Macro-Finance Determinants of the Long-Run Stock-Bond Correlation: The DCC-MIDAS Specification*

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Abstract: We investigate the long-run stock-bond correlation using a novel model that combines the dynamic conditional correlation model with the mixed-data sampling approach. The long-run correlation is affected by both macro-finance variables (historical and forecasts) and the lagged realized correlation itself. Macro-finance variables and the lagged realized correlation are simultaneously significant in forecasting the long-run stock-bond correlation. The behavior of the long-run stock-bond correlation is very different when estimated taking the macro-finance variables into account. Supporting the flight-to-quality phenomenon for the total stock-bond correlation, the long-run correlation tends to be small/negative when the economy is weak.

Keywords: DCC-MIDAS model; Long-run correlation; Macro-finance variables; Stock-bond correlation

JEL Classifications: C32; C58; E32; E44; G11; G12

1. Introduction

Stocks and bonds are the two main asset classes. Thus, it is of importance to investigate further the behavior of the stock-bond correlation. Here, we introduce an innovation to the literature by decomposing the total stock-bond correlation into its long-run and short-run components and by using financial and economic variables to predict the long-run component. We use the Dynamic Conditional Correlation (DCC) model coupled with the Mixed-Data Sampling (MIDAS) approach. The new DCC-MIDAS model allows the long-run correlation to be affected by both macro-finance variables and the lagged realized correlation itself.

The MIDAS regression is introduced by Anderou and Ghysels (2004) and Ghysels et al. (2006). It allows data from different frequencies to enter into the same model. This approach makes it possible to combine high-frequency returns with macro-finance data that are only observed at lower frequencies (such as monthly and quarterly). Engle and Rangel (2008) apply this technique to the GARCH framework to form the spline GARCH model. Combining the spline GARCH framework and the volatility decomposing approach (see Ding and Granger, 1996; Engle and Lee, 1999; Bauwens and Storti, 2009; Amado and Teräsvirta, 2013), Engle et al. (2012) introduce the GARCH-MIDAS model. The model has the advantage that it allows us to directly incorporate information on the macroeconomic environment into the long-run component. Conrad and Loch (2012) use the GARCH-MIDAS framework to decompose the stock returns into short-run and long-run components. They examine the long-run volatility component using economic factors. Baele et al. (2010) and Colacito et al. (2011) apply the MIDAS technique to the DCC model of Engle (2002) to decompose the comovement of stocks and bonds into short-run and long-run components. Finally Conrad et al. (2012) extend the DCC-MIDAS model by allowing macro-finance variables to enter the long-run component of the correlation of crude oil and stock returns.

The comovement of stock and bond returns may stem from several sources. Stock and bond returns are expected to be correlated because their future cash flows and the pertinent discount rates can be affected by the same economic factors. Previous research investigates the predictive power of various macro-finance variables for the stock-bond comovement. Viceira (2012) finds that the yield spread and the short rate are important determinants of the stock-bond comovement. Campbell and Ammer (1993) decompose the bond and stock returns into unexpected components of future cash flows and future discount rates and employ a vector autoregression model with asset returns and macro variables. They show that stock and bond returns are influenced by different factors, which might be the reason why stock and bond returns are not strongly correlated.

Stock and bond returns may also be correlated since they are alternative investments. There are a number of empirical studies addressing the effect of money transfer between the two markets on the assets' liquidity, volatility, and returns. Agnew and Balduzzi (2006) find that investors rebalance portfolios as responses to changes in asset prices, and that this results in a negative correlation between transfers in stocks and bonds, which in turn leads to a negative correlation between returns in these two markets. Baele et al. (2010) show that liquidity related variables hold predictive power for the stock-bond comovement, whereas macroeconomic variables hardly do. In general, stock and bond comovement is expected to be positive except in periods of "flight-to-quality". Flight-to-quality implies that the transfer of money from the high-risk stock market to the low-risk bond market at times of high uncertainty increases the bond prices relative to the stock prices, which makes the stock-bond correlation weaker and perhaps even negative. Fleming et al. (1998) find that there are volatility linkages between the stock, bond, and money markets due to cross market hedging. Connolly et al. (2005, 2007) investigate how the stock market uncertainty (measured by the VXO volatility index) influences the stock-bond comovement and show that the comovement is positive (negative) following periods with low (high) uncertainty.

In this paper, we study the impact of a large group of macro-finance variables on the long-run component of the stock and bond return volatility and correlation. We have selected a wide range of variables suggested by different studies on stock-bond co-movement. The variables include standard macro-finance variables (short rate, inflation), a liquidity variable (volume of S&P 500 future contract), the equity uncertainty variable (VXO), variables reflecting the current state of the economy (the industrial production growth, the unemployment rate, the default spread, the producer confidence index (PMI), the consumer confidence index (CC), and the National Activity Index (NAI)), as well as the Survey of Professional Forecaster data (SPF).

Further, different from most of the previous studies, we use the bond and stock returns at the daily frequency and other macro-variables at quarterly frequency within the same model using the MIDAS technique. We first decompose the stock and bond volatility into its short-run and long-run components by estimating a univariate GARCH-MIDAS model for stock and bond returns, where we allow for the direct impact of a macro-finance variable on the long-run component of the volatility. We then study the macro-finance variable's impact on the long-run correlation within the DCC-MIDAS framework. For this purpose we estimate the model with a number of different specifications of the long-run correlation equation, i.e., a specification that only includes lagged realized correlations, a specification with only a macro-finance variable, and a specification with both lagged realized correlation and a macro-finance variable.

Our results indicate that certain macro-finance variables including inflation, industrial production, the short rate, the default spread, the S&P volume, the producer confidence, and the consumer confidence affect the long-run stock-bond correlation. However, in order for the model to perform well, it is important to take the lagged realized correlation into account in the MIDAS modeling, in addition to the macro-finance variables. Second, we find that the long run stock-bond correlation is negative when the state of economic is weak, indicating the existence of the flight-to-quality phenomenon. We also find that survey data contain rich information for determining the bond and stock correlations, which suggest that the perceived stance of the economy is an important determinant of stock and bond correlation.

This paper contributes to the literature in several ways. This is the first study based on the DCC-MIDAS model which includes macro-finance variables directly in the equation for the long-run component of the stock-bond correlation. We use a broader range of specifications of the DCC-MIDAS model compared to the existing literature. We use a wide range of macro-finance variables, including both historical data and forecasted data. By investigating the long-run stock-bond correlation and relating it to the economic variables, we are able to provide new empirical evidence on the flight-to-quality phenomenon. Finally, by using a wavelet approach, we provide further indications of the usefulness of smoothing technics such as the DCC-MIDAS for predicting the long-run component of the stock-bond correlation.

The remaining part of the paper is structured as follows. First, in Section 2, we lay out the econometric framework, including our suggested DCC-MIDAS model with macro-finance variables. Then, we introduce the data in Section 3. In Section 4 we discuss some opening results that lead up to our main empirical findings in Section 5. We conclude in Section 6.

2. DCC-MIDAS Stock-Bond Correlation Model

This section outlines the econometric models used in this paper. First, we discuss the bivariate DCC-MIDAS model of Colacito et al. (2011). Second, we introduce the new DCC-MIDAS-XC model in which the long-run stock-bond correlation depends on a macro-finance variable (denoted by "X") as well as the lagged realized correlation (denoted by "C"). Third, we introduce forecast data (denoted by "F") into the model using the DCC-MIDAS-XCF specification.

2.1 The DCC-MIDAS Model

It is convenient to describe two related econometric models before we get to the DCC-MIDAS model itself, that is, the GARCH-MIDAS model, and the Dynamic Conditional Correlation (DCC) model.

We begin with the univariate **GARCH-MIDAS** framework of Engle et al. (2010). Consider a return series on day *i* in a period t (e.g., month, quarter, etc.) that follows the process:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\,\varepsilon_{i,t}, \quad \forall i = 1,\ldots,N_t. \tag{1}$$

$$\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1)$$

where N_t is the number of trading days in the period *t* and $\Phi_{i-1,t}$ is the information set up to day (*i*-1) of period *t*. Equation (1) expresses the variance into a short-run component defined by $g_{i,t}$ and a long-run component defined by τ_t which only changes every period t. The total conditional variance is defined as:

$$\sigma_{it}^2 = \tau_t g_{i,t}\,. \tag{2}$$

The conditional variance dynamics of the component $g_{i,t}$ follows a GARCH (1, 1) process,

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{3}$$

where $\alpha > 0$ and $\beta \geq 0$, $\alpha + \beta < 1$ and τ_t is defined as smoothed realized volatility in the MIDAS regression:

$$\log(\tau_t) = m + \theta\sum_{k=1}^{K}\varphi_k(w_1, w_2)RV_{t-k} \tag{4}$$

$$RV_t = \sqrt{\sum_{i=1}^{N_t} r_{i,t}^2}\ . \tag{5}$$

K is the number of lags over which we smooth the realized volatility. Following Asgharian et al. (2013), we modify this equation by including the economic variables along with the lagged realized volatility (*RV*) in order to study the impact of these variables on the long-run return variance:

$$\log(\tau_t) = m + \theta_1\sum_{k=1}^{K}\varphi_k(w_1, w_2)RV_{t-k} + \theta_2\sum_{k=1}^{K}\varphi_k(w_1, w_2)X_{t-k}^{Q} \tag{6}$$

where X_{t-k}^{Q} represents a macro-finance variable (measured at quarterly frequency). Note that we use a fixed window for the MIDAS, which means that the component τ_t used in our analysis does not change within a fixed period *t*.

The weighting scheme used in equations (4) and (5) is described by a beta lag polynomial as follows:

$$\varphi_k(w) = \frac{\left(k/K\right)^{w_1-1}\left(1-k/K\right)^{w_2-1}}{\sum_{j=1}^{K}\left(j/K\right)^{w_1-1}\left(1-\frac{j}{K}\right)^{w_2-1}}, \quad k = 1,...K. \tag{7}$$

For $w_1 = 1$, the weighting scheme guarantees a decaying pattern, where the rate to decay is determined by w_2.

