Macroeconomic expectations and the time-varying stock-bond correlation: international evidence*

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Abstract

We explain the time-varying correlation between stock and bond returns by survey expectations on the future macroeconomic development. A modified DCC-MIDAS specification allows us to relate daily changes in the correlation to monthly expectations data. For a cross-section of countries, we show that the stock-bond correlation is mainly determined by expectations regarding the future course of monetary policy as well as stress in financial markets. From a European perspective, the asymmetry in the response of the stock-bond correlation to heightened stock market volatility in the UK, Germany and France on the one hand, and Italy on the other hand is of high policy relevance.

Keywords: Stock-bond correlation, DCC-MIDAS, survey data, macro expectations.

JEL Classification: E44, C32, C58

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1 Introduction

The correlation between stock and bond returns is close to zero on average but varies strongly over time. For the US, the correlation was positive during the 1980 to 1998 period and then turned negative following the default of Russian bonds and the Long-Term Capital Management crisis. Since then, the correlation almost exclusively remained negative but still fluctuates considerably. A similar picture is evident for many other countries. Obviously, understanding the nature and the drivers of the time variation in the stock-bond correlation is important from a portfolio or risk management perspective, since the risk of a portfolio consisting of stocks and bonds depends on what this correlation will be in the future. Since changes in the stock-bond correlation are caused by news events that lead to revisions in future expected dividend payments and future expected returns, the stock-bond correlation should also be informative about the market participants' expectations regarding the future state of the economy. Hence, certain changes in the correlation might anticipate a worsening of macroeconomic conditions and, hence, might serve as an early warning indicator.

We provide first international evidence on the determinants of the low-frequency stock-bond correlation using a modified DCC-MIDAS specification. The DCC-MIDAS model has been introduced by Colacito et al. (2011) and separates the conditional correlation between two return series into a short- and a long-term component. Colacito et al. (2011) specify the long-term component as a linear function of the lagged realized correlations of the two return series. Conrad et al. (2014) suggest a modification of the DCC-MIDAS which is based on the Fisher-z transformation of the long-term component and allows to include explanatory variables that are not restricted to the minus one to plus one interval. While this specification is already quite flexible, its main drawback is that it is computationally difficult to include more than one explanatory variable at a time. We therefore suggest a further modification by adapting the RiskMetrics approach to the specification of the long-term correlation component. That is, we impose the same exponentially decaying lag structure on all explanatory variables. The new specification allows us decompose the long-term correlation into the parts that are due to the individual explanatory variables. Within this specification the relative importance of the individual drivers of the correlation can change over time.

We use expectations data from Consensus Economics for explaining the long-term evolution of the stock-bond correlation. 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.[1] We base our analysis on data for the US, UK, Germany, France and Italy.[2] Our main results can be summarized as follows.

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. This expectation leads to upward revisions in future expected returns which requires stock and bond prices to decline today. That is, higher CPI 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.

As expected, stress in financial markets is another important driver of the stock-bond correlation. We measure financial stress by the realized volatility in each country's stock market. We find that elevated levels of realized volatility significantly reduce the stock-bond correlation in the US, UK, Germany and France. This observation can be rationalized by a flight-to-quality. That is, in times of turbulent stock markets investors reduce their risk exposure by selling stocks and buying bonds which induces a negative correlation. We also find that realized volatility in the US stock market (or alternatively the VIX index) can be considered as a proxy for global financial stress which explains the stock-bond correlation in all countries but Italy. 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. However, while for the other countries the explanation relies on a domestic rebalancing of stock and bond holdings, it appears that investors withdraw money from both Italian stocks and bonds and invest in safe haven countries. This is line with the findings in Conrad and Zumbach (2015) for the period of the European sovereign debt crisis. From a European perspective, the asymmetry in the response of the stock-bond correlation to heightened stock market volatility in the UK, Germany and France on the one hand, and Italy on the other hand is of high policy relevance.

In summary, our results suggest that the long-term stock-bond correlation is mainly

[1] Conrad and Loch (2015) show that SPF data can be highly informative for anticipating future developments in long-term US stock market volatility.

[2] For these countries the longest time series of expectations data starting in April 1991 are available.

driven by expectations regarding future monetary policy and phases of stress in financial markets. Based on the decomposition of the long-term correlation into its individual drivers, we show that for the US expected future monetary policy was the main determinant of the correlation during the mid 1990s and from 2011 until recently. On the other hand, realized volatility was the dominant driver when the dot-com bubble burst as well as during the Great Recession. For the UK, Germany and France, expectations regarding future monetary policy are the main driver over the entire sample period. Finally, we show that the long-term correlation based on macro expectations has indeed explanatory power for future industrial production growth beyond that contained in lagged industrial production growth.

The papers most closely related to ours are Andersson et al. (2008) and Asgharian et al. (2015a,b). Andersson et al. (2008) also employ Consensus Economics expectations data to analyze the stock-bond correlation. However, they rely on predictive regressions of rolling window and DCC estimates of the dynamic correlation and regress those on the expectations data. That is, their approach does not allow for the direct modeling of the daily conditional correlations as a function of the monthly expectations data. This, however, is essential for an application to portfolio choice or risk management.

Asgharian et al. (2015a,b) analyze the US stock-bond correlation by using the DCC-MIDAS specification of Conrad et al. (2014). Based on SPF data, they show that the correlation is positively related to inflation expectations and forecaster disagreement. In addition, their findings suggest a flight-to-quality explanation for periods with a negative stock-bond correlation. Thus, their findings for the US are broadly in line with ours.

Our contribution is to extend the previous papers by considering a wider set of countries in combination with highly informative monthly expectations data, to suggest a DCC-MIDAS specifications that allows for more the one variable at time and, hence, for a decomposition of the long-term component into its individual driving forces. As we will show, our results are important from a portfolio choice and risk management perspective, since our model allows for more accurate estimation of portfolio risk. In addition, the model enables us to quantify portfolio risks as a function of expected macroeconomic conditions and, hence, are important from a regulatory perspective. Specifically, our model might be used for stress testing based on alternative macroeconomic scenarios. Finally, our findings highlight the crucial role of monetary policy for the risk of a portfolio consisting of stocks and bonds. For example, an expected tightening of monetary policy will increase the stock-bond correlation and, therefore, (everything else equal) increase the risks of stock-bond portfolios. Since we have identified asymmetries in the response of the stock-bond correlation to changes in macroeconomic expectations across the different countries of the Eurozone, policy expectations with respect to the ECB can lead to unintended asymmetric effects on the risk structure of domestic stock-bond portfolios. In particular, this last point is highly relevant from a European policy and regulatory perspective.

The remaining paper is organized as follows. In Section 2 we provide some theoretical considerations on the stock-bond correlation and discuss the previous empirical evidence. Section 3 outlines the modified DCC-MIDAS specification. Section 4 introduces our dataset and Section 5 presents the empirical results. Finally, conclusions are provided in Section 6.

