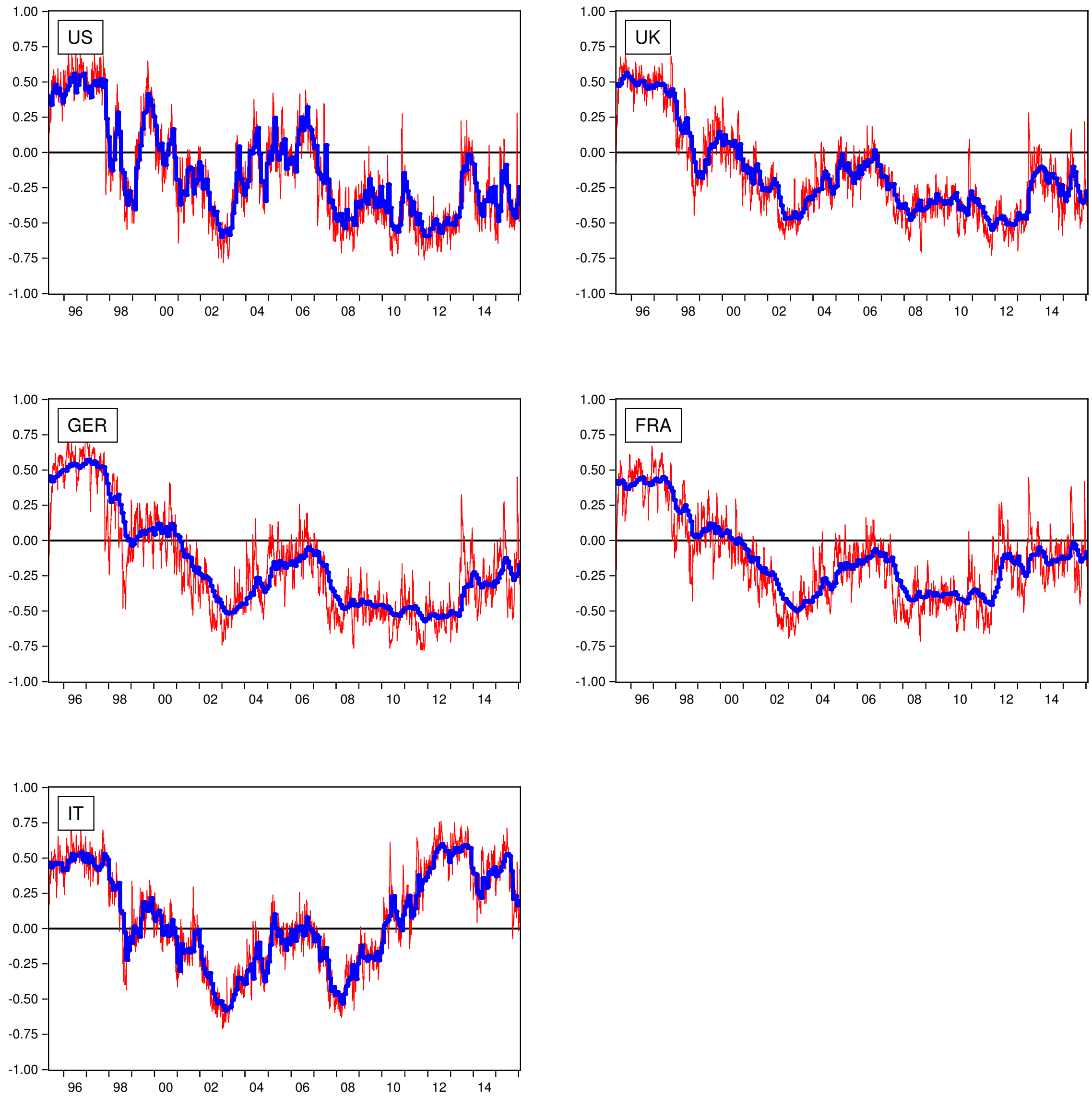

Figure 4: Country-wise daily conditional correlations (red) and monthly long-term correlation component (blue) from the DCC-RC model in Table 5.