In the bivariate **DCC** model of Engle (2002), the return vector follows the process: $r_t \sim N(\mu, H_t)$ and the conditional covariance matrix is specified as $H_t = D_t R_t D_t$, where D_t is a diagonal matrix with standard deviations of returns on the diagonal and R_t is the conditional correlation matrix of the standardized return residuals. The conditional volatilities for asset *S* and *B* ($q_{SS,t+1}$ and $q_{BB,t+1}$) follow regular univariate GARCH models, e.g., the GARCH(1,1) specification. These are estimated first and seperately. Then in a second estimation step, their conditional covariance is estimated. The conditional correlation is given as $R_t = diag\ (Q_t)^{-1/2}\ Q_t\ diag\ (Q_t)^{-1/2}$ and Q_t (in elementary form) is specified as

$$q_{SBt} = \rho_{SB,t}(1-a-b) + a(\xi_{S,t-1}\xi_{B,t-1}) + b(q_{SB,t-1}) \tag{8}$$

hereby giving us the conditional correlation as

$$\rho_{SB,t} = \frac{q_{SB,t}}{\sqrt{q_{SS,t+1}q_{BB,t}}} \tag{9}$$

where $\xi_{S,t}$ and $\xi_{B,t}$ are the standaized residuals from the univariate models. $\rho_{SB,t}$ is the unconditional correlation between the standardized residuals.

The **DCC-MIDAS** model of Colacito et al. (2011) is a natural extension and combination of the DCC model and the GARCH-MIDAS model. The DCC-MIDAS model uses the standardized residuals from the univariate GARCH-MIDAS model to estimate the conditional volatilities and the dynamic correlation between the asset returns. The conditional covariance is now given as:

$$q_{SB,t} = \bar{\rho}_{SB,t}(1-a-b) + a\,\xi_{S,t-1}\xi_{B,t-1} + bq_{SB,t-1} \tag{10}$$

$$\bar{\rho}_{SB,t} = \sum_{k=1}^{K}\varphi_k(w_k)C_{SB,t-1} \tag{11}$$

$$C_{SB,t} = \frac{\sum_{k=t-N}^{t}\xi_{S,k}\xi_{B,k}}{\sqrt{\sum_{k=t-N}^{t}\xi_{S,k}^2}\sqrt{\sum_{k=t-N}^{t}\xi_{B,k}^2}} \tag{12}$$

where $\xi_{S,k}$ and $\xi_{B,k}$ are the standardized residuals from the GARCH-MIDAS model of different return series. The correlations can then be computed as in eq. (8). The $q_{SB,t}$ is the short-run correlation between assets S and B, whereas $\overline{\rho}_{SB,t}$ is a slowly moving long-run correlation.

2.2 The DCC-MIDAS-XC Model

We provide a completely new extension of the DCC-MIDAS model to allow a macro-finance variable and the lagged realized correlation to affect the long-run stock-bond correlation. This is similar to the Asgharian et al. (2013) extenstion of the GARCH-MIDAS model. We update the long-run correlation in eq. (10) so that we have the **DCC-MIDAS-XC** model:

$$q_{SB,t} = \overline{\rho}_{SB,t}(1 - a - b) + a\xi_{S,t-1}\xi_{B,t-1} + bq_{SB,t-1} \tag{13}$$

$$\overline{\rho}_{SB,t} = \frac{\exp(2\overline{z}_{SB,\tau}) - 1}{\exp(2\overline{z}_{SB,\tau}) + 1} \tag{14}$$

$$\overline{z}_{SB,\tau} = m_{SB} + \theta_{RC}\sum_{k=1}^{K}\varphi_k(w_1, w_2)RC_{SB,t-k} + \theta_X\sum_{k=1}^{K}\varphi_k(w_1, w_2)X_{t-k}^{Q} \tag{15}$$

$$RC_{SB,t} = \frac{\sum_{i=1}^{N_t}\xi_{S,i}\xi_{B,i}}{\sqrt{\sum_{i=1}^{N_t}\xi_{S,i}^2}\sqrt{\sum_{i=1}^{N_t}\xi_{B,i}^2}} \tag{16}$$

where $RC_{SB,t}$ is the realized correlation (measued at the quarterly frequency). X_t^Q is a macro-finance variable measued at the quarterly frequency. The usage of the Fisher transformation in eq. (14) follows Christodoulakis and Satchell (2002).

By imposing the parameter restriction that $\theta_{RC} = 0$, the **DCC-MIDAS-X** model of Cornad et.al. (2012) appears. By imposing the parameter restriction that $\theta_x = 0$, another new model appears, the **DCC-MIDAS-C** model, in which only the lagged realized correlation affects the long-run stock-bond correlation.

2.3 The Two-Sided Extension: DCC-MIDAS-XCF

Engle et al. (2012) suggest that the performance of the GARCH-MIDAS model can be improved by including the future values of the macro variables (i.e. so called two-sided filter) when anticipating the long term volatility. We apply the two-sided filter here. We make use of the DCC-MIDAS-XC model simultaneously using forecasted and observed macro-finance variables, i.e., the two-sided version of the model, the **DCC-MIDAS-XCF** model.

Imposing θ_{RC} to be zero and applying the two-sided filter of Engle et al. (2012), eq. (15) can be modified as follows:

$$\overline{z}_{SB,\tau} = m + \theta_X\sum_{k=1}^{K_{lag}}\varphi_k(w_1, w_2)X_{t-k}^{Q} + \theta_X\sum_{k=-K_{lead}}^{0}\varphi_k(w_1, w_2)X_{t-k|t}^{SPF}. \tag{17}$$

Notice that the future unknown values are replaced with forecasted data. Ideally, we would model the impact of the forecasted variables on the long-run dynamic correlations according to eq. (17), i.e., the same parameter θ should be shared by both the historical and the forecasted data, and it would be estimated with a two-sided filter. In this case the optimal weighting schemes for the variables do not decay monotonically but are rather hump-shaped. However, the forecasters perform the prediction given the first release data and not the finally revised data, while X^{Q}_{t-k} used in the equation is the historical (finally revised) data. Hence, it is difficult to integrate and combine the historical data and the forecasted data based on the first release data with a two-sided filter.[1] Therefore, we decide to model the impact of the forecasted data with a modified two-sided filter in which we treat the forecasted data as an individual variable. The specification is in the following:,

$$\bar{z}_{SB,\tau} = m + \theta_X \sum_{k=1}^{K_{lag}} \varphi_k(w_1, w_2) X^{Q}_{t-k} + \theta_{FX} \sum_{k=-K_{lead}}^{0} \varphi_k(w_1, w_2) X^{SPF}_{t-k|t} . \tag{18}$$

Intuitively, for the weight of the forecasted data, we would expect that the highest weight should be given to the most recent variables. Consequently, we should also give the highest weight to the most leaded lags. Therefore, we set w_1=1 for the weighting scheme of the historical data, estimate $w_{2,}$ and set w_2=1 for the weighting scheme of the forecasted data while estimating w_1.

2.4 Estimation Method

N_t is set to be the number of the trading days within each quarter, the total number of lags is $K_{lag} = 16$ quarters (four years), and the total number of leads is $K_{lead} = 3$. Following Engle (2002) and Colacito et al. (2011), we estimate the model parameters using a two-step quasi-maximum likelihood method. The quasi-maximum likelihood function to be maximized is

$$L = -\sum_{t=1}^{T} \left(T \log(2\pi) + 2\log|D_t| + \xi_t' D_t^{-2} \xi_t \right) - \sum_{t=1}^{T} \left(\log|R_t| + \xi_t' R_t^{-1} \xi_t - \xi_t' \xi_t \right) \tag{19}$$

where the matrix D_t is a diagonal matrix with standard deviations of returns on the diagonal, and R_t is the conditional correlation matrix of the standardized return residuals.

The model involves a large number of parameters, and it does not always converge to a global optimum by the conventional optimization algorithms. Therefore, we use the simulated annealing approach for the estimation (cf. Goffe et al. 1994). This method is very robust and seldom fails, even for very complicated problems.

3. Data

We use a combination of quarterly macro-finance variables and daily stock and bond returns. We consider the sample period from the first quarter of 1986 to the second quarter of 2013. The expectation data are obtained from the Survey of Professional Forecasters (SPF) database at the Federal Reserve Bank of Philadelphia. The survey is conducted by the American Statistical Association and the National Bureau of Economic Research. The remaining data are obtained from DataStream.

[1] Conrad and Lonch (2012) allow the model to be entirely based on SPF expectation and replace the first release data with the corresponding real-time SPF expectations.

3.1 Stock and Bond Data

The two main variables of interest are the stock and bond returns. The Realized Volatility is calculated based on the daily returns from the settlement prices of the S&P500 futures contracts traded at the CME and the 10-year Treasury note futures contract traded at the CBT.

3.2 Macro-Finance Variables

We have selected a wide range of variables suggested by different studies on the stock and bond return co-movement.

Inflation and short rates: These two are the standard variables featured in macroeconomic models. They are expected to affect both the cash flow and the discount rate. However, their effects on bond and stock returns may differ. Because bonds have fixed nominal cash flows, inflation may generate different exposures between stocks and bond returns. The prominent role of inflation for predicting future stock-bond correlation is documented by Li (2002a). It is well known that the level of the interest rate drives the inflation. Therefore we include the short-term rate. Viceira (2012) documents that the short rate and the term spread are both key determinants of the stock-bond correlation.

Liquidity variable: The literature on bond (Amihud & Mendelson 1991) and equity pricing (Amihud 2002) has increasingly stressed the importance of the liquidity effect, which may also be connected with the "flight-to-quality" phenomenon. Crisis periods may drive investors and traders from less liquid stocks into highly liquid bonds, and the resulting price-pressure effects may include negative stock-bond correlations. Therefore, as in Baele et al. (2010), we include the trading volume of S&P500 future contracts as the liquidity-related variable in the paper.

State of economy variables: Ilmanen (2003), Guidolin and Timmermann (2006), and Aslanidis and Christiansen (2013) show that the general state of the macro economy provides information about the future stock-bond correlation. Aslanidis and Christiansen (2012) show that the short rate, the term spread, and the VXO volatility index are the most influential transition variables for determining the regime of the realized stock-bond correlation. Here we let prominent variables such as the industrial production growth, the unemployment rate, the default spread, the producer confidence index (PMI), the consumer confidence index (CC), and the National Activity Index (NAI) represent the state of the macro economy.