2 Theory and Empirical Evidence

Asset returns comove when news that affect future expected dividend payments and future expected returns of the individual assets are correlated. The correlation between stock and bond returns has been intensively investigated but is still not fully understood. In particular, it is not clear which econometric specification is most appropriate to model and forecast the dynamic correlation given macroeconomic fundamentals. While early papers such as Shiller and Beltratti (1992) and Campbell and Ammer (1993) essentially assumed that the correlation is constant, more recent papers specify a time-varying dynamic correlation, see, for example, Andersson et al. (2008) or Asgharian et al. (2015a). Andersen et al. (2007) take a high-frequency perspective and investigate how news about macroeconomic fundamentals affect stock and bond returns. In a second step, they explore the realized stock-bond correlation on news event days. In line with the present value relations described in Campbell and Shiller (1988) and Campbell (1991), 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)”. To the contrary, since there is little uncertainty about dividend payments for government bonds, unexpected bond returns should be mainly due to surprises in future expected returns. That is, whether a news event increases or decreases the stock-bond correlation might vary over the business cycle. Andersen et al. (2007, p.257) conclude that their results should serve “as a warning that it may be important to control explicitly for macroeconomic fundamentals when interpreting asset market correlations".

The DCC-MIDAS approach advocated in this paper follows their suggestion by explicitly modeling the dynamic stock-bond correlation as a function of macroeconomic fundamentals. As explanatory variables, we consider macro data that have been shown to affect stock and bond returns as well as their correlation in the pervious literature. For example, Andersson et al. (2008) find that expectations of CPI inflation are a major determinant of the stock-bond correlation. In line with this empirical evidence, David and Veronesi (2013) provide a general equilibrium model about composite economic and inflation regimes which predicts that the stock-bond correlation should be strongly related to expected inflation. In their model, positive inflation shocks decrease the stock-bond correlation if agents believe in a stagflationary regime, but increase the correlation in a deflationary or "normal" regime. Since our data sample begins in 1991 and, hence, covers mainly normal times as well as the deflationary regime of the most recent years, we expect a positive relation. Also, since inflation expectations are closely linked to expectations about the future course of monetary policy, we will consider expectations on future short-term interest rates.

We also include expectations on GDP growth. However, the previous empirical evidence on this variable has been mixed. While Andersson et al. (2008) do not find a significant effect of GDP expectations on the stock-bond correlation, Asgharian et al. (2015b) report a positive effect.

Finally, a negative correlation between stocks and bonds can also be rationalized by a flight-to-quality phenomenon (see, e.g., Connolly et al., 2005). During phases of financial turmoil investors sell stocks and buy bonds which implies negative stock and positive bond returns. We measure stress in financial markets by the realized stock market volatility in each country.

Also, the same news can have asymmetric effects in bond markets in different countries. For example, Conrad and Zumbach (2015) show that negative statements by European politicians regarding economic developments in the periphery countries lead to negative returns in the Italian bond market but to positive returns in the German bond market and explain this reaction by a flight-to-safety. When in addition both stock markets decline, the same news might lead to an increase in the stock-bond correlation in Italy but to a decrease in Germany.

3 Econometric Model

We follow Conrad et al. (2014) and specify a DCC-MIDAS model for the dynamic stock-bond return correlations. We denote the 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 decomposed as follows $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$, where

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

and $\rho_{SB,t}$ denotes the conditional correlation between the stock and bond returns.[3] We model the conditional variances $h_{S,t}$ and $h_{B,t}$ as GARCH(1,1) processes with parameters ω_i, α_i and β_i, $i \in \{S, B\}$, 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). As in Conrad et al. (2014), the quasi-correlations $\mathbf{Q}_t = [q_{ij,t}]_{i,j=S,B}$ are given by

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

where $\boldsymbol{z}_t = (Z_{S,t}, Z_{B,t})'$. The matrix $\bar{\mathbf{R}}_t$ contains the time-varying long-term correlations. Our model reduces to Engle's (2002) DCC specification with correlation targeting when $\bar{\mathbf{R}}_t$ is assumed to be constant and equal to the sample correlation matrix of the volatility-adjusted residuals. Instead, we allow the off-diagonal elements $\bar{\rho}_{SB,t}$ of the $\bar{\mathbf{R}}_t$ matrix to be driven by exogenous explanatory variables that are observed at a lower frequency than the daily returns. We will denote the explanatory variables by $X_{j,\tau}$, $j = 1, \ldots, J$, where τ refers to the lower frequency. In the empirical application, t is the daily frequency of the returns and τ is the monthly frequency of the macro data. Note that the quasi-correlations can also be written as

$$q_{B,t} = \bar{\rho}_{12,\tau} + a(Z_{S,t-1}Z_{B,t-1} - \bar{\rho}_{SB,\tau}) + b(q_{SB,t-1} - \bar{\rho}_{SB,\tau}), \tag{4}$$

[3] If $\mathbf{R}_t$ is constant, the model reduces to the constant conditional correlation model of Bollerslev (1990).

i.e. as evolving around the long-term correlation. In order to ensure that the long-term correlation $\bar{\rho}_{SB,t}$ 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

$$\begin{aligned} m_{SB,\tau} &= \lambda m_{SB,\tau-1} + \sum_{j=1}^{J} \theta_j X_{j,\tau-1} && (6) \\ &= \theta_1 \sum_{s=0}^{\infty} \lambda^s X_{1,\tau-1-s} + \ldots + \theta_J \sum_{s=0}^{\infty} \lambda^s X_{J,\tau-1-s} && (7) \\ &= m_{1,\tau} + \ldots + m_{J,\tau} && (8) \end{aligned}$$

with $0 < \lambda < 1$. Equation (6) differs from the specification of the long-term component suggested in Conrad et al. (2014). A shortcoming of the specification used in Conrad et al. (2014) is that it is not straightforward to allow for more than one explanatory variable at a time. This is because each variable requires its own MIDAS weighting scheme. For example, for an unrestricted Beta weighting scheme two parameters have to be estimated for each explanatory variable which makes the estimation of the model computationally demanding if no further restrictions are imposed. Instead, equation (6) is parsimoniously specified as an 'Exponential Smoother' (ES) in the spirit of the RiskMetrics model. By assuming that $m_{SB,\tau}$ depends on its first lag, the parameter λ determines the weighting schemes of all J explanatory variables. For simplicity, we follow the RiskMetrics specification and impose that $\lambda = 0.94$. In addition, we truncate the infinite sums at 48 lags, i.e. four MIDAS lag years.[4] In the empirical application, each explanatory variable $X_{j,\tau}$ is standardized so the θ_j's are directly 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. Equation (8) also provides a decomposition of the effects of the individual explanatory variables on the long-term correlation. This decomposition can be used to infer which variable is most relevant at a given point in time. Finally, the short-term correlation is obtained by rescaling:

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

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

Colacito et al. (2011) use the monthly realized correlation, RC_τ, between the volatility-adjusted residuals as the only explanatory variable:

$$RC_\tau = \frac{\sum_{t=N_{\tau-1}+1}^{N_\tau} Z_{S,t} Z_{B,t}}{\sqrt{\sum_{t=N_{\tau-1}+1}^{N_\tau} Z_{S,t}^2 \sum_{t=N_{\tau-1}+1}^{N_\tau} Z_{B,t}^2}}, \tag{10}$$

where $N^{(i)}$ is the number of days within month τ, $N_\tau = \sum_{i=1}^{\tau} N^{(i)}$ and $N_0 = 0$. We refer to this specification with $J = 1$ and $X_{1,\tau} = RC_\tau$ as DCC-MIDAS-RC.

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

$$\mathcal{L} = -\sum_{t=1}^{T} \left(2\log(2\pi) + 2\log(|\mathbf{D}_t|) + \boldsymbol{\varepsilon}_t' \mathbf{D}_t^{-2} \boldsymbol{\varepsilon}_t\right) - \sum_{t=1}^{T} \left(\log(|\mathbf{R}_t|) + \boldsymbol{z}_t' \mathbf{R}_t^{-1} \boldsymbol{z}_t - \boldsymbol{z}_t' \boldsymbol{z}_t\right) \tag{11}$$

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

4 Data

In our empirical analysis, 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 October 2015 and includes 6415 daily and 295 monthly observations.