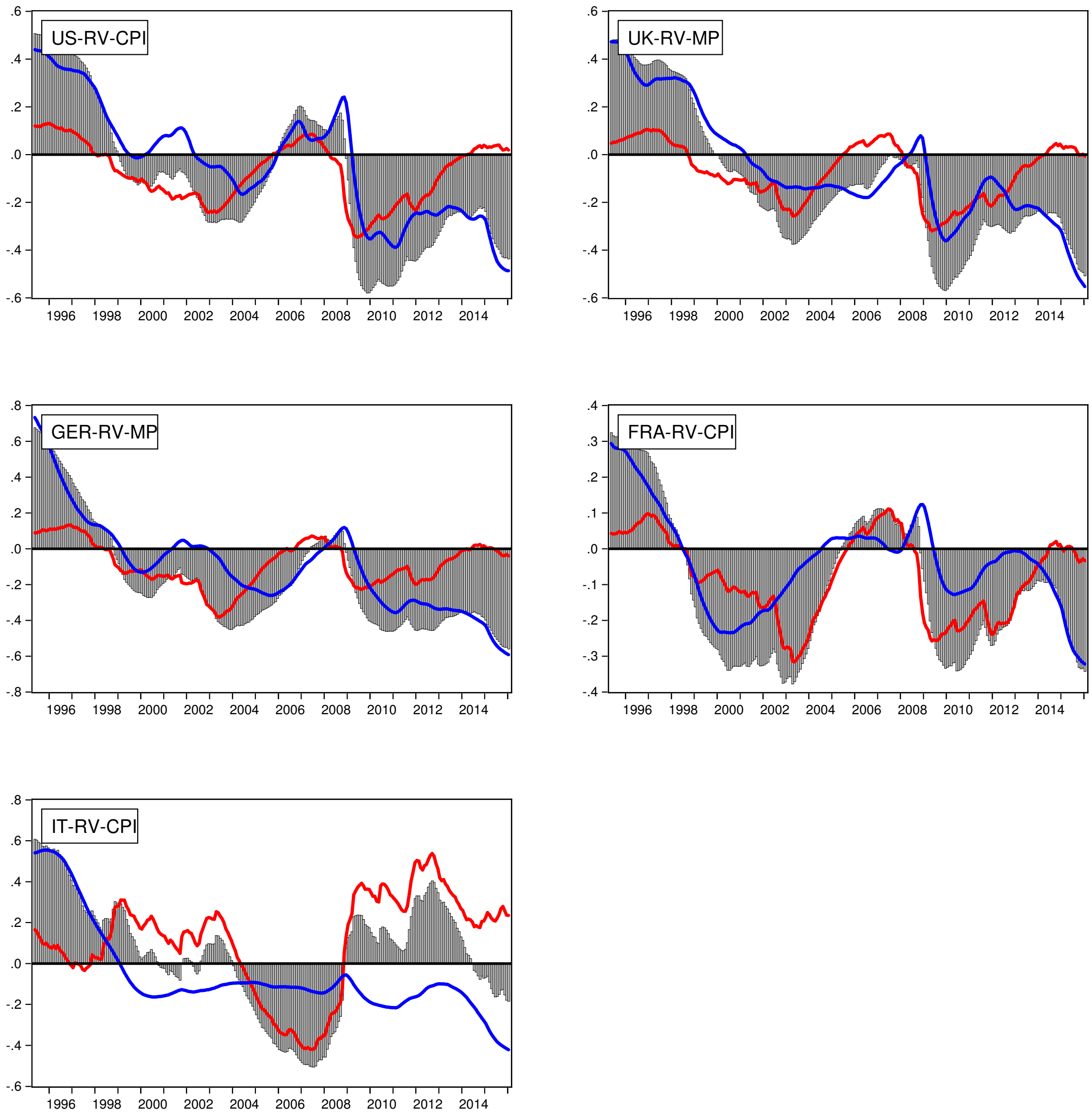

Figure 5: Country-wise monthly long-term correlation component (gray area) and its contributions from realized volatility (m_{RV}, red line) and the macro variable X (m_X, blue line) from the bivariate DCC-RV-X model estimations in Table 5. For the US, FRA, and IT we include CPI and for the UK and GER we include MP.