Stock market uncertainty: Many papers (e.g., Connolly et al. 2005, 2007 and Bansal et al. 2010) have used the VIX-implied volatility measure as a proxy for stock market uncertainty and shown that the stock-bond co-movements are negatively and significantly related to stock market uncertainty. As the data start in 1986, we use the VXO index as a proxy for stock market uncertainty.

In summary, we use the following quarterly macro-finance variables:

- **Inflation**, computed as the log-difference of the seasonally adjusted CPI.
- **Industrial production growth**, computed as the log-difference of the quarterly values of the industrial production.
- **Unemployment rate**, computed as the first differences of the quarterly unemployment rates.
- **Term spread**, computed as the first differences of the yield spread between 10-year Treasury bond and 3-month Treasury bill.
- **Short rate**, computed as the first differences of yield on the 3-month US Treasury bill.

- **Default spread**, computed as the first differences of the yield spread between Moody's Baa and Aaa corporate bonds.
- **S&P500 volume** is the first differences of the volume of the S&P500 futures contract.
- **VXO**, defined as the log-differences of the volatility index.
- **PMI**, defined as the log-differences of producer confidence index.
- **CC**, defined as the log-differences of consumer confidence index.
- **NAI** is the value of the National Activity Index.

3.3 Forecasted Macro-Finance Variables

The Survey of Professional Forecasters is conducted after the release of the advance report of the Bureau of Economic Analysis, implying that the participants know the data for the previous quarter when they make their predictions. Due to data availability, we only include the forecasted inflation rate, unemployment rate, term spread, and short rate.[2] We use median forecasts for the first three coming quarters. The forecasted data are denoted by $X^{SPF}_{t+k|t}, k = 1,2,3$.

4. Opening Results: Stock-Bond Correlation and Smoothed Variables

We start by investigating if smoothing of macro-finance variables strengthens the correlation between macro-finance variables and the stock-bond correlation. We use the wavelet approach to smooth the macro-finance variables and then look at the correlation of the smoothed variables and the future realized stock-bond correlations at different leads.

A discrete wavelet approach divides a time-series, z_t, into a set of components of different time frequencies. The smooth (low-frequency) components of a time series are represented by

$$A_{J,t} = \sum_l 2^{-\frac{J}{2}} \nu\left(2^{-J} t - l\right) \int_{-\infty}^{\infty} z_t \ \nu_{J,l,t} \, dt \tag{20}$$

and the detailed (high-frequency) parts are represented by

$$B_{j,t} = \sum_l \frac{1}{\sqrt{s^j}} \upsilon\left(\frac{t - lps^j}{s^j}\right) \int_{-\infty}^{\infty} z_t \ \upsilon_{j,l,t} \, dt \ , \tag{21}$$

where s is the scale factor, p is the translation factor, and $\sqrt{s^j}$ is the factor for normalization across the different scales. The index $j = 1, 2, \ldots, J$, the scale where J is the maximum scale possible given the number of observations for z_t, and l is the number of translations of the wavelet for any given scale. The notations $\nu_{J,l,t}$ and $\upsilon_{J,l,t}$ are the wavelet functions. The scaling functions are orthogonal, and the original time series can be reconstructed as a linear combination of these functions and the related coefficients:

[2] The forecasted industrial production is also available. However, we exclude it as the forecasted data are quite different from the historical data obtained from DataStream.

$$z_t = A_{J,t} + \sum_{j=1}^{J} B_{j,t} \,. \tag{22}$$

The scale $B_{j,t}$ captures information within $2^{j-1}$and 2^j time intervals. To construct the smoothed series, we exclude all $B_{j,t}$ up to the frequency of interest. For example, with quarterly data, eliminating all $B_{j,t}$ for $j \leq 3$ excludes all the variations that belong to frequencies higher than 2^3 quarters, i.e., two years.[3]

Insert **Figure 1**: Wavelet Correlation

Figure 1 shows the wavelet correlation of the realized stock-bond correlation with the non-smoothed and smoothed values of the macro-finance variables. We use up to forth order wavelet smoothing. We use a random walk model (lagged realised correlation) as the benchmark for the comparison. Without smoothing of the macro variable, the random walk model outperforms the macro-finance variables and shows the strongest correlation with the future realised correlation. Still, the correlation is reduced as we increase the number of leads. More specifically, the correlation between realised bond-stock correlations at time t and t+1 is around 0.8. Between time t and t+4 it is around 0.6. The maximum correlation between macro-finance variables and future stock-bond correlation is around 0.4 when we use no smoothing, but for almost all of the macro-finance variables the correlation increases when we we use the wavelet smoothed series. With four levels of wavelet smoothing (smoothing up to 16 quarters), the S&P volume has a stronger correlation than the lagged realized correlation itself, especially for longer forecast horizons.

The wavelet findings motivate that smoothing technics such as the DCC-MIDAS model are useful in modeling the long-run component of the stock-bond correlation. An advantage of the DCC-MIDAS over alternative smoothing technics such as the wavelet technich is that the optimal smoothing level is endogenousely determined by the data for the DCC-MIDAS model.

5. DCC-MIDAS-XC Results

In this section we describe the central empirical results.[4] First, we show the univariate GARCH-MIDAS-XC results. Second, we show the results of the DCC-MIDAS-XC model where the macro-finance variables influence the long-run component of the stock-bond correlation. Third, we show the results from using forecasts for the macro-finance variables in DCC-MIDAS-XCF model to estimate the long-run component of the stock-bond correlation.

5.1. Macro-Finance Determinants of Long-Run Volatility

Table 1 shows the results from estimating the various GARCH-MIDAS-XC specifications for stock volatility (Panel A) and bond volatility (Panel B).

Insert **Table 1**: GARCH-MIDAS-XC

For stock volatility the best model fit is obtained for the specifications that allow for both realized volatility and a macro-finance variable (smallest AIC), followed by the models with only realized volatility which is again followed by the models that only include macro-finance variables. Most of the macro-finance variables are significant in explaining the long-run component of the stock volatility even when taking the realized volatility into account, the only exceptions being the default

[3] See Gencay et al. (2001) for a detailed discussion on the wavelet method.

[4] Throughout we use the 10% level of significance.

spread and the VXO volatility index. The best fit is observed in specifications where both the realized volatility and the macro-finance variable are significant simultaneously. This is the case for the inflation rate, the PMI, and the NAI. These three macro-finance variables are all measures of real economic activity, i.e., they are related to the business cycle. The sign of the effect is different across macro-finance variables. There is a positive effect from inflation, such that the larger the inflation rate is, the larger the long-run stock volatility is. For the PMI and the NAI the effect is negative, so that the smaller the PMI or NAI is, the larger is the long-run stock volatility. The signs of the effects from the macro-finance variables imply that the long-run stock volatility is smaller in times of positive overall economic conditions (low inflation, high producer confidence, and high activity).

Our results confirm the counter-cyclical behavior of stock market volatility first observed by Schwert (1989). The results are also consistent with Conrad and Loch (2012). They employ the GARCH-MIDAS framework on the US stock market and find that long-term stock volatility is negatively related to measures of economic activity.

For the bond volatility the ranking of the best performing models is similar to stock volatility. It is preferable to include both realized volatility and macro-finance variables when describing the long-run volatility, followed by realized volatility alone, and macro-finance variables alone. Yet, only few of the macro-finance variables are significant when additionally accounting for the realized volatility (GARCH-MIDAS-XC specification), namely only the term spread, the default spread, and the VXO volatility index. For these variables both the realized volatility and the variables themselves are simultaneously significant. So, for the bond volatility, fixed income related variables are of importance, which is very different for the stock volatility results. It is worth noting that the signs of the coefficients to the term spread and the default rate are opposite the signs they have in the stock volatility.

To some extent the default spread is related to the business cycle conditions. The VXO volatility index also provides information about the state of the economy, in that large VXO is connected with high uncertainty. The effect from the variables upon the long-run bond volatility is positive, so that the larger the term spread, the default spread, and the VXO volatility index is, the larger is the long-run bond volatility. As for stocks, this implies that long-run bond volatility is large when the general economic conditions are weak (large term spread, default spread rate, and large VXO volatility).

To our knowledge, there are no previous studies of the effect of macro-finance variables upon the long-run bond volatility for comparison of our results.

Insert **Figure 2**: Long-Run Stock Volatility

Insert **Figure 3**: Long-Run Bond Volatility

Figures 2 and 3 show the long-run volatility for stocks and bonds for the various specifications. The long-run component is a lot smoother when it is estimated based on (significant) macro-finance variables than when it is based on lagged realized volatility. For the combination based on (significant) macro-finance variables and lagged realized correlation, the long-run component is still fairly smooth, but a little less so than with only macro-finance variables. Thus, in order to obtain stable long-run stock and bond volatility, it is of importance to take into account the state of the economy (as measured by various macro-finance variables).

5.2. Macro-Finance Determinants of the Long-Run Correlation

In Table 2 we show the results where both the lagged realized correlation and one macro-finance variable at a time is included in the long-run stock-bond correlation equation (the DCC-MIDAS-XC model). In addition, we show the restricted versions with only the realized correlation (DCC-MIDAS-C) and with only the macro-finance variables (DCC-MIDAS-X).

Insert **Table 2**: DCC-MIDAS-XC

The results from the DCC-MIDAS-X model show that the sign of the influence of the macro-finance variables is positive and significant for inflation, industrial production, S&P trade volume, and NAI, and it is negative and significant for unemployment. This clearly indicates that the long-run stock-bond correlation tends to be small/negative when the economy is weak, and it supports the previous literature on the existence of the flight-to-quality phenomenon.

However, we do not find such a clear pattern for the coefficients related to these variables in the DCC-MIDAS-XC model. The reason that the coefficient of the macro-finance variables in the DCC-MIDAS-XC cannot fully reflect the relationship between the economic conditions and the long-term correlation is that the realized correlation itself to a large extent already captures this effect (the coefficient of this variable is positive and highly significant in all the cases). Therefore, the coefficients of the macro-finance variables in this model indicate the impact on the long-term correlation after considering what is already captured by the variable realized correlation in the model.