4.1 Stock and bond market data

For each country, we consider daily returns on MSCI stock prices and 10-year government bond prices.[5] 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 market volatilities, defined as $RV_\tau = \sqrt{\sum_{t=N_{\tau-1}+1}^{N_\tau} r_{S,t}^2}$, in

[5] 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*.

Panel B. For all countries the average 22-days rolling window correlation is close to zero. However, the minimum and maximum correlation over the sample period are roughly between ± 0.9, i.e. the correlations fluctuate heavily over time. Figure 1 illustrates this behavior by plotting the 22-days rolling window correlations and, in addition, the much smoother 252-days rolling window correlations. Roughly speaking, for all countries but Italy, the correlations have been positive from the beginning of the sample in 1991, then became negative during the 1998 default of Russian bonds, came back into the positive territory again, but turned and stayed 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 correlations behave similarly until 2008/9 but then became and stayed positive until the end of the sample period.

Table 1: Descriptive statistics

Country	Variable	Min	Max	Mean	SD	Skew.	Kurt.
Panel A: Daily return data							
US							
	Stock market	-9.51	11.04	0.03	1.12	-0.27	12.30
	Bond market	-2.88	4.05	0.01	0.46	-0.16	5.89
	RC RW(22)	-0.91	0.85	-0.07	0.46	0.17	1.83
UK							
	Stock market	-9.16	9.26	0.01	1.10	-0.15	9.56
	Bond market	-2.36	3.60	0.01	0.40	-0.02	6.34
	RC RW(22)	-0.91	0.94	-0.07	0.44	0.32	2.02
GER							
	Stock market	-10.55	11.13	0.02	1.38	-0.19	8.27
	Bond market	-2.53	2.25	0.01	0.34	-0.35	5.90
	RC RW(22)	-0.91	0.94	-0.08	0.49	0.30	1.88
FR							
	Stock market	-9.31	10.36	0.02	1.34	-0.08	7.83
	Bond market	-2.02	2.30	0.01	0.36	-0.17	5.65
	RC RW(22)	-0.88	0.89	-0.05	0.44	0.16	1.91
IT							
	Stock market	-8.63	10.99	0.01	1.45	-0.10	6.94
	Bond market	-3.69	5.93	0.01	0.46	0.18	16.70
	RC RW(22)	-0.90	0.91	0.11	0.42	-0.27	2.16
Panel B: Monthly realized volatility							
US	RV	1.24	23.91	4.49	2.70	2.87	15.86
UK	RV	1.20	22.64	4.48	2.47	2.66	14.83
GER	RV	1.44	23.25	5.68	3.09	1.91	8.07
FR	RV	1.98	23.86	5.59	2.76	2.28	11.03
IT	RV	2.08	24.23	6.13	2.90	1.79	8.78
Panel C: Monthly expectation data							
US							
	CPI	-0.66	4.28	2.39	0.77	-0.84	4.84
	GDP	-2.06	4.62	2.58	1.00	-1.75	8.67
	I3M	0.06	6.50	3.06	2.12	-0.14	1.50
UK							
	CPI	0.44	5.55	2.79	0.75	0.48	4.80
	GDP	-2.45	3.39	1.95	1.07	-1.80	7.10
	I3M	0.52	11.45	4.56	2.64	0.03	2.45
GER							
	CPI	0.45	3.96	1.86	0.79	1.03	3.72
	GDP	-3.27	3.02	1.52	1.04	-1.93	8.52
	I3M	-0.02	9.50	3.29	2.24	0.82	3.68
FR							
	CPI	0.18	3.17	1.67	0.61	0.42	3.49
	GDP	-1.78	3.59	1.68	0.97	-0.81	4.19
	I3M	0.00	9.71	3.37	2.37	0.85	3.53
IT							
	CPI	-0.07	6.20	2.51	1.34	1.05	3.46
	GDP	-2.76	2.96	1.19	1.13	-1.14	4.51
	I3M	0.00	13.94	4.35	3.63	0.96	2.94

Notes: The reported statistics include the minimum (Min) and maximum (Max) observation, the mean, standard deviation (SD), Skewness (Skew.), and Kurtosis (Kurt.). The data covers the period from April 1991 to October 2015 and includes 6415 daily and 295 monthly observations.

Table 2 shows the cross-country correlations of the monthly realized stock market volatilities. The table illustrates that the correlations are very high suggesting that stress in financial markets is very much globally synchronized. The only country that deviates from this behavior is Italy. The domestic realized volatility in Italy has the weakest correlation with all other countries, in particular with the US volatility.

Table 2: Correlation Matrix

Variable	Country	US	UK	GER	FR	IT
RV						
	US	1.00				
	UK	0.89	1.00			
	GER	0.83	0.88	1.00		
	FR	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 monthly stock market realized volatilities over the full April 1991 to October 2015 sample period.

4.2 Macro expectations data

We employ monthly expectations data for inflation, GDP growth and the three-month interest rate from Consensus Economics. 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*, $\bar{y}_{\tau,this}$, and the *next*, $\bar{y}_{\tau,next}$, year fixed event forecasts over the cross-section of forecasters, where τ refers to the month in which the prediction is produced. Second, fixed horizon one-year ahead predictions are obtained as

$$\hat{y}_\tau = \frac{s}{12}\bar{y}_{\tau,this} + \frac{12-s}{12}\bar{y}_{\tau,next},$$

where $s = 1, \ldots, 12$ refers to the number of remaining month in the year. The three-month interest rate predictions are directly for a fixed horizon of twelve month and, hence, we simply average over the forecasters. Panel C of Table 1 presents the summary statistics for the expectations data and Figure 2 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.

Figure 1: Country-wise daily stock and bond prices as well as 22-days and 252-days rolling window stock-bond return correlations over the full April 1991 to October 2015 sample period.