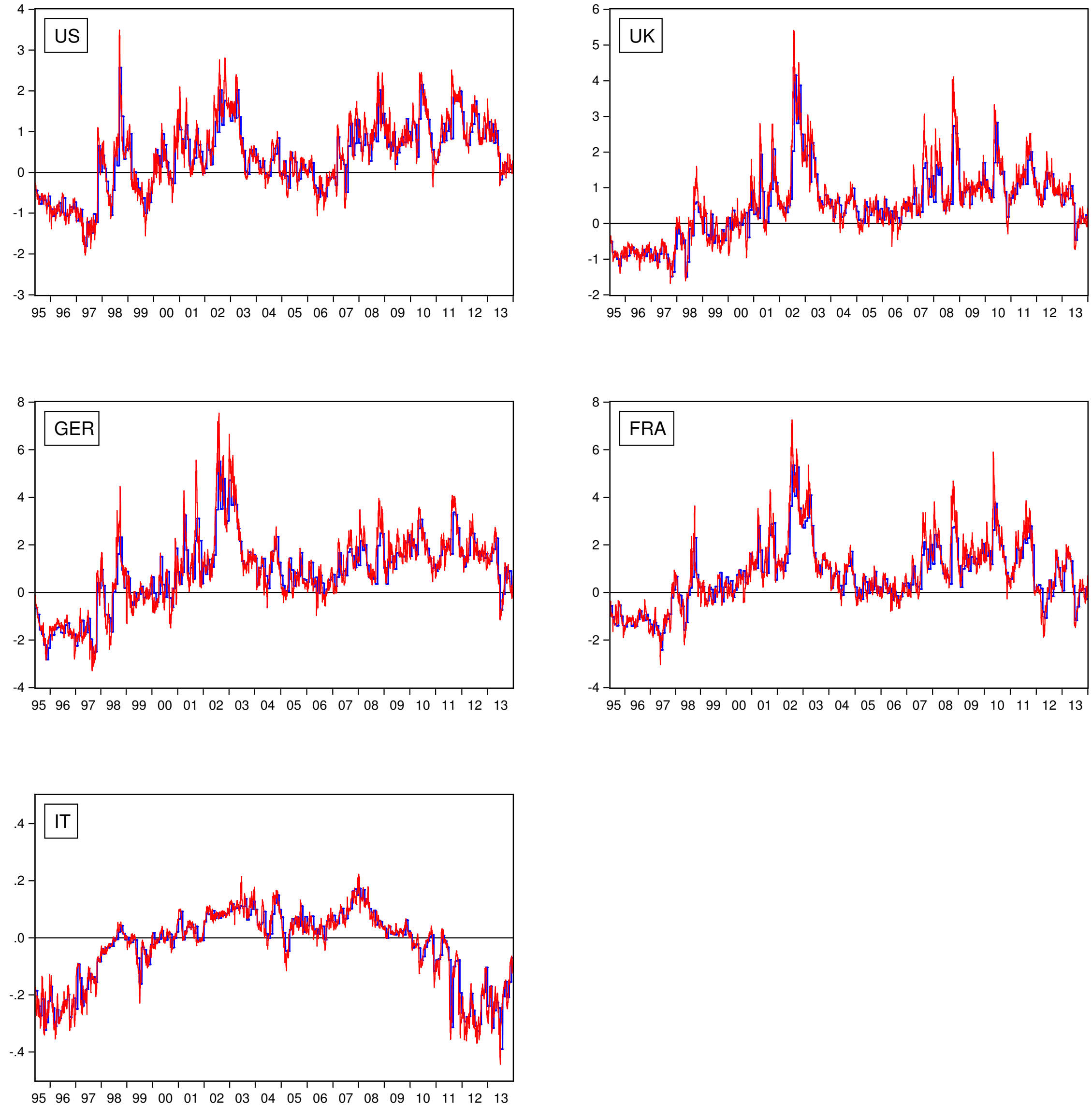

Figure 6: Optimal daily (red) and monthly (blue) weights on bonds for the US, the UK, GER, and FRA and on stocks for IT from the DCC-MIDAS models over the full 1995-2013 in-sample period. For the US, FRA, and IT we consider the DCC-RV-CPI model and for the UK and GER we consider the DCC-RV-MP model.