The best model fit (based on AIC) is obtained in the models with both realized correlation and a macro-finance variable which is followed by models with the realized correlation only. Amacro-finance variable alone gives the worst fit. This is similar to the ranking of the univariate models for the stock and bond volatility. However, the variables that influence the long-run stock-bond correlation differ from those that influence the long-run stock and bond volatility. The inflation rate, the industrial production, the short rate, the default spread, the S&P volume, the PMI, and consumer confidence are all significant variables when considered jointly with the lagged realized correlation for explaining the long-run stock-bond correlation. Only the inflation rate, the default spread, and the PMI are recurring from the long-run volatility for stocks and bonds,. The other important macro-finance variables for explaining the long-run stock volatility (NAI) and bond volatility (term spread) and VXO are not significant for the long-run stock-bond correlation. The forecasting ability of the inflation is consistent with Ilmanen (2003) who finds that changes in discount rates dominate the cash flow expectations during periods of high inflation, thereby inducing a positive stock-bond correlation. This is, however, in contrast with Campbell and Ammer (1993) who report that variations in expected inflation promote a negative correlation since an increase in inflation is bad news for bonds and ambiguous news for stocks. The authors also find that variation in interest rates promotes a positive correlation since the prices of both stocks and bonds are negatively related to the discount rate.

The S&P volume is a measure of liquidity. The larger the S&P volume is, the larger the long-run stock-bond correlation is. So, high liquidity implies large/positive stock-bond correlation. The usefulness of liquidity in forecasting the long-run stock-bond correlation is in line with the findings in Baele et al. (2010) who show that liquidity related variables hold predictive power for the stock-bond comovement.

Insert **Figure 4**: DCC-MIDAS-C Long-Run Correlation

Figure 4 shows the long-run component of the correlation as well as the daily correlation stemming from the DCC-MIDAS-C model. The long-run component is a lot less variable, i.e., smoother than the total correlation.

Insert **Figure 5**: DCC-MIDAS-X Daily Correlation

Insert **Figure 6**: DCC-MIDAS-XC Daily Correlation

Figures 5 and 6 show that the different specifications, i.e., the DCC-MIDAS-X and the DCC-MIDAS-XC, provide very similar estimations of the daily correlation. So, in this regard the specific model choice is of little relevance.

Insert **Figure 7**: Long-Run Correlation DCC-MIDAS-XC

Figure 7 shows the long-run correlations for the various specifications with only lagged realized correlation, only a macro-finance variable, and the combination. Similar to the long-run stock and bond volatility, the long-run stock-bond correlation is smoothest when only using macro-finance variables and the least smooth when using only lagged realized correlation. The smoothness falls in-between for the combination of macro-finance variables and lagged realized correlation. The graphical presentation of the estimated long-run correlations underscores that we get a lot of innovative and useful information by the new model specification that is not otherwise available.

Insert **Figure 8**: Mean Absolute Errors

Figure 8 shows the mean absolute error (MAE) for predicting the correlation up to four periods ahead using various models. The MAE is generally increasing with the forecast horizon. At the one-quarter horizon the MAE is lowest when only considering the effect from the realized correlation on the long-run correlation, but for longer horizons the MAE is improved by considering both the realized correlation and the macro-finance variables. Thus, the MAE results emphasize the usefulness of the new DCC-MIDAS-XC model specification. Among the macro-finance variables, S&P volume performs best in forecasting future volatility, both alone and in combination with the realized correlation.

5.3 Effect of Forecasted Macro-Finance Variables

Table 3 shows the results from estimating the two-sided models that rely on both historical observations and forecasts of four macro-finance variables, the DCC-MIDAS-XCF model.

Insert **Table 3**: DCC-MIDAS-XCF

Adding the forecasted macro-finance variables improves model performance (lower AIC) compared to that of the models based only on observed macro-finance variables. Not surprisingly, the specification including all three types of information (the realized correlation, the observed macro-finance variable, and the forecasted macro-finance variable) provides the best fit of all.

The forecasts of the inflation rate are not significant in predicting the long-run correlation with the most general model, while all three types of information have explanatory power for the long-run correlation when we use other macroeconomic variables (unemployment, short rate, and term spread). The effect from the forecasted variable is positive in all cases. Yet, the effect from the historical observed unemployment rate turns negative when used in combination with the unemployment forecasts. Thus, in total, the effect from the unemployment rate observations and forecasts work towards cancelling each other out. The short rate and term spread have positive effects from both historical observations and forecasts. Thus, for these two variables the effects upon the long-run correlation are made stronger by adding the forecasts data.

Insert **Figure 9**: Long-Run Correlation DCC-MIDAS-XCF

Figure 9 shows the long-run correlation for the specifications based only on lagged realized correlation, only macro-finance variables (historical and forecasts), and the combination. There are large differences in the estimated long-run correlations depending on the model specification. Thus, the new model specification provides additional information that could otherwise not have been obtained. So, this once again stresses that the new model specification is highly relevant.

6. Conclusion

In this paper we scrutinize the long-run stock bond correlation. We make use of the dynamic conditional correlation model (DCC) combined with the mixed-data sampling (MIDAS) methodology. We provide an extension of the existing DCC-MIDAS models by which we allow the long-run correlation to depend upon the lagged realized correlation itself (C) as well as a macro-finance variable (X). In addition, extend the DCC-MIDAS-XC model to allow the corresponding forecasted macro-finance variable to influence the long-run stock-bond correlation. The empirical findings in this paper convincingly document the usefulness of the new DCC-MIDAS-XC models.

The estimated long-run stock-bond correlation is very different depending on which variables that enters into its estimation. When only a macro-finance variable is used, the long-run stock bond correlation is very smooth, while it is fairly volatile when only the lagged realized correlation is used. When both the lagged realized correlation and a macro-finance variable is used, the estimated long-run stock-bond correlation falls in-between the smooth and variable extremes. This underscores that it is important to take both the lagged realized correlation as well as the macro-finance variable into account when forecasting long-run stock-bond correlation.

The inflation rate, the industrial production, the short rate, the default spread, the S&P volume, the producer confidence, and the consumer confidence are all significant in forecasting the long-run stock-bond correlation. Moreover, forecasts of some macro-finance variables are helpful in forecasting the long-run stock-bond correlation.

The effects from the macro-finance variables upon the long-run stock-bond correlation are such that the long-run stock-bond correlation tends to be large when the economy is strong. This effect supports the conjecture of the flight-to-quality effect on the long-run correlation component.

References

Agnew, J. and P. Balduzzi (2006). Rebalancing Activity in 401 (k) Plans. Unpublished manuscript.

Andreou, E. and E. Ghysels (2004). The Impact of Sampling Frequency and Volatility Estimators on Change-Point Tests. *Journal of Financial Econometrics*, 2, 290-318.

Amado, C. and T. Teräsvirta (2013). Modelling Volatility by Variance Decomposition. *Journal of Econometrics*, 175, 142-153.

Asgharian, H., A.J. Hou, and F. Javed (2013). Importance of the macroeconomic variables for variance prediction A GARCH-MIDAS approach. *Journal of Forecasting,* Forthcoming.

Aslanidis, N. and C. Christiansen (2012). Smooth Transition Patterns in the Realized Stock-Bond Correlation. *Journal Empirical Finance* 19, 454-464.

Aslanidis, N. and C. Christiansen (2013). Quantiles of the Realized Stock-Bond Correlation. CREATES Working Paper.

Baele, L., G. Bekaert, and K. Inghelbrecht (2010). The Determinants of Stock and Bond Return Comovements. *Review of Financial Studies* 23, 2374–2428.

Bansal, N., R.A. Connolly, and C.T. Stivers (2010). Regime-Switching in Stock and T-Bond Futures Returns and Measures of Stock Market Stress. *Journal of Futures Markets* 30, 753–779.

Bauwens, L. and G. Storti (2009). A Component GARCH Model with Time Varying Weights. *Studies in Nonlinear Dynamics & Econometrics* 13, 1-33.

Campbell, J.Y. and J. Ammer (1993). What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns. *Journal of Finance* 48, 3-37.

Christodoulakis, G.A. and S.E. Satchell (2002). Correlated ARCH (CorrARCH): Modelling the Time-Varying Conditional Correlation Between Financial Asset Returns. *European Journal of Operational Research* 139, 351-370.

Connolly, R., C. Stivers, and L. Sun (2005). Stock Market Uncertainty and the Stock-Bond Return Relation, *Journal of Financial and Quantitative Analysis,* 40, 161-194.

Connolly, R., C. Stivers, and L. Sun (2007). Commonality in the Time-Variation of Stock-Stock and Stock-Bond Return Comovements. *Journal of Financial Markets* 10, 192-218.

Colacito, R., R.F. Engle, and E. Ghysels (2011). A Component Model for Dynamic Correlations. *Journal of Econometrics* 164, 45-59.

Conrad, C. and K. Loch (2012). Anticipating Long-Term Stock Market Volatility. Working Papers 0535, Department of Economics, University of Heidelberg.

Conrad, C., K. Loch, and D. Ritter (2012). On the Macroeconomic Determinants of the Long-Term Oil-Stock Correlation. Working Papers 0525, Department of Economics, University of Heidelberg.

Ding, Z. and C.W.J. Granger (1996). Varieties of Long Memory Models. *Journal of Econometrics 73*, 61-77.

Engle, R. (2002). Dynamic Conditional Correlation - A Simple Class of Multivariate GARCH Models. *Journal of Business and Economic Statistics* 20, 339-350.

Engle, R. and G. Lee (1999). A permanent and transitory component model of stock return volatility. in ed. R.F. Engle and H. White, Cointegration, Causality, and Forecasting: A Festschrift in Honor of Clive W.J. Granger, (Oxford University Press), 475–497.

Engle R, E. Ghysels, and B. Sohn (2012). On the Economic Sources of Stock Market Volatility. *Review of Economics and Statistics*, Forthcoming.

Engle, R. and J.G. Rangel (2008). The Spline GARCH Model for Low Frequency Volatility and Its Global Macroeconomic Causes. *Review of Financial Studies* 21, 1187-1222.