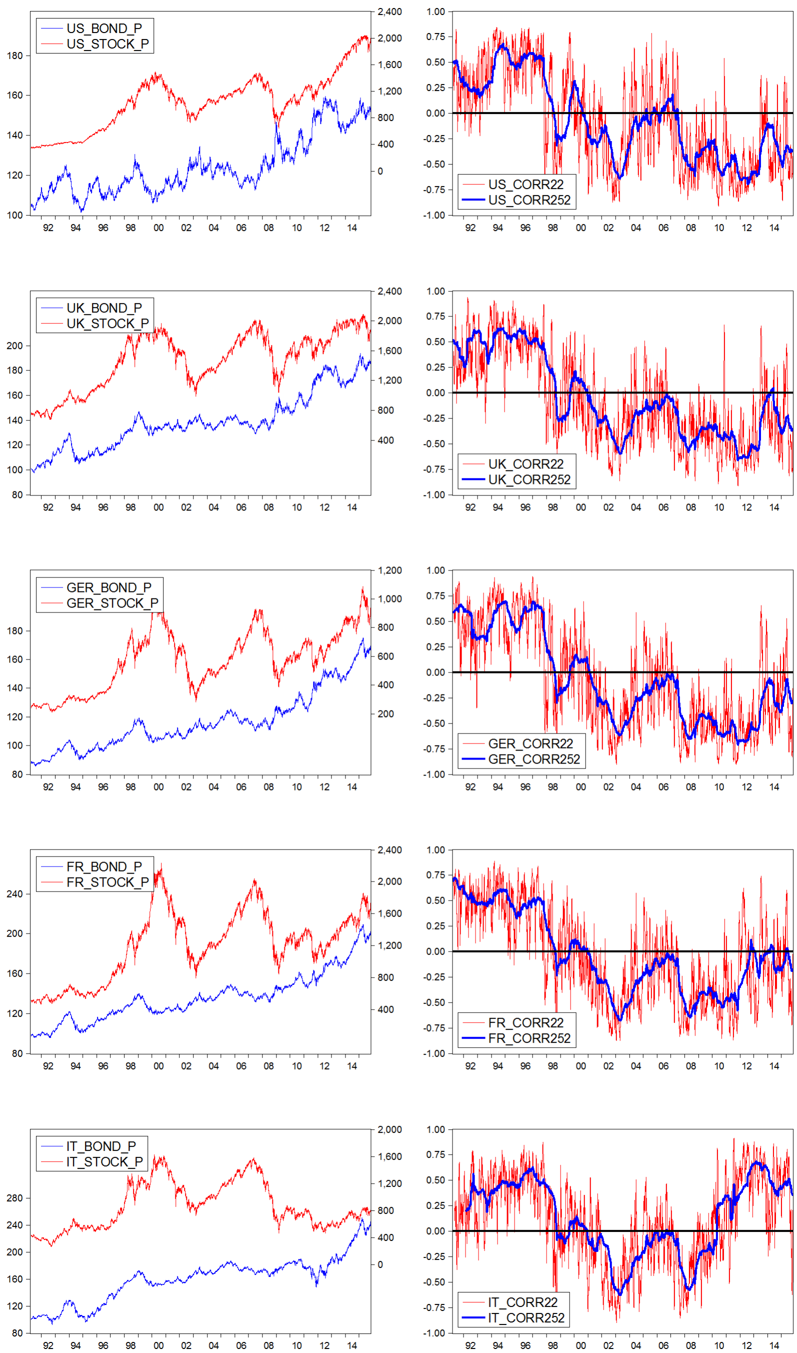
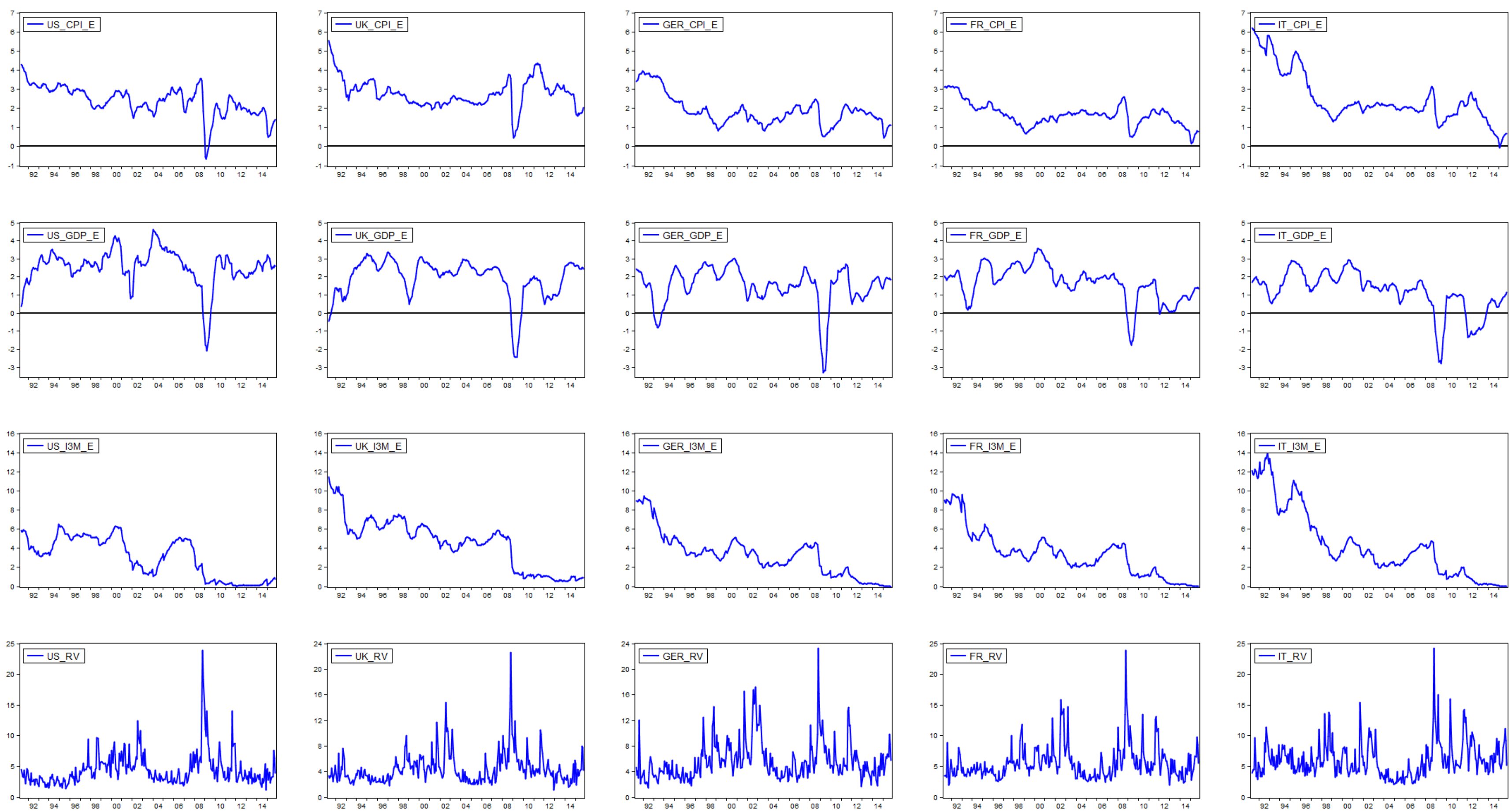


Figure 2: Country-wise monthly macroeconomic expectations data and realized volatility over the full April 1991 to October 2015 sample period.



For each country, Table 3 provides an overview of the correlation between the expectations data and realized volatility. In particular, the table reveals are very strong correlation between expectations on CPI inflation and the three-month interest rate. This can be viewed as evidence that forecasters believe in central banks following a Taylor type policy rule with sufficient weight given to the inflation objective, so that higher CPI inflation expectations imply an increase in short-term interest rates due to the expected monetary policy response.

Table 3: Correlation Matrix

Country	Variable	CPI	GDP	I3M	*RV*
US					
	CPI	1.00			
	GDP	0.30	1.00		
	I3M	0.66	0.25	1.00	
	RV	-0.25	-0.4	-0.14	1.00
UK					
	CPI	1.00			
	GDP	0.02	1.00		
	I3M	0.28	0.20	1.00	
	RV	-0.12	-0.33	-0.09	1.00
GER					
	CPI	1.00			
	GDP	0.05	1.00		
	I3M	0.80	0.14	1.00	
	RV	-0.29	-0.10	-0.13	1.00
FR					
	CPI	1.00			
	GDP	0.15	1.00		
	I3M	0.75	0.44	1.00	
	RV	-0.12	-0.10	-0.09	1.00
IT					
	CPI	1.00			
	GDP	0.31	1.00		
	I3M	0.92	0.49	1.00	
	RV	-0.09	-0.24	-0.09	1.00

Notes: Country-wise correlations of the monthly macroeconomic expectations and stock market realized volatility over the full April 1991 to October 2015 sample period.