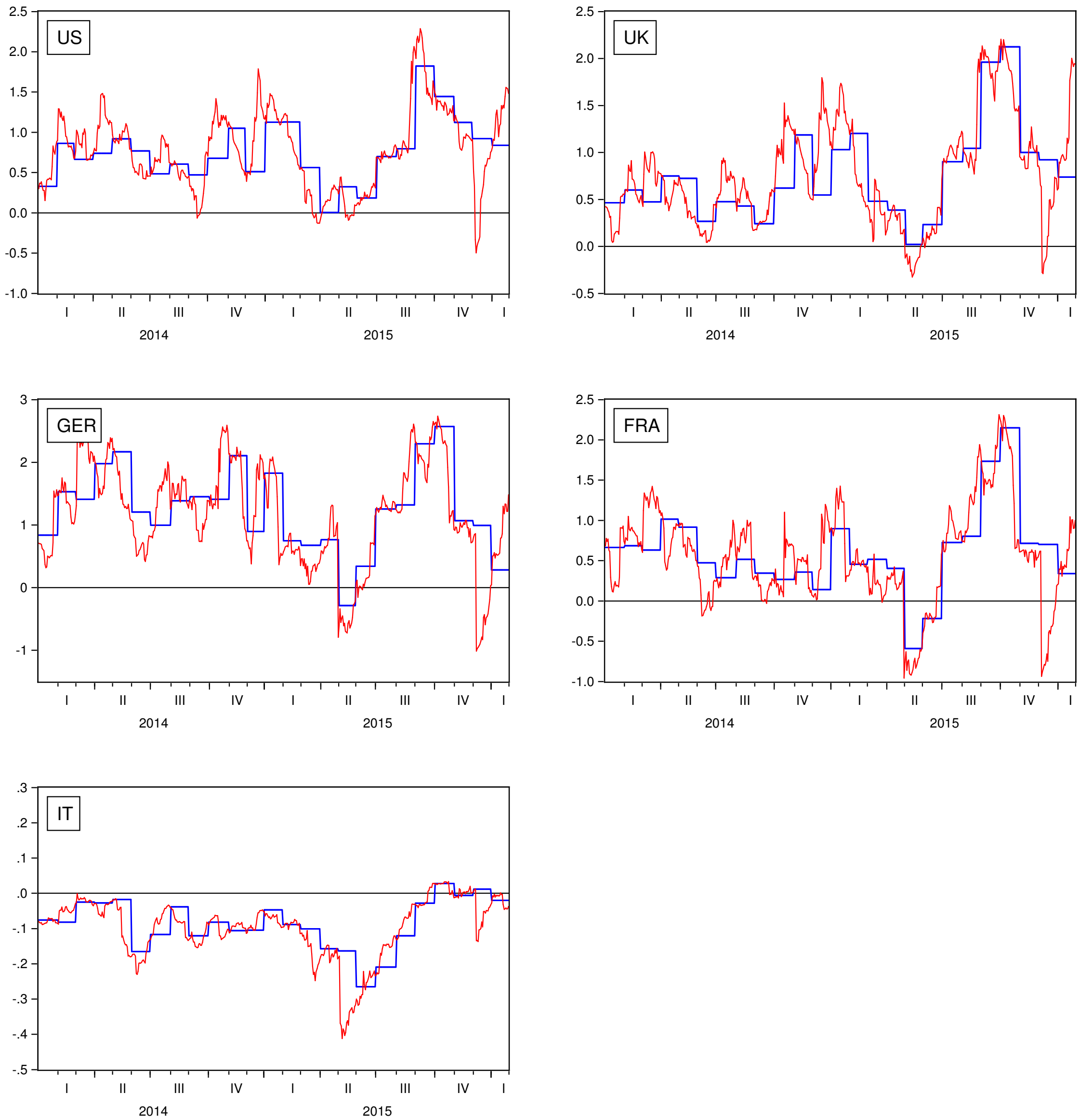

Figure 7: Optimal daily (red) and monthly (blue) weights on bonds for the US, the UK, GER, and FRA and on stocks for IT from the DCC-MIDAS models over the 2014-2016 out-of-sample period. For the US, FRA, and IT we consider the the DCC-RV-CPI model and for the UK and GER we consider the DCC-RV-MP model.