Fleming, J., C. Kirby, and B. Ostdiek (1998). Information and Volatility Linkages in the Stock, Bond, and Money Markets. *Journal of Financial Economics* 49, 111-137.

Fleming, J., C. Kirby, and B. Ostdiek (2003). The economic value of volatility timing using "realized" volatilities. *Journal of Financial Economics* 67, 473-509

Gencay, R., F. Selcuk, and B. Whitcher (2001). *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics.* Academic Press, San Diego, CA.

Ghysels, E., A. Sinko, and R. Valkanov (2006). MIDAS Regressions: Further Results and New Directions. *Econometric Reviews* 26, 53-90.

Goffe W.L., G.D. Ferrier, and J. Rogers (1994). Global Optimization of Statistical Functions with Simulated Annealing. *Journal of Econometrics* 60, 65–99.

Guidolin, M. and A. Timmermann (2006). An Econometric Model of Nonlinear Dynamics in the Joint Distribution of Stock and Bond Returns. *Journal of Applied Econometrics* 21, 1–22.

Gulko, L. (2002). Decoupling. *Journal of Portfolio Management* 28, 59-66.

Hartmann, P., S. Straetmans, and C. Devries. (2001). Asset Market Linkages in Crisis Periods. *Working Paper* 71, European Central Bank.

Ilmanen A. (2003). Stock–bond correlations. *Journal of Fixed Income* 13, 55–66.

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

Li, L. (2002b). Correlation of Stock and Bond Returns. Working Paper, Yale University.

Schwert, G.W. (1989). Why Does Stock Market Volatility Change over Time?.*Journal of Finance* 44, 1115-1153.

Viceira, L.M. (2012). Bond Risk, Bond Return Volatility, and the Term Structure of Interest Rates. *International Journal of Forecasting* 28, 97–117.

Table 1. Estimation of the time varying variances by using univariate GARCH-MIDAS

The table reports the results of the univariate GARCH-MIDAS model for estimating the time-varying stocks and bonds. Panel A shows the results for the return variance for the stocks and Panel B gives the estimation results of the bond returns. The first row of each panel gives the result of the model that only includes the realized volatility (*RV*) in the MIDAS equation, the second part of the panel reports the results of the model which only includes different macro-finance variables in the MIDAS equation, and the results of the model with both *RV* and the macro-finance variables are reported in the last part of each panel. μ is the intercept term in the mean equation for returns, α and β are the parameters of the short term variance (equation 3), W_{RV} and W_X are the estimated weight parameters of the realized volatility and the macro-finance variables respectively, m is the intercept term in the long-run variance equation, and θ_{RV} and θ_X are the estimated parameters of the realized volatility and the macro-finance variables in the long-run variance (equations 4 and 6), respectively. The estimations are based on daily data for returns over the period from 1989 until 2013, and quarterly data for *RV* and the macro-finance variables from 1986 until 2013 (we use 12 lags in the equation for MIDAS). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A. stocks returns

	μ	α	β	W_{RV}	W_X	m	θ_{RV}	θ_X	AIC
RV	0.008***	0.069***	0.918***	1.037***		-3.931***	37.116***		-17982
Inflation	0.008***	0.066***	0.926***		2.069*	-3.499***		0.398**	-17973
Industrial Prod.	0.008***	0.068***	0.921***		3.203**	-3.565***		-0.293***	-17974
Unemployment	0.008***	0.068***	0.921***		4.436*	-3.575***		0.219***	-17974
Term spread	0.008***	0.092***	0.898***		1.000***	-3.317***		-0.999***	-17945
Short rate	0.008***	0.067***	0.924***		1.426***	-3.519***		0.612***	-17976
Default rate	0.008***	0.066***	0.925***		3.915	-3.506***		-0.046	-17969
Volume S&P	0.008***	0.068***	0.922***		1.625***	-3.554***		-0.632***	-17978
VXO	0.008***	0.070***	0.917***		1.358***	-3.630***		0.996***	-17975
PMI	0.008***	0.069***	0.919***		1.000***	-3.577***		-0.852***	-17978
CC	0.008***	0.068***	0.920***		1.000***	-3.604***		-0.941***	-17977
NAI	0.008***	0.069***	0.919***		5.071**	-3.604***		-0.272***	-17976
Inflation	0.008***	0.069***	0.919***	1.146***	1.931**	-4.072***	51.844***	0.483***	-17994
Industrial Prod.	0.008***	0.070***	0.918***	86.407	3.362**	-3.645***	6.560	-0.287***	-17976
Unemployment	0.008***	0.069***	0.919***	1.001***	6.413	-3.613***	3.028	0.198*	-17975
Term spread	0.008***	0.063***	0.925***	1.001***	8.691**	-3.664***	3.986	0.218***	-17979
Short rate	0.008***	0.068***	0.922***	100.871	1.478***	-3.593***	5.675	0.590***	-17978
Default rate	0.008***	0.069***	0.920***	1.000***	1.021	-3.677***	10.908	0.327	-17976
Volume S&P	0.008***	0.070***	0.917***	6.668	1.679***	-3.735***	16.479	-0.569***	-17981
VXO	0.008***	0.069***	0.920***	1.000***	1.808	-3.621***	3.863	0.591	-17976
PMI	0.008***	0.072***	0.910***	1.001***	1.130***	-4.032***	40.544***	-1.027***	-17999
CC	0.008***	0.069***	0.917***	1.000***	1.005***	-3.785***	16.176	-0.796***	-17984
NAI	0.008***	0.073***	0.912***	1.000***	8.645*	-3.855***	26.860***	-0.182**	-17985

Table 1. Estimation of the time varying variances by using univariate GARCH-MIDAS (continued)

Panel B. Bond returns

	μ	α	β	W_{RV}	W_X	m	θ_{RV}	θ_X	AIC
RV	0.001^{*}	0.042^{***}	0.936^{***}	7.063^{**}		-5.787^{***}	349.905^{***}		-27684
Inflation	0.001	0.038^{***}	0.952^{***}		2.089^{*}	-5.260^{***}		-0.234^{*}	-27678
Industrial Prod.	0.001	0.038^{***}	0.953^{***}		1.189	-5.256^{***}		-0.101	-27675
Unemployment	0.001	0.038^{***}	0.953^{***}		1.002^{***}	-5.263^{***}		0.232^{**}	-27678
Term spread	0.001	0.037^{***}	0.951^{***}		1.113^{***}	-5.296^{***}		0.633^{***}	-27687
Short rate	0.001	0.038^{***}	0.951^{***}		1.187^{**}	-5.270^{***}		0.274	-27677
Default rate	0.001^{*}	0.047^{***}	0.946^{***}		2.563	-5.048^{***}		-0.029	-27677
Volume S&P	0.001	0.038^{***}	0.953^{***}		1.000^{***}	-5.244^{***}		0.018	-27676
VXO	0.001^{*}	0.039^{***}	0.950^{***}		1.171^{***}	-5.284^{***}		0.581^{**}	-27678
PMI	0.001	0.038^{***}	0.952^{***}		1.172	-5.252^{***}		0.274	-27676
CC	0.001	0.038^{***}	0.953^{***}		2.294	-5.245^{***}		0.038	-27675
NAI	0.001	0.038^{***}	0.952^{***}		1.060	-5.272^{***}		-0.183^{*}	-27677
Inflation	0.001^{*}	0.042^{***}	0.936^{***}	7.778^{**}	1.724	-5.740^{***}	316.993^{***}	-0.093	-27685
Industrial Prod.	0.001^{*}	0.042^{***}	0.936^{***}	7.051^{***}	6.598	-5.816^{***}	371.899^{***}	0.040	-27684
Unemployment	0.001^{*}	0.040^{***}	0.941^{***}	5.485^{**}	1.000^{***}	-5.712^{***}	295.283^{***}	0.070	-27684
Term spread	0.001^{*}	0.040^{***}	0.937^{***}	11.427^{*}	1.291^{***}	-5.664^{***}	246.991^{***}	0.454^{***}	-27694
Short rate	0.001^{*}	0.042^{***}	0.935^{***}	8.009^{**}	1.256^{*}	-5.740^{***}	309.064^{***}	0.191	-27686
Default rate	0.001^{*}	0.042^{***}	0.933^{***}	5.183^{***}	75.366	-5.870^{***}	403.037^{***}	0.085^{***}	-27691
Volume S&P	0.001^{*}	0.042^{***}	0.937^{***}	5.791	141.405	-5.814^{***}	368.820^{***}	0.043	-27675
VXO	0.001^{*}	0.042^{***}	0.936^{***}	6.713^{**}	1.126^{**}	-5.743^{***}	304.206^{***}	0.460^{*}	-27687
PMI	0.001^{*}	0.042^{***}	0.936^{***}	7.751^{**}	1.501	-5.778^{***}	343.434^{***}	0.129	-27685
CC	0.002^{*}	0.042^{***}	0.936^{***}	6.441^{***}	6.802	-5.808^{***}	362.093^{***}	-0.062	-27685
NAI	0.001^{*}	0.042^{***}	0.936^{***}	7.960^{**}	1.027	-5.742^{***}	314.439^{***}	-0.057	-27684

Table 2. Estimation of the time varying stock-bond correlations by using DCC-MIDAS