5 Empirical Results

5.1 GARCH, DCC, and DCC-MIDAS-RC estimates

We first briefly present the parameter estimates for the GARCH, DCC and DCC-MIDAS-RC models in Tables 4 and 5. We begin with the GARCH models in Table 4. Clearly, in all countries the estimate of μ is higher for the stock than for the bond market. The parameter estimates for α and β are highly significant and take the usual values. As expected, both stock and bond returns have considerable volatility persistence as measured by $\alpha + \beta$ being close to one. Interestingly, for all countries the α (β) 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.[6] Table 5 presents the parameter estimates for the DCC and DCC-MIDAS-RC model. For both model specifications the estimates of α_{SB} and β_{SB} are quite similar across countries. As for the conditional variances, we observe that conditional correlations are strongly persistent. Finally, the θ estimate in the DCC-MIDAS-RC model is 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.

Figure 3 shows the estimated short- and long-term components. Broadly, the behavior of the long-term correlations is the same as for the 252-days rolling window components in Figure 2. The specific role of Italy as the only country with a positive correlation towards the end of the sample period is again clearly evident.

5.2 DCC-MIDAS-X: 'univariate' long-term component

Table 6 shows the θ_j parameter estimates of the DCC-MIDAS model. For the time being, we estimate models that include only a single explanatory variable (i.e. $J = 1$). Each column presents the parameter estimates for a given country, the rows allow to compare the effect of a given variable across countries.

First, note that expected CPI inflation is significant in all countries. The estimated coefficients are positive, suggesting that in all countries an increase in expected inflation

[6] As in Asgharian et al. (2015), we could alternatively estimate GARCH-MIDAS models for the conditional variances. However, then the volatility-adjusted residuals depend on the macro variable that is used in the long-term volatility component. Since it is unclear whether the same variables that drive long-term volatility also drive the long-term correlation, it is not obvious which combination of variables should be chosen. We thus prefer to rely on simple GARCH models in the first step.

Table 4: GARCH(1,1) model estimations

Country	μ	ω	α	β	LLF	BIC	AIC
Panel A: Stock market							
US	0.0505*** (0.0099)	0.0112*** (0.0031)	0.0762*** (0.0104)	0.9142*** (0.0115)	-8472.95	2.6471	2.6429
UK	0.0383*** (0.0101)	0.0133*** (0.0033)	0.0899*** (0.0120)	0.8991*** (0.0132)	-8516.16	2.6605	2.6563
GER	0.0562*** (0.0133)	0.0270*** (0.0083)	0.0827*** (0.0105)	0.9022*** (0.0105)	-10098.39	3.1538	3.1496
FR	0.0480*** (0.0136)	0.0278*** (0.0084)	0.0768*** (0.0100)	0.9063*** (0.0122)	-10068.72	3.1446	3.1404
IT	0.0382*** (0.0140)	0.0181*** (0.0054)	0.0732*** (0.0116)	0.9201*** (0.0121)	-10684.10	3.3364	3.3322
Panel B: Bond market							
US	0.0078 (0.0051)	0.0018*** (0.0005)	0.0386*** (0.0051)	0.9532*** (0.0063)	-3742.08	1.1721	1.1679
UK	0.0101** (0.0045)	0.0014*** (0.0005)	0.0411*** (0.0073)	0.9507*** (0.0090)	-2879.02	0.9031	0.8988
GER	0.0133*** (0.0037)	0.0009*** (0.0003)	0.0442*** (0.0062)	0.9481*** (0.0072)	-1706.72	0.5376	0.5334
FR	0.0132*** (0.0040)	0.0016*** (0.0005)	0.0440*** (0.0063)	0.9433*** (0.0091)	-2106.17	0.6621	0.6579
IT	0.0173*** (0.0042)	0.0012*** (0.0004)	0.0783*** (0.0133)	0.9202*** (0.0128)	-2927.13	0.9181	0.9138

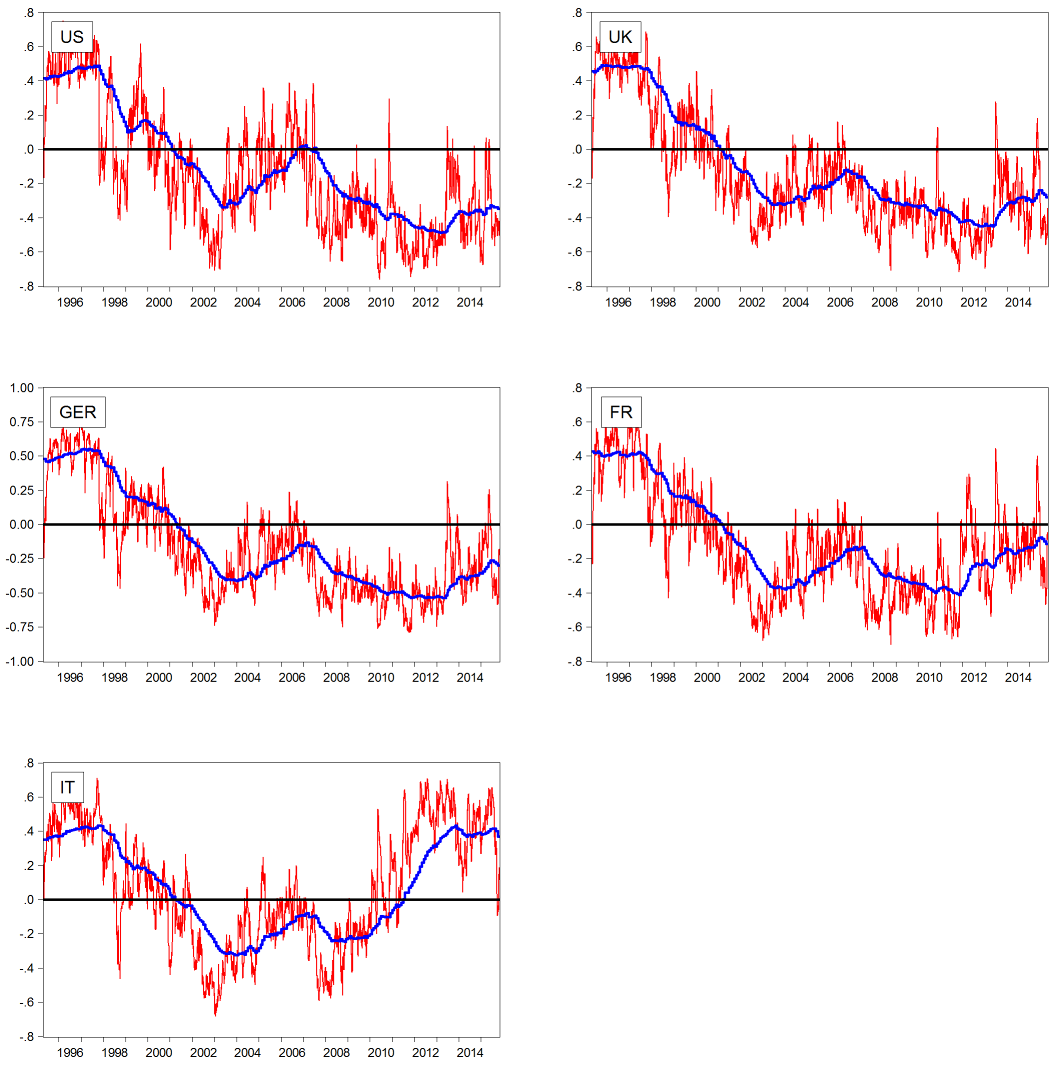
Notes: The table reports country-wise estimation results for the GARCH(1,1) model estimation over the full April 1991 - October 2015 sample. The numbers in parentheses are Bollerslev-Wooldridge (1992) robust standard errors. ***, **, * indicate significance at the 1%, 5%, and 10% level. LLF is the value of the maximized likelihood function, BIC is the Bayesian information criterion and AIC is the Akaike information criterion.