D Appendix

Table 14: GARCH(1,1) model subsample estimations

Country	μ	ω	α	β	BIC	AIC
Panel A: Stock market						
US	0.0533***	0.0104***	0.0750***	0.9167***	2.7065	2.7019
	(0.0107)	(0.0031)	(0.0109)	(0.0118)		
UK	0.0419***	0.0123***	0.0866***	0.9036***	2.7154	2.7108
	(0.0108)	(0.0031)	(0.0108)	(0.0117)		
GER	0.0582***	0.0287***	0.0842***	0.9000***	3.1890	3.1844
	(0.0141)	(0.0094)	(0.0113)	(0.0111)		
FRA	0.0485***	0.0286***	0.0811***	0.9025***	3.1852	3.1806
	(0.0147)	(0.0094)	(0.0112)	(0.0139)		
IT	0.0372**	0.0177***	0.0792***	0.9149***	3.3409	3.3363
	(0.0147)	(0.0053)	(0.0124)	(0.0127)		
Panel B: Bond market						
US	0.0069	0.0021***	0.0425***	0.9483***	1.2182	1.2135
	(0.0055)	(0.0006)	(0.0059)	(0.0073)		
UK	0.0093*	0.0016***	0.0450***	0.9461***	0.9274	0.9227
	(0.0048)	(0.0005)	(0.0082)	(0.0098)		
GER	0.0116***	0.0011***	0.0472***	0.9442***	0.5638	0.5591
	(0.0040)	(0.0003)	(0.0071)	(0.0082)		
FRA	0.0109**	0.0017***	0.0467***	0.9402***	0.6832	0.6786
	(0.0042)	(0.0005)	(0.0073)	(0.0105)		
IT	0.0153***	0.0012**	0.0846***	0.9144***	0.9193	0.9147
	(0.0043)	(0.0005)	(0.0162)	(0.0155)		

Notes: The table reports country-wise estimation results for the GARCH(1,1) model estimation over the April 1991 - December 2013 subsample. The numbers in parentheses are Bollerslev-Wooldridge (1992) robust standard errors. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. BIC is the Bayesian information criterion and AIC is the Akaike information criterion.