The table reports the results of the bivariate DCC-MIDAS model for estimating the time-varying correlation between stock and bond returns. The first row of the table gives the result of the DCC-MIDAS-C model that only includes the realized correlation (*RC*) in the MIDAS equation, the second part of the table reports the results of the DCC-MIDAS-X model which only includes different macro-finance variables in the MIDAS equation, and the last part of the table gives the results of the model with both *RC* and the macro-finance variables, i.e. DCC-MIDAS-XC model. a and b are the parameters of the short term correlation (equation 13), W_{RC} and W_X are the estimated weight parameters of the realized correlation and the macro-finance variables respectively, m is the intercept term in the long-run correlation equation, and θ_{RC} and θ_X are the estimated parameters of the realized correlation and the macro-finance variables in the long-run correlation (equation 15), respectively. The estimations are based on daily standardized residuals from 1993 until 2013, and quarterly data for *RC* and the macro-finance variables from 1989 until 2013 (we use 16 lags in the equation for MIDAS). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	a	b	W_{RC}	W_X	m	θ_{RC}	θ_X	AIC
RC	0.049***	0.929***	3.233**		-0.023	1.071***		40632
Inflation	0.037***	0.956***		1.057***	0.068		1.617***	40636
Industrial Prod.	0.039***	0.956***		1.000*	-0.018		0.454***	40654
Unemployment	0.039***	0.956***		1.000**	-0.003		-0.441***	40653
Term spread	0.038***	0.959***		160.463	-0.013		0.184	40656
Short rate	0.036***	0.960***		211.566	0.291		1.198*	40648
Default rate	0.035***	0.962***		73.144	-0.020		0.423	40653
Volume S&P	0.042***	0.947***		1.156***	-0.068		1.501***	40634
VXO	0.036***	0.961***		21.170	-0.022		0.428	40654
PMI	0.036***	0.961***		6.547	0.002		-0.480	40655
CC	0.035***	0.963***		11.961	0.052		-0.839	40652
NAI	0.039***	0.955***		1.216**	-0.025		0.396***	40653
Inflation	0.056***	0.917***	4.480*	1.000***	0.023	0.855***	0.504***	40620
Industrial Prod.	0.052***	0.920***	4.916**	32.512	-0.005	1.116***	-0.079**	40628
Unemployment	0.049***	0.929***	3.124**	3.295	-0.025	1.050***	-0.027	40632
Term spread	0.049***	0.929***	3.607**	105.302	-0.021	1.070***	0.058	40630
Short rate	0.051***	0.922***	7.005**	14.947	-0.002	1.047***	0.132***	40624
Default rate	0.052***	0.919***	7.368**	14.975	-0.012	1.030***	0.111**	40626
Volume S&P	0.053***	0.914***	12.921**	1.317***	-0.028	0.690***	0.638***	40620
VXO	0.053***	0.915***	10.380**	11.339	-0.008	0.981***	0.152	40628
PMI	0.053***	0.917***	8.599**	5.359**	-0.002	1.001***	-0.173*	40628
CC	0.051***	0.921***	8.717**	5.511**	0.003	1.066***	-0.238**	40627
NAI	0.052***	0.922***	4.980*	103.644	-0.007	1.107***	-0.061	40630

Table 3. Estimation of the time varying stock-bond correlations by using two sided DCC-MIDAS with SPF data

The table reports the results of the two-sided bivariate DCC-MIDAS model for estimating the time-varying correlation between stock and bond returns. The first part of the table reports the results of the DCC-MIDAS-XF model which includes historical and forecast data (SPF) for macro-finance variables in the MIDAS equation and the second part of the table gives the results of the model augmented by *RC*, i.e., DCC-MIDAS-XCF model. *a* and *b* are the parameters of the short term correlation equation (equation 13), W_{RC}, W_X and W_{FX} are the estimated weight parameters of the realized correlation, the historical data on the macro-finance variables and the forecast data on these variables respectively, *m* is the intercept term in the long-run correlation equation, and θ_{RC}, θ_X and θ_{FX} are the estimated parameters of the realized correlation, the macro-finance variables, and the forecast data for the macro-finance variables in the long-run correlation (equation 17), respectively. The estimations are based on daily standardized residuals from 1993 until 2013, and quarterly data for RC and the macro-finance variables from 1989 until 2013 (we use 16 lags for historical data and 3 leads for the SPF data in MIDAS). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	a	***b***	W_{RC}	W_X	W_{FX}	***m***	θ_{RC}	θ_X	θ_{FX}	**AIC**
Inflation	0.037***	0.956***		1.001***	3.601	0.077		1.319***	0.388**	40635
Unemployment	0.033***	0.963***		8.961**	39.013	-0.160		-0.819**	1.020**	40647
Short rate	0.036***	0.960***		10.131	3.193	0.248		-0.114	1.143	40650
Term spread	0.028***	0.970***		2.405***	161.053	2.687***		84.857***	-129.978***	40646
Inflation	0.056***	0.906***	10.736**	1.005***	18.859	0.007	0.872***	0.542***	-0.082	40614
Unemployment	0.052***	0.918***	9.103**	6.261*	54.105	-0.028	0.978***	-0.130**	0.171***	40625
Short rate	0.049***	0.927***	2.785**	12.456	3.666	0.054	1.067***	0.135**	0.207*	40619
Term spread	0.051***	0.920***	2.781***	1.089**	37.848	-0.035	1.170***	0.219*	0.136**	40626

Figure 1. Correlation between the realized stock-bond correlation and the smoothed macro-finance variables

The figure shows the wavelet correlation between the realized stock-bond correlation and the values of the macro-finance variables. The macro variables are smoothed by using a wavelet approach. We use four different degree of smoothing. Wavelt j captures information within $2^{j-1}$and 2^{j} time intervals, so with wavelet 4 all the variations which belong to a higher frequency than two years (eight quarters) are eliminated. We estimate the correlation between the values of the macro variables at time t with the realized stock-bond correlation at time $t+s$, where $s = 1,\ldots,4$. We use a random walk model (lagged realised correlation) as the benchmark for the comparison. The correlations are based on quarterly data from 1993 until 2013.

Figure 2. Long-run variance of stock returns estimated by the univariate GARCH-MIDAS

The figure plots the realized quarterly stock return variance against the estimated long-run component of the return variances from the GARCH-MIDAS model with three different specifications: the model that includes only the realized volatility (*RV*) in the MIDAS equation, the model that includes the macro-finance variables in the MIDAS equation, and finally the model with both *RV* and a macro-finance variable. The estimations are based on daily data for returns over the period from 1989 until 2013, and quarterly data for *RV* and the macro-finance variables from 1986 until 2013 (we use 12 lags in the equation for MIDAS).

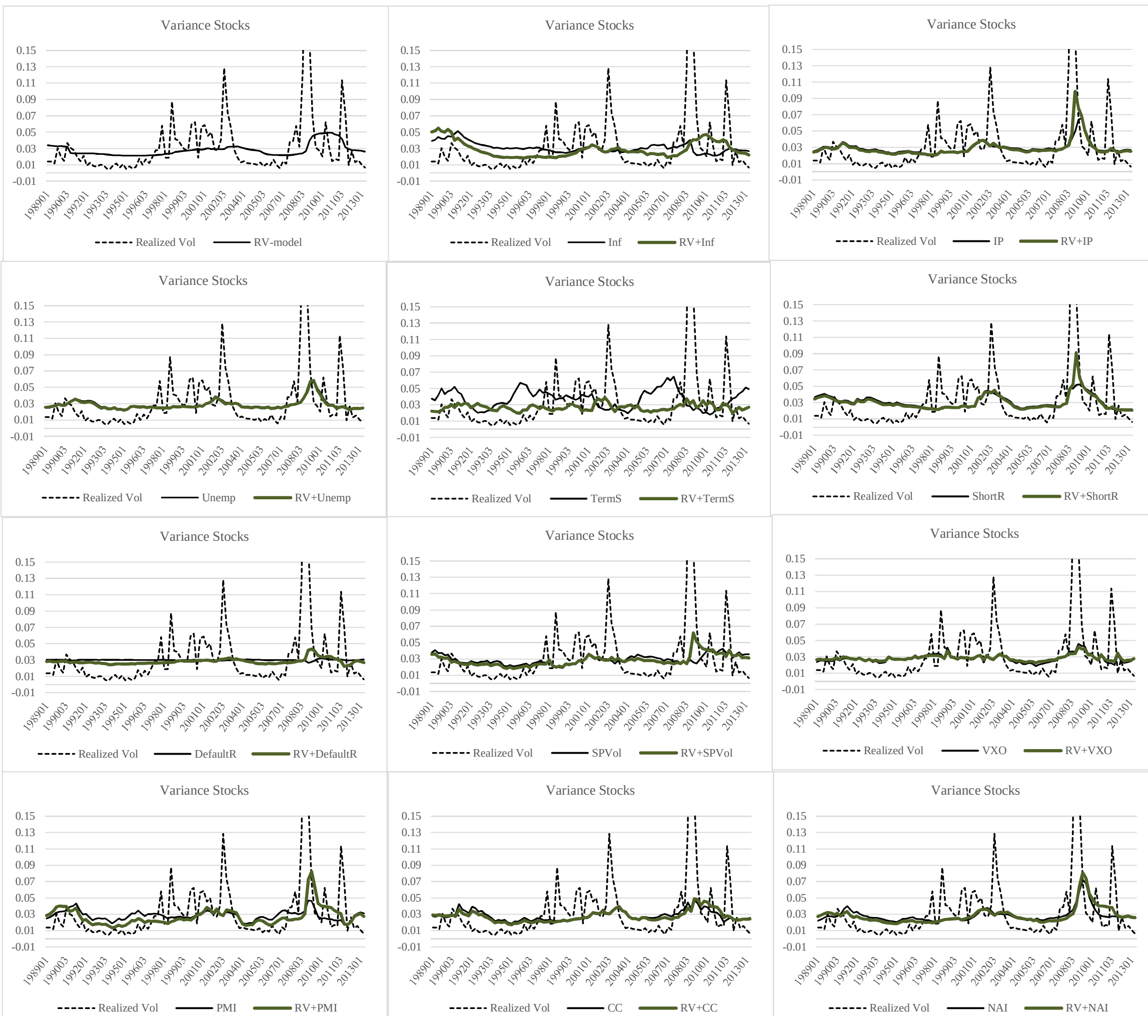

Figure 3. Long-run variance of bond returns estimated by the univariate GARCH MIDAS

The figure plots the realized quarterly bond return variance against the estimated long-run component of the return variances from the GARCH-MIDAS model with three different specifications: the model that includes only the realized volatility (*RV*) in the MIDAS equation, the model that includes the macro-finance variables in the MIDAS equation, and finally the model with both *RV* and a macro-finance variable. The estimations are based on daily data for returns over the period from 1989 until 2013, and quarterly data for *RV* and the macro-finance variables from 1986 until 2013 (we use 12 lags in the equation for MIDAS).