Table 5: DCC and DCC-RC model estimations

Country	α_{SB}	β_{SB}	θ_{RC}	LLF	BIC	AIC
US	0.0389*** (0.0075)	0.9552*** (0.0095)	-	-4989.27	1.8684	1.8659
	0.0469*** (0.0097)	0.9325*** (0.0167)	0.0453*** (0.0065)	-9954.34	3.7261	3.7224
UK	0.0302*** (0.0064)	0.9655*** (0.0079)	-	-4968.52	1.8606	1.8581
	0.0414*** (0.0075)	0.9308*** (0.0158)	0.0456*** (0.0049)	-9908.58	3.7090	3.7053
GER	0.0356*** (0.0071)	0.9610*** (0.0083)	-	-4825.39	1.8071	1.8046
	0.0451*** (0.0073)	0.9343*** (0.0129)	0.0494*** (0.0052)	-9612.87	3.5984	3.5947
FR	0.0363*** (0.0077)	0.9563*** (0.0098)	-	-5022.01	1.8806	1.8781
	0.0429*** (0.0072)	0.9344*** (0.0131)	0.0423*** (0.0062)	-10021.85	3.7513	3.7476
IT	0.0245** (0.0096)	0.9727*** (0.0112)	-	-4904.49	1.8367	1.8342
	0.0354*** (0.0125)	0.9521*** (0.0220)	0.0414*** (0.0103)	-9802.35	3.6692	3.6656

Notes: The table reports country-wise estimation results for the DCC and DCC-RC model estimations based on standardized residuals from the GARCH(1,1) models in Table 4. Otherwise, see notes of Table 4.

Figure 3: Country-wise daily conditional correlations (red) and monthly long-term correlation component (blue) from the DCC-MIDAS-RC model in Table 5.



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.[7] In response, investors require higher expected returns in stocks and bonds in the future which (everything else unchanged) induces a decline on stock and bond prices today. Note that our finding that the stock-bond correlation is strongly positively related to expected inflation confirms the prediction made by the general equilibrium model in David and Veronesi (2013) for normal or deflationary regimes.

Second, expectations on future GDP growth are insignificant for all countries. As argued in Andersen et al. (2007), a potential explanation for this finding could be that the sign of the effect of positive news on economic activity depends on the state of the business cycle.

Third, in all countries an increase in the expected three-month interest rate is associated with a significant upswing in the stock-bond correlation. This effect is fully 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. For example, for the US the correlation between the one-year-ahead expectations for the three-month interest rate and CPI inflation is 0.66.

Fourth, stock market volatility has a negative and significant effect in all countries but Italy. The negative sign of the effect is in line with a flight-to-quality phenomenon. In times of turbulence in stock markets investors require a higher risk premium on stocks which is achieved by a decline in stock prices. Investors rebalance their portfolio risks by selling stocks and buying bonds which results in a negative stock-bond correlation. Only for Italy, we find a significantly positive effect. This may be explained by the fact that investors do 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.[8]

This first set of results complements previous findings on the time-varying stock bond correlation. In particular, our findings regarding expected inflation and stock market

[7]Conrad and Lamla (2010) show that statements by the president of the ECB about an unexpected increase in inflation lead to an instantaneous appreciation of the EUR against the US Dollar and explain the appreciation by market participants revising upwards their expectations regarding future policy rates.

[8]Conrad and Zumbach (2015) provide strong evidence for this behavior during the European sovereign debt crisis.

volatility are in line with Andersson et al. (2008) and Asgharian et al. (2015a). However, recall that Andersson et al. (2008) exclusively rely on predictive regressions, while Asgharian et al. (2015a) consider US data only.

Table 6: Univariate DCC-MIDAS-X model estimation: θ_X estimates

Variable	US	UK	GER	FR	IT
CPI	0.0270*** (0.0052)	0.0167* (0.0092)	0.0384*** (0.0062)	0.0234*** (0.0072)	0.0152* (0.0081)
I3M	0.0122*** (0.0043)	0.0120** (0.0052)	0.0278*** (0.0086)	0.0134** (0.0067)	0.0089 (0.0080)
GDP	0.0120 (0.0081)	0.0078 (0.0070)	0.0141 (0.0110)	0.0032 (0.0058)	−0.0050 (0.0065)
RV	−0.0196** (0.0077)	−0.0151* (0.0085)	−0.0259*** (0.0088)	−0.0175** (0.0070)	0.0201** (0.0096)

Notes: The table reports country-wise parameter estimates of θ_X from univariate DCC-MIDAS model estimations including four years of lags of a monthly explanatory variable X. The models are based on standardized residuals from the GARCH(1,1) models in Table 4. Otherwise, see notes of Table 4.

5.3 DCC-MIDAS-X: 'multivariate' long-term component

The previous results suggest that the long-term stock-bond correlation is mainly driven by expectations regarding future monetary policy and a flight-to-quality phenomenon during crisis times while expectations on GDP growth do not appear to be relevant.

As mentioned above, the main advantage of our new specification of the long-term component in equation (7) is that we can include several explanatory variables at the same time. We thus consider 'multivariate' DCC-MIDAS-X models that include expected CPI inflation, the expected three-month interest rate and realized volatility at the same time (i.e. $J = 3$). Table 7 presents the estimation results. In all countries CPI inflation is highly significant and has the same positive sign as before. The three month interest rate is now significantly positive for the UK and Germany, while it is negative and significant for Italy. Realized volatility is now significant for Italy only; as before, the sign is positive. While these results broadly confirm our previous findings, the mainly insignificant parameter estimates for realized volatility and the negative sign on the three-month interest rate for Italy may be due to 'multicollinearity'. As discussed in Section 4, the two variables that proxy future monetary policy (expected CPI inflation and the expected three month interest rate) are highly correlated for the US. This is also true for the other countries. The maximum correlation of 0.92 is observed for Italy (see Table 3). In order to avoid this 'multicollinearity' issue, we thus construct a 'monetary policy factor' (MP) as the (first) principal component from these two variables. As before, we proxy for stress in financial markets by realized volatility.

Table 7: Multivariate DCC-MIDAS-X model estimation: θ_{X_j} estimates

Country	θ_{CPI}	θ_{I3M}	θ_{RV}	LLF	BIC	AIC
US	0.0299** (0.0145)	−0.0042 (0.0071)	−0.0053 (0.0089)	-9952.37	3.7285	3.7224
UK	0.0192*** (0.0049)	0.0163*** (0.0036)	−0.0066 (0.0053)	-9911.61	3.7133	3.7071
GER	0.0243** (0.0111)	0.0104* (0.0061)	−0.0083 (0.0088)	-9612.86	3.6016	3.5955
FR	0.0150* (0.0084)	0.0048 (0.0056)	−0.0091 (0.0075)	-10031.31	3.7580	3.7519
IT	0.0465*** (0.0119)	−0.0285*** (0.0105)	0.0194*** (0.0068)	-9789.92	3.6678	3.6617

Notes: The table reports country-wise parameter estimates of $\theta_{X_j}, j = 1, 2$, from multivariate DCC-MIDAS model estimations including four years of lags of three monthly explanatory variables X_1, X_2. The models are based on standardized residuals from the GARCH(1,1) models in Table 4. Otherwise, see notes of Table 4.