Table 15: DCC and DCC-RC-X model subsample estimations

Model	α_{SB}	β_{SB}	λ_{RC}	θ_{RC}	θ_{RV}	θ_X	BIC	AIC	CR_1	CR_2
US-DCC	0.0388*** (0.0077)	0.9560*** (0.0094)					3.7422	3.7395		
US-DCC-RC	0.0606*** (0.0142)	0.8647*** (0.0509)	0.5873*** (0.1712)	0.3884** (0.1573)			3.7358	3.7303	86.24	
US-DCC-RC-RV-CPI	0.0593*** (0.0142)	0.8607*** (0.0471)	0.4223*** (0.1441)	0.4117*** (0.1014)	−0.0034 (0.0033)	0.0084** (0.0033)	**3.7332**	**3.7249**	**90.15**	**10.60**
US-DCC-RC-RV-I3M	0.0597*** (0.0139)	0.8600*** (0.0464)	0.4204*** (0.1413)	0.4219*** (0.1000)	−0.0060* (0.0033)	0.0032* (0.0017)	3.7356	3.7273	88.83	7.83
US-DCC-RC-RV-MP	0.0596*** (0.0140)	0.8599*** (0.0465)	0.4111*** (0.1404)	0.4198*** (0.0988)	−0.0053* (0.0032)	0.0037** (0.0016)	3.7346	3.7263	89.51	9.47
US-DCC-RC-RV-GDP	0.0595*** (0.0141)	0.8616*** (0.0486)	0.5054*** (0.1581)	0.4027*** (0.1211)	−0.0046 (0.0034)	0.0010 (0.0024)	3.7374	3.7292	87.35	2.87
UK-DCC	0.0314*** (0.0072)	0.9646*** (0.0087)					3.6971	3.6944		
UK-DCC-RC	0.0475*** (0.0078)	0.8892*** (0.0246)	0.7642*** (0.0744)	0.2317*** (0.0717)			**3.6858**	3.6804	90.76	
UK-DCC-RC-RV-CPI	0.0469*** (0.0079)	0.8907*** (0.0249)	0.7740*** (0.0749)	0.2175*** (0.0704)	0.0004 (0.0031)	0.0038 (0.0027)	3.6882	3.6800	90.24	1.43
UK-DCC-RC-RV-I3M	0.0475*** (0.0078)	0.8891*** (0.0247)	0.7589*** (0.0913)	0.2317*** (0.0765)	−0.0007 (0.0032)	0.0001 (0.0025)	3.6894	3.6812	89.80	0.07
UK-DCC-RC-RV-MP	0.0477*** (0.0079)	0.8903*** (0.0235)	0.6991*** (0.0885)	0.2386*** (0.0658)	−0.0012 (0.0031)	0.0065* (0.0038)	3.6878	**3.6796**	**91.48**	**5.82**
UK-DCC-RC-RV-GDP	0.0473*** (0.0078)	0.8896*** (0.0251)	0.7746*** (0.0867)	0.2212*** (0.0799)	−0.0010 (0.0033)	−0.0011 (0.0023)	3.6893	3.6811	89.36	0.13
GER-DCC	0.0356*** (0.0077)	0.9609*** (0.0090)					3.6309	3.6282		
GER-DCC-RC	0.0489*** (0.0077)	0.9140*** (0.0216)	0.8647*** (0.0845)	0.1392 (0.0849)			3.6183	3.6128	89.18	
GER-DCC-RC-RV-CPI	0.0469*** (0.0075)	0.9141*** (0.0184)	0.8176*** (0.0659)	0.1580*** (0.0612)	0.0055 (0.0041)	0.0158*** (0.0049)	**3.6156**	**3.6074**	**88.93**	9.66
GER-DCC-RC-RV-I3M	0.0492*** (0.0076)	0.9122*** (0.0203)	0.7914*** (0.1077)	0.1753** (0.0852)	−0.0032 (0.0044)	0.0065 (0.0046)	3.6209	3.6127	87.02	4.82
GER-DCC-RC-RV-MP	0.0481*** (0.0075)	0.9134*** (0.0187)	0.7718*** (0.0793)	0.1749*** (0.0666)	−0.0006 (0.0038)	0.0099*** (0.0035)	3.6179	3.6097	88.04	**11.22**
GER-DCC-RC-RV-GDP	0.0482*** (0.0078)	0.9170*** (0.0214)	0.9006*** (0.0850)	0.1077 (0.0882)	−0.0000 (0.0047)	−0.0036 (0.0044)	3.6214	3.6133	87.22	1.15
FRA-DCC	0.0377*** (0.0087)	0.9550*** (0.0110)					3.7277	3.7250		
FRA-DCC-RC	0.0495*** (0.0097)	0.9115*** (0.0260)	0.8834*** (0.0468)	0.1105** (0.0448)			**3.7216**	3.7161	77.38	
FRA-DCC-RC-RV-CPI	0.0481*** (0.0095)	0.9122*** (0.0255)	0.8939*** (0.0446)	0.0930** (0.0428)	0.0022 (0.0042)	0.0098** (0.0044)	**3.7216**	**3.7135**	**83.71**	**7.52**
FRA-DCC-RC-RV-I3M	0.0489*** (0.0098)	0.9136*** (0.0260)	0.9016*** (0.0660)	0.0952* (0.0553)	−0.0008 (0.0043)	−0.0021 (0.0063)	3.7250	3.7169	79.05	0.53
FRA-DCC-RC-RV-MP	0.0500*** (0.0099)	0.9088*** (0.0280)	0.8523*** (0.0742)	0.1220** (0.0602)	−0.0005 (0.0041)	0.0049 (0.0037)	3.7240	3.7158	81.23	4.21
FRA-DCC-RC-RV-GDP	0.0477*** (0.0094)	0.9152*** (0.0236)	0.9351*** (0.0369)	0.0687* (0.0362)	−0.0008 (0.0045)	−0.0053* (0.0030)	3.7233	3.7151	79.89	7.43
IT-DCC	0.0254** (0.0106)	0.9720*** (0.0120)					3.6301	3.6274		
IT-DCC-RC	0.0561*** (0.0117)	0.8511*** (0.0468)	0.7190*** (0.0615)	0.2856*** (0.0615)			**3.6184**	3.6129	88.97	
IT-DCC-RC-RV-CPI	0.0529*** (0.0114)	0.8594*** (0.0457)	0.7077*** (0.0636)	0.2628*** (0.0606)	0.0054* (0.0028)	0.0037 (0.0024)	3.6196	**3.6114**	**93.13**	**3.11**
IT-DCC-RC-RV-I3M	0.0541*** (0.0115)	0.8551*** (0.0464)	0.7188*** (0.0604)	0.2712*** (0.0596)	0.0040 (0.0027)	0.0011 (0.0018)	3.6207	3.6125	93.00	1.20
IT-DCC-RC-RV-MP	0.0536*** (0.0114)	0.8573*** (0.0460)	0.7137*** (0.0611)	0.2694*** (0.0596)	0.0046* (0.0028)	0.0015 (0.0015)	3.6203	3.6122	93.06	1.80
IT-DCC-RC-RV-GDP	0.0559*** (0.0117)	0.8467*** (0.0482)	0.7391*** (0.0655)	0.2538*** (0.0640)	0.0026 (0.0026)	−0.0017 (0.0016)	3.6203	3.6121	93.11	1.47