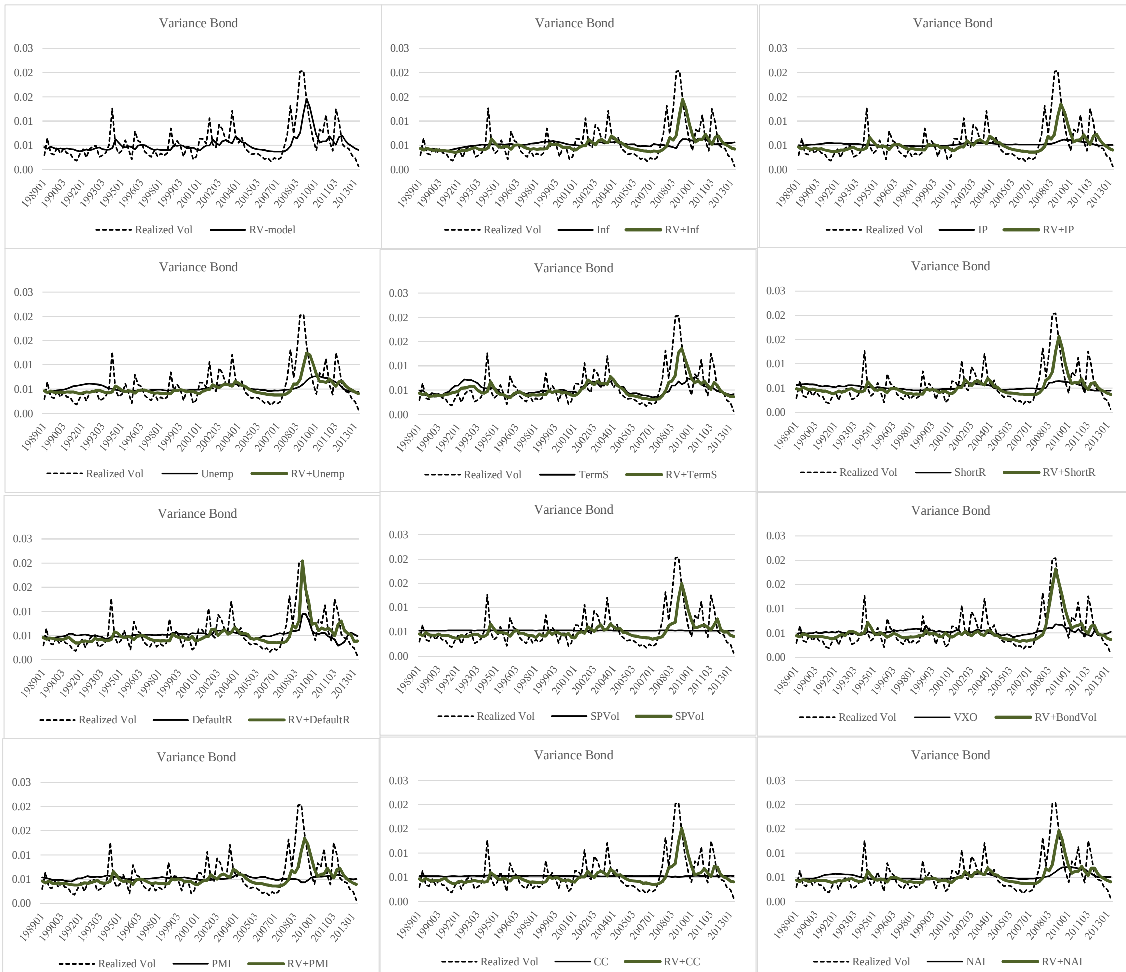

Figure 4. Short term and long-run stock-bond correlation estimated by DCC-MIDAS-C

The figure plots the estimated short term and long-run components of the stock-bond return correlation from the DCC-MIDAS-C model. The model includes the realized correlation in the MIDAS equation for the long-run correlation. The estimations are based on daily standardized residuals from 1993 until 2013, and quarterly data for *RC* from 1989 until 2013 (we use 16 lags in the equation for MIDAS).

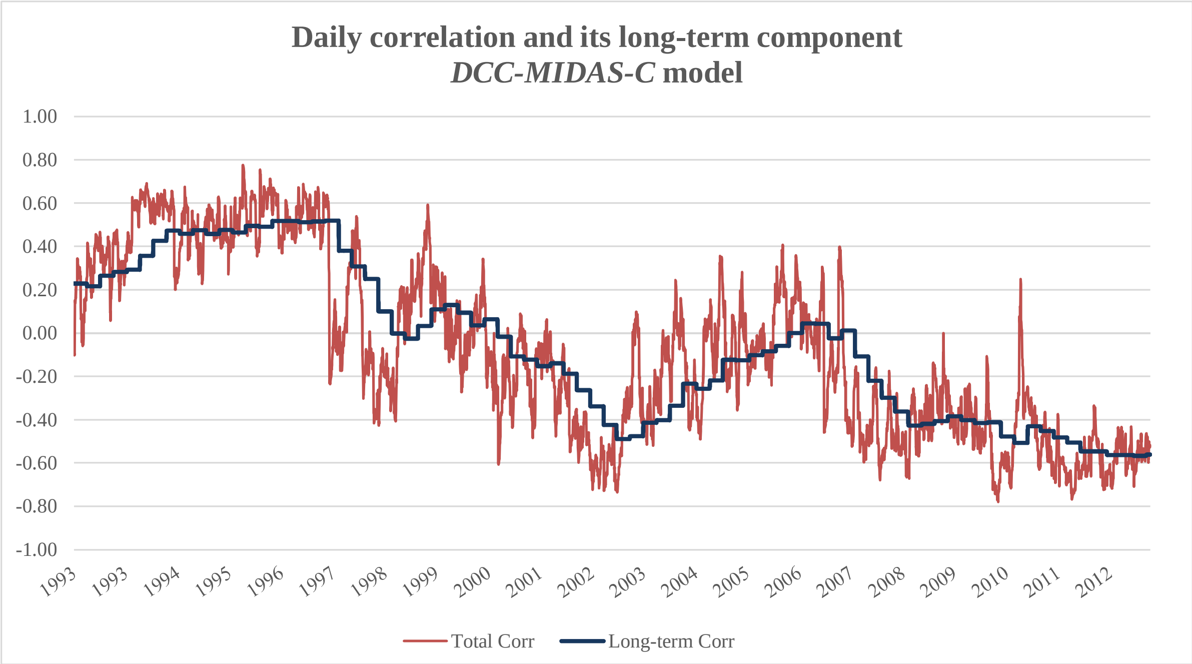

Figure 5. Short term stock-bond correlation estimated by DCC-MIDAS-X models with macro-finance variables

The figure plots the estimated short term component of the stock-bond return correlation from the DCC-MIDAS-X model that only includes macro-finance variables in the MIDAS equation for the long-run correlation. For comparison we also plot the results from the DCC-MIDAS-C model that only includes the realized correlation (*RC*) in the MIDAS equation. The estimations are based on daily standardized residuals from 1993 until 2013, and quarterly data for macro-finance variables from 1989 until 2013 (we use 16 lags in the equation for MIDAS).

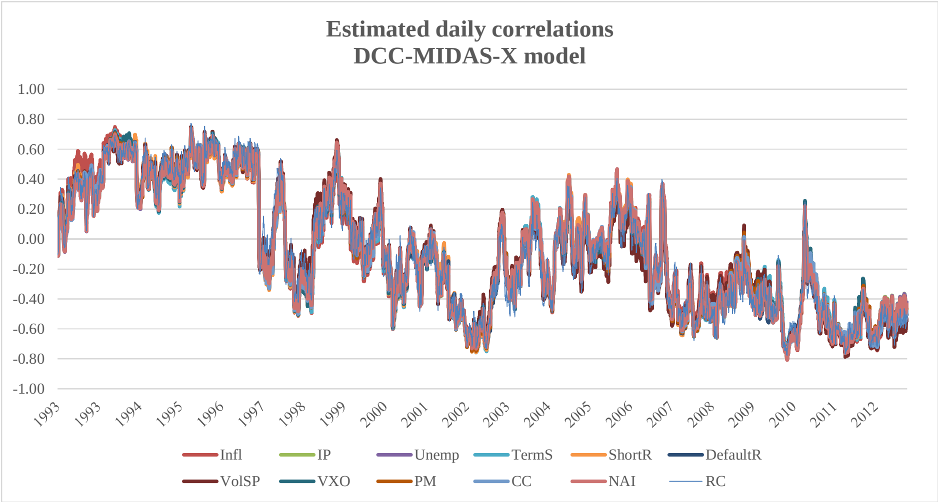

Figure 6. Short term stock-bond correlation estimated by DCC-MIDAS-XC models with realized correlation and macro-finance variables

The figure plots the estimated short term component of the stock-bond return correlation from the DCC-MIDAS-XC model that includes both realized correlation and macro-finance variables in the MIDAS equation for the long-run correlation. For comparison we also plot the results from the DCC-MIDAS-C model that only includes the realized correlation (*RC*) in the MIDAS equation. The estimations are based on daily standardized residuals from 1993 until 2013, and quarterly data for *RC* and the macro-finance variables from 1989 until 2013 (we use 16 lags in the equation for MIDAS).

