Stock-bond return correlations: Moving away from "one-frequency-fits-all" by extending the DCC-MIDAS approach[*†]

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Abstract

This paper explores the determinants of U.S. stock-bond correlations estimated at various frequencies. For this purpose, the two-component DCC-MIDAS model of correlation (Colacito et al. 2011) is used and extended to incorporate a third correlation frequency component. Subsequently, macroeconomic and financial variables are studied as determinants of each component. We show that the daily correlation component is driven by financial market factors, while the monthly component is more influenced by macroeconomic factors. Finally, the yearly component is determined by funding opportunities in the economy. These results are important as they show that different correlation components and determinants should be considered for different investment horizons.

Keywords: stock-bond correlation, frequency-variation, macroeconomic factors, financial factors, DCC-MIDAS model.

JEL classifications: C32, C58, E44, G11, G12.

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1 Introduction

Diversification is at the heart of finance. Since the seminal work of Harry Markowitz (1952) on modern portfolio theory, practitioners and academics have written and developed portfolio strategies leading, for example, to the maximization of returns for a given level of risk. A key ingredient of diversification is the correlation of returns between the assets included in a portfolio. All else being equal, a portfolio made of assets with highly correlated returns has reduced diversification power. In this paper, we study the financial and economic determinants of time-varying correlation between stocks and government bonds, two of the most important financial asset classes.

It is widely recognized that stock-bond correlations are time-varying (Guidolin & Timmermann 2006). Throughout the second half of the 20th century, the correlation between stock and bond returns in the United States was positive, largely fluctuating between zero and 60%. However, at the end of the 20th century, correlations dropped slightly below zero, becoming extremely negative in the early 21st century (Baele et al. 2010). Following this empirical evidence, several scholars tried to link this time-variation in correlations with a broad range of macroeconomic and financial factors; see, among others, Asgharian et al. (2016), Baele et al. (2010), Connolly et al. (2005), Skintzi (2019), and Yang et al. (2009). While consensus seems to exists on the fact that financial factors are important drivers of stock-bond correlations (among others, see Baele et al. (2010) for liquidity proxies and Connolly et al. (2005) for a flight-to-safety phenomenon), the quest for understanding the fundamental macroeconomic drivers of stock-bond correlations is still open; and the existing literature does not provide a unique answer to this question. For example, while Yang et al. (2009) find that both the economic conditions and inflation are important determinants of U.S. stock-bond correlations, Baele et al. (2010) conclude the opposite, i.e. that macroeconomic shocks do not explain stock-bond correlations.

One of the possible explanations for these contradictory findings is the fact that different studies use correlations measured at different frequencies, i.e. they reflect different