Notes: The table reports country-wise estimation results for the DCC, DCC-RC and DCC-RC-X model estimations based on standardized residuals from the GARCH(1,1) models in Table 14. Otherwise, see the notes for Table 14.

Table 16: DCC-MIDAS-RV-X model subsample estimations

Model	α_{SB}	β_{SB}	θ_{RV}	θ_X	BIC	AIC	CR_1
US-DCC-RV-GDP	0.0402*** (0.0081)	0.9498*** (0.0115)	−0.0194*** (0.0063)	0.0025 (0.0069)	3.7416	3.7361	40.59
US-DCC-RV-CPI	0.0429*** (0.0088)	0.9428*** (0.0133)	−0.0113* (0.0060)	0.0199*** (0.0067)	**3.7362**	**3.7307**	**69.12**
US-DCC-RV-I3M	0.0429*** (0.0087)	0.9435*** (0.0131)	−0.0181*** (0.0051)	0.0082** (0.0034)	3.7386	3.7331	59.67
US-CC-RV-MP	0.0432*** (0.0088)	0.9425*** (0.0134)	−0.0157*** (0.0053)	0.0089*** (0.0033)	3.7375	3.7320	64.65
UK-DCC-RV-GDP	0.0341*** (0.0082)	0.9586*** (0.0116)	−0.0159** (0.0076)	0.0016 (0.0062)	3.6996	3.6942	32.70
UK-DCC-RV-CPI	0.0331*** (0.0081)	0.9597*** (0.0114)	−0.0143** (0.0072)	0.0118 (0.0073)	3.6982	3.6927	44.43
UK-DCC-RV-I3M	0.0372*** (0.0090)	0.9516*** (0.0142)	−0.0148*** (0.0053)	0.0087* (0.0045)	3.6979	3.6924	55.92
UK-DCC-RV-MP	0.0399*** (0.0092)	0.9424*** (0.0163)	−0.0094** (0.0045)	0.0220*** (0.0051)	**3.6922**	**3.6867**	**83.25**
GER-DCC-RV-GDP	0.0403*** (0.0079)	0.9519*** (0.0104)	−0.0193*** (0.0072)	0.0092 (0.0068)	3.6291	3.6237	38.10
GER-DCC-RV-CPI	0.0395*** (0.0077)	0.9499*** (0.0106)	0.0009 (0.0079)	0.0380*** (0.0098)	3.6204	3.6149	76.96
GER-DCC-RV-I3M	0.0430*** (0.0075)	0.9445*** (0.0108)	−0.0176*** (0.0049)	0.0225*** (0.0058)	3.6230	3.6176	72.28
GER-DCC-RV-MP	0.0423*** (0.0074)	0.9444*** (0.0107)	−0.0092* (0.0053)	0.0232*** (0.0049)	**3.6198**	**3.6144**	**77.15**
FRA-DCC-RV-GDP	0.0407*** (0.0085)	0.9483*** (0.0115)	−0.0163*** (0.0053)	0.0011 (0.0043)	3.7299	3.7245	28.35
FRA-DCC-RV-CPI	0.0398*** (0.0089)	0.9478*** (0.0124)	−0.0091 (0.0056)	0.0188** (0.0077)	**3.7262**	**3.7208**	**56.58**
FRA-DCC-RV-I3M	0.0416*** (0.0085)	0.9462*** (0.0118)	−0.0149*** (0.0051)	0.0098 (0.0062)	3.7284	3.7229	43.87
FRA-DCC-RV-MP	0.0414*** (0.0087)	0.9453*** (0.0124)	−0.0109** (0.0052)	0.0141** (0.0056)	3.7262	3.7208	56.32
IT-DCC-RV-GDP	0.0254** (0.0112)	0.9713*** (0.0132)	0.0164 (0.0114)	−0.0018 (0.0079)	3.6325	3.6271	24.81
IT-DCC-RV-CPI	0.0294** (0.0132)	0.9636*** (0.0175)	0.0223*** (0.0064)	0.0201*** (0.0066)	**3.6279**	**3.6224**	**64.88**
IT-DCC-RV-I3M	0.0266** (0.0115)	0.9692*** (0.0138)	0.0227** (0.0090)	0.0123* (0.0067)	3.6307	3.6252	50.27
IT-DCC-RV-MP	0.0275** (0.0122)	0.9673*** (0.0151)	0.0228*** (0.0078)	0.0113** (0.0049)	3.6296	3.6242	56.91