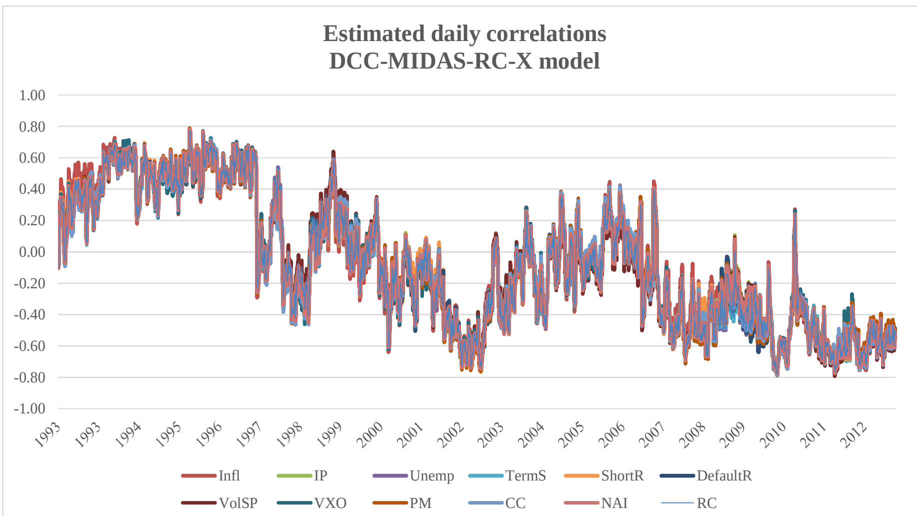

Figure 7. Long-run stock-bond correlation estimated by DCC-MIDAS models

The figure plots the realized quarterly correlations against the estimated long-run component of the stock-bond return correlation from the DCC-MIDAS model with three different specifications: DCC-MIDAS-C, which includes only realized correlation (*RC*) in the Midas equation, DCC-MIDAS-X, which includes the macro-finance variables in the MIDAS equation and DCC-MIDAS-XC, which includes both *RC* and a macro-finance variable in the MIDAS equation. The estimations are based on daily standardized residuals from 1993 until 2013, and quarterly data for *RC* and the macro-finance variables from 1989 until 2013 (we use 16 lags in the equation for MIDAS).

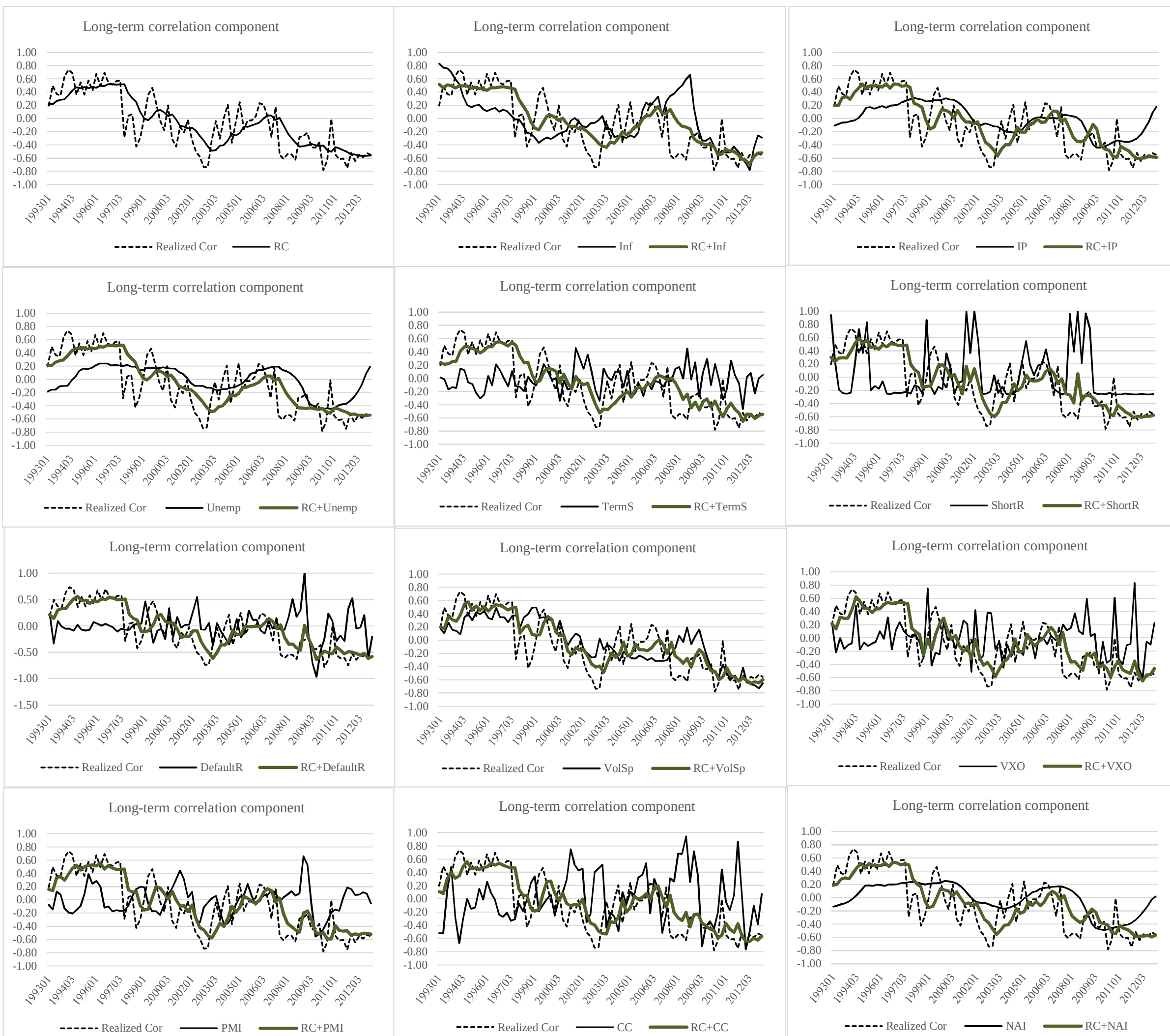

Figure 8. The computed mean absolute errors (MAE) for prediction of the future quarterly correlations

The figure shows the mean absolute errors for the prediction of the future relaized stock-bond correlation using the estimated long-run correlations from DCC-MIDAS with different specifications: DCC-MIDAS-X includes the macro-finance variables and DCC-MIDAS-XC includes both *RC* and the macro-finance variables. For comparison we also plot the results from the DCC-MIDAS-C model that only includes the realized correlation (*RC*) in the MIDAS equation. We compare the estimated correlations with the realized stock-bond correlation at time *t*+*s*, where *s* = 1,…,4. We use the forecast with a random walk model (lagged realised correlation) as the benchmark for the comparison. The correlations are based on quarterly data from 1993 until 2013.

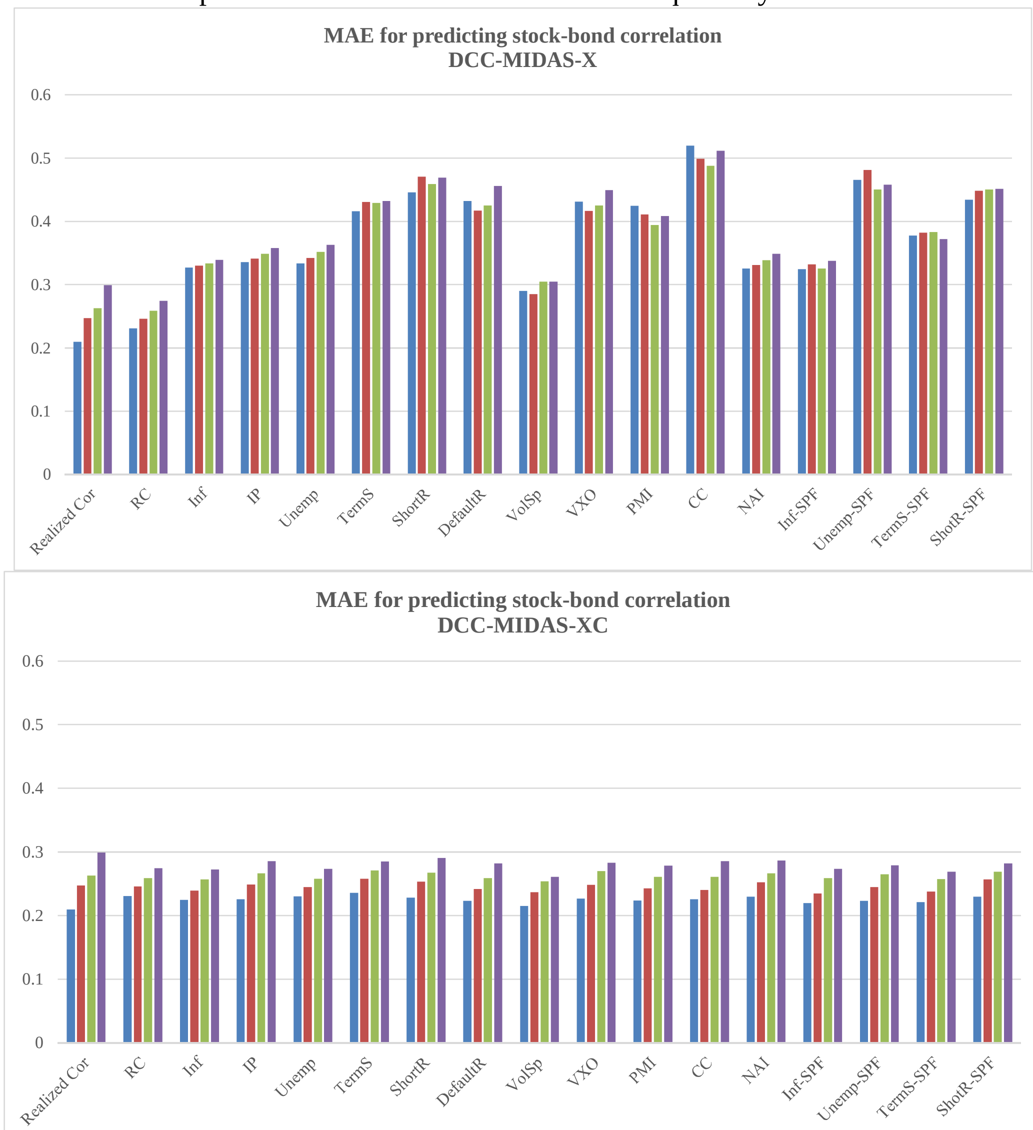

Figure 9. Long-run stock-bond correlation estimated by DCC-MIDAS-XCF models and SPF data

The figure plots the realized quarterly correlations against the estimated long-run component of the stock-bond return correlation from the DCC-MIDAS model with two different specifications: DCC-MIDAS-C, which includes only realized correlation (C) in the Midas equation and DCC-MIDAS-XF, which includes the observed and forecasted macro-finance variables in the MIDAS equation. The estimations are based on daily standardized residuals from 1993 until 2013, and quarterly data for realized correlation and the macro-finance variables, including both historical and forecast data (SPF), from 1989 until 2013 (we use 16 lags for historical data and 3 leads for the SPF data in MIDAS).