We reestimate the DCC-MIDAS models with these two variables included. Table 8 provides the regression results. As can be seen, for all countries the monetary policy factor is highly significant and negative. That is, the expectation of a more contractive monetary policy in the future increases the stock-bond correlation. Realized volatility has a significantly negative effect in the US and Germany and, as before, has a positive effect for Italy. It is insignificant in the UK and France. Overall, this bivariate DCC-MIDAS-X model confirms our previous finding that monetary policy and stress in financial markets are key drivers of the long-term stock-bond correlation.

Next, we have a closer look at the estimated long-term components as implied by the estimates from Table 8. For each country, Figure 4 shows the long-term stock-bond correlation as predicted by the DCC-MIDAS model as well as its decomposition into the individual contributions from the two explanatory variables as defined in equation (8). 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 observed at the beginning of the sample period. The decline of the correlation which turned negative at the end of 2001 is clearly driven by the increase in realized volatility, i.e. a negative value of m_{RV}, after the burst of the dot-com bubble. The second, and even sharper decrease in the correlation occurred in 2008 and, as before, is triggered by a massive increase in volatility during the financial crisis. The fact that the correlation stays negative towards

Table 8: Bivariate DCC-MIDAS-X model estimation: θ_{X_j} estimates

Country	θ_{MP}	θ_{RV}	LLF	BIC	AIC
US	0.0103^{***} (0.0029)	-0.0136^{**} (0.0062)	-9957.83	3.7290	3.7240
UK	0.0235^{***} (0.0049)	-0.0073 (0.0052)	-9912.19	3.7119	3.7070
GER	0.0214^{***} (0.0046)	-0.0134^{**} (0.0063)	-9614.13	3.6005	3.5956
FR	0.0123^{**} (0.0051)	-0.0113 (0.0069)	-10032.53	3.7569	3.7520
IT	0.0103^{**} (0.0046)	0.0281^{**} (0.0111)	-9800.89	3.6703	3.6654

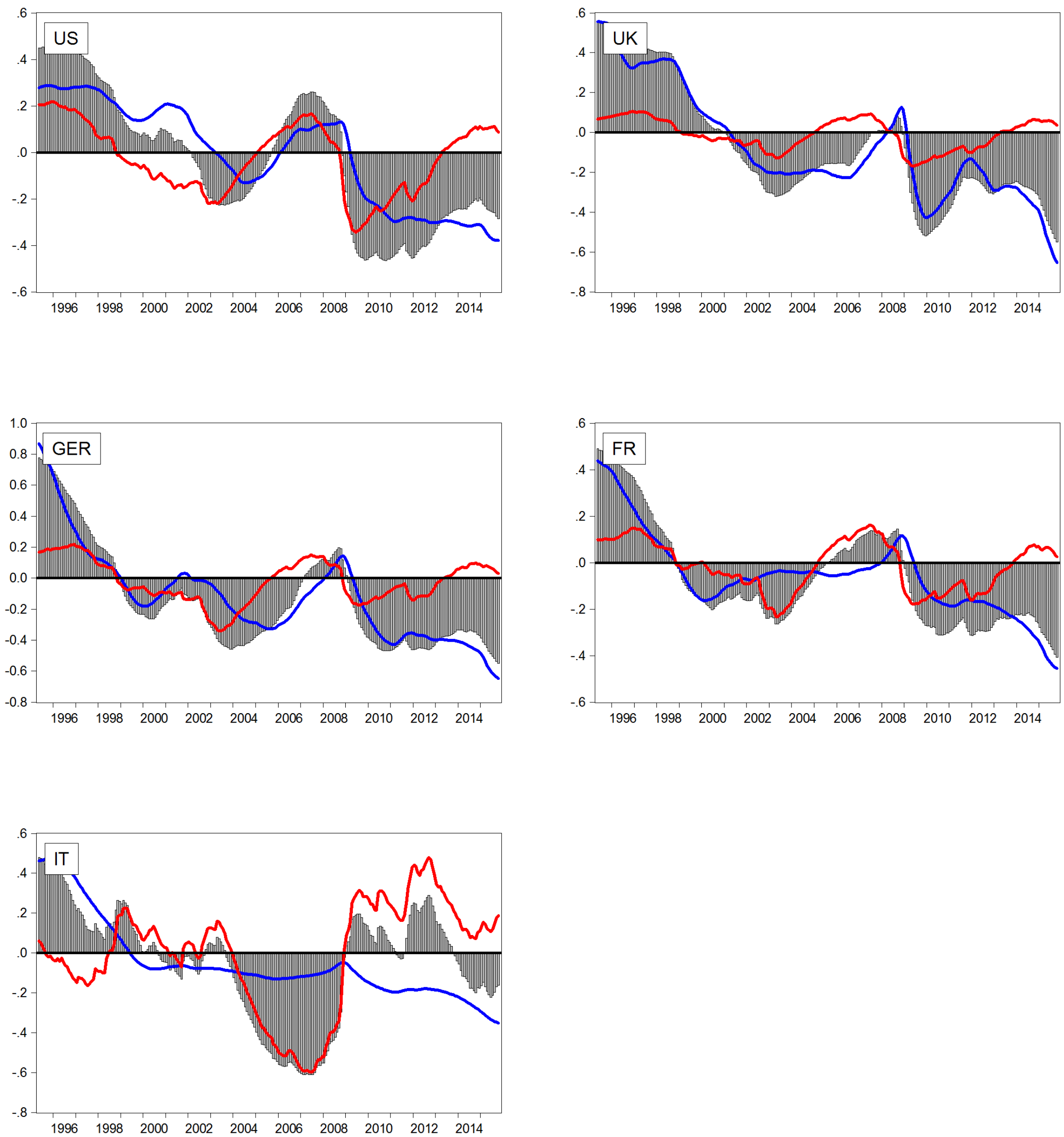
Notes: The table reports country-wise parameter estimates of $\theta_{X_j}, j = 1, 2$, from bivariate DCC-MIDAS model estimations including four years of lags of monthly explanatory variables X_1, X_2. MP refers to monetary policy factor that is given by the first principal component of CPI and I3M expectations. The models are based on standardized residuals from the GARCH(1,1) models in Table 4. Otherwise, see notes of Table 4.

the end of the sample period is due to the strongly negative monetary policy factor, m_{MP}. That is, the expectation of an ongoing expansive monetary policy keeps the correlation in the negative territory. Similarly, David and Veronesi (2013, p.685) argue that market fears of a deflationary regime "pushed the prices of stocks and Treasuries in opposite directions" during recent years. In summary, at the beginning and at the end of our sample period, the monetary policy factor appears to determine the behavior of the long-term stock-bond correlation. On the other hand, realized volatility dominates during periods of financial stress. The behavior of the stock-bond correlation in the UK, Germany and France is broadly similar to the one in the US. However, for those three countries the monetary policy factor, m_{MP}, appears to be the dominant driver over almost the entire sample period. Again, Italy is different. The model predicts a strongly negative stock-bond correlation for the 2004 to 2008 period. Thereafter, the correlation turns positiv which reflects the flight-to-quality argument from before. From 1999 to the of the sample the correlation is almost exclusively determined by realized volatility.