Notes: The table reports country-wise estimation results for the DCC-X model estimations based on standardized residuals from the GARCH(1,1) models in Table 14. Otherwise, see the notes for Table 14.

Table 17: Cross-country correlations: stock market RV

Country	US	UK	GER	FR	IT
US	1.00				
UK	0.89	1.00			
GER	0.83	0.88	1.00		
FRA	0.86	0.94	0.93	1.00	
IT	0.69	0.77	0.75	0.83	1.00

Notes: Cross-country correlations of the realized stock market volatilities over the full April 1991 to January 2016 sample period.

Table 18: DCC-MIDAS-X with a global financial stress factor

Model	α_{SB}	β_{SB}	$\theta_{RV\star}/\theta_{VIX}$	θ_X	BIC	AIC	ΔCR_1
Panel A:							
UK-DCC-RV*-MP	0.0394*** (0.0083)	0.9401*** (0.0151)	−0.0122*** (0.0037)	0.0182*** (0.0042)	3.7042	3.6992	-0.81
GER-DCC-RV*-MP	0.0453*** (0.0074)	0.9377*** (0.0110)	−0.0146*** (0.0043)	0.0171*** (0.0043)	3.6436	3.6386	-1.89
FRA-DCC-RV*-CPI	0.0394*** (0.0079)	0.9460*** (0.0115)	−0.0137*** (0.0048)	0.0105 (0.0070)	3.7551	3.7502	3.98
IT-DCC-RV*-CPI	0.0256** (0.0108)	0.9715*** (0.0124)	0.0098 (0.0136)	0.0196 (0.0131)	3.6433	3.6383	-29.89
Panel B:							
US-DCC-VIX-CPI	0.0453*** (0.0090)	0.9386*** (0.0139)	−0.0091** (0.0043)	0.0203*** (0.0052)	3.7299	3.7249	-1.82
UK-DCC-VIX-MP	0.0393*** (0.0083)	0.9410*** (0.0150)	−0.0101*** (0.0032)	0.0191*** (0.0042)	3.7042	3.6992	-1.25
GER-DCC-VIX-MP	0.0452*** (0.0075)	0.9402*** (0.0108)	−0.0104** (0.0044)	0.0181*** (0.0049)	3.6450	3.6400	-3.81
FRA-DCC-VIX-CPI	0.0387*** (0.0081)	0.9495*** (0.0113)	−0.0088 (0.0054)	0.0123 (0.0089)	3.7567	3.7517	-0.83
IT-DCC-VIX-CPI	0.0258** (0.0106)	0.9712*** (0.0123)	0.0079 (0.0108)	0.0190 (0.0121)	3.6433	3.6383	-30.49

Notes: The table reports country-wise estimation results for the DCC-RV-X model estimations based on standardized residuals from the GARCH(1,1) models in Table 3. For all countries, Panel A includes the US-RV, $RV*$, and Panel B the standardized VIX. ΔCR_1 denotes the change in CR_1 compared to the respective DCC-RV-X model from Table 5. Otherwise, see the notes for Table 3.