5.4 A global financial stress factor

As discussed in Section 4, the realized volatility measures are highly correlated across countries. The highest correlation is observed between the stock markets in the UK and France (0.94) and the lowest between the US and Italy (0.69). The high correlations suggest that is might be a single global financial stress factor that drives the flight-to-quality

Figure 4: Country-wise monthly long-term correlation component (gray area) and its contributions from the monetary policy factor (m_{MP}, blue line) and from realized volatility (m_{RV}, red line) from the bivariate DCC-MIDAS-X model estimations in Table 8.



phenomenon. We simply proxy the this global factor by the realized volatility in the US stock market. We then reestimate the DCC-MIDAS models from Table 8 by replacing the local realized volatility with US realized volatility. As is evident from Table 9, the global financial stress indicator significantly drives the long-term stock-bond correlation in the UK, Germany and France, but not in Italy. In the UK, Germany and France the US realized volatility has a highly significant and negative effect, although we sill control for the country-specific monetary policy factors that also remain significant. Recall that in Table 8 the local realized volatilities in the UK and France were not significant. Thus, for this countries the global financial stress factor – as measured by the US realized volatility – has more explanatory power than the local stress factor. The fact that we do not find significant effects for Italy is not that surprising, given the peculiarity observed in Table 8 that higher realized volatility in Italy increases rather than decreases the correlation. That is, the Italian stock-bond correlation is rather driven by domestic than global factors. Note that our results remain basically unchanged when we replace US realized volatility by the VIX index which is often referred to as the 'fear index'.

Table 9: DCC-MIDAS-X model estimation: including a global financial stress factor

Estimate	US	UK	GER	FR	IT
Panel A:					
θ_{MP}	0.0103***	0.0222***	0.0201***	0.0108**	0.0115
	(0.0029)	(0.0047)	(0.0040)	(0.0046)	(0.0085)
US RV	−0.0136**	−0.0094**	−0.0160***	−0.0132**	0.0097
	(0.0062)	(0.0046)	(0.0050)	(0.0053)	(0.0168)
Panel B:					
θ_{MP}	0.0105***	0.0228***	0.0214***	0.0125**	0.0109
	(0.0029)	(0.0045)	(0.0047)	(0.0050)	(0.0075)
US VIX	−0.0115**	−0.0079**	−0.0104**	−0.0082	0.0074
	(0.0053)	(0.0039)	(0.0052)	(0.0051)	(0.0119)

Notes: The table reports country-wise parameter estimates of $\theta_{X_j}, j = 1, 2$, from multivariate DCC-MIDAS model estimations including four years of lags of two monthly explanatory variables X_1, X_2. MP refers to monetary policy factor that is given by the first principal component of CPI and I3M expectations. Panel A includes monthly US realized volatility and Panel B the end-of-month VIX realization as a second explanatory variable. The models are based on standardized residuals from the GARCH(1,1) models in Table 4. Otherwise, see notes of Table 4.

5.5 Predicting economic activity

Since the time-varying stock-bond correlation reflects the market participants' beliefs concerning future macroeconomic conditions, it might contain information that is valuable for predicting future economic activity and, potentially, recessions. However, the daily correlations should be considered as a noisy proxy for the smoothly evolving long-term correlation and, hence, might not be that informative. Thus, we first test whether monthly realized correlations of stock and bond returns do Granger cause industrial production (IP) growth.[9] In a second step, we consider the long-term correlation component from the DCC-MIDAS-RC model. This component can essentially be viewed as a smoothed version of many lags of the realized monthly correlations, i.e. is purely backward-looking. Note that both measures rely entirely on stock and bond return data. Finally, we employ the long-term components that we estimated in Table 8 and that are based on m_{MP} and m_{RV}. Table 10 provides the results of Granger causality test for 6 and 12 lags. The Table shows that the monthly realized correlation has predictive ability for the US and France only, while the DCC-MIDAS-RC long-term component does not Granger cause IP growth at all (apart from a marginally significant effect for the US at a horizon of half a year). In sharp contrast, the long-term component based on the DCC-MIDAS-X model does Granger cause IP growth for all countries and both horizons (with a single exception). Interestingly, the significance of the long-term component is the highest at the 12 months horizon. Thus, our explorative analysis suggests that the estimated long-term correlation components have significant long-run predictability for IP growth and, hence, might also serve as early warning indicators. This may be the case because the long-term component is the best approximation of the stock-bond correlation based on expected macro fundamentals. Since the DCC-MIDAS-X long-term component is simply a weighted sum of lagged values of expectations as well as realized volatility, it seems that this parsimonious aggregation of available information is essential for constructing a valuable leading indicator.

[9] We focus on IP rather than GDP growth, since IP is available at a monthly frequency. Also, note that we did not use expectations on IP in the previous analysis.

Table 10: Granger causality tests between industrial production growth and $\bar{\rho}_{SB,\tau}$

Variable	lags	US	UK	GER	FR	IT
Realized Correlation	6	3.33***	1.79	1.74	1.90*	0.80
	12	1.831**	2.19**	1.17	2.01**	0.70
DCC-MIDAS-RC	6	1.99*	1.09	0.81	1.14	1.35
	12	1.44	1.27	0.89	1.30	1.15
DCC-MIDAS-MP-RV	6	2.70**	2.24**	2.13*	1.55	4.16***
	12	2.33***	2.19**	2.62***	2.41***	2.83***

Notes: The table reports F-statistics from Granger causality tests with the null hypothesis that the long-run correlation component $\bar{\rho}_{SB,\tau}$ does not Granger cause industrial production growth. We include either 6 or 12 lags of monthly data. The long-run correlation component is either obtained from the DCC-MIDAS model with RC (see Table 5) or from the DCC-MIDAS model with MP and RV (see Table 8). ***, **, * indicate significance at the 1%, 5%, and 10% level.

6 Conclusions

We suggest a modified version of the DCC-MIDAS specification that allows us to model the long-term stock-bond correlation as a function of several explanatory variables. Our findings suggest that expected inflation and the expected future three-month interest rate as well as realized stock market volatility are the main drivers of the correlation. The relative importance of the variables varies over time and countries. In particular, the special role played by Italy appears highly relevant from a European policy perspective.

As originally conjectured in Andersen et al. (2007, p.276), our results imply that the long-term correlation might be useful for a "more refined classification of the phase of the business cycle" and potentially serve as an early warning indicator. 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 and, hence, should lead to more accurate estimates of the risk of a portfolio. From a regulatory perspective, the new insights might be used to construct refined stress test scenarios that explicitly consider the risk of a stock-bond portfolio as a function of macroeconomic fundamentals. Finally, our results highlight the crucial role of monetary policy in the determination of the stock-bond correlation. Statements or actions of a central bank that induce the belief of a tightening of monetary policy increase the stock-bond correlation and, thereby, might increase the risk of stock-bond portfolios. Thus, our results point to a transmission channel of monetary policy that has not received much attention in the past. Specifically, if responses of the stock-bond correlation are different across countries of the Eurozone, the ECB's policy can have unintended asymmetric effects on the risk structure of domestic stock-bond portfolios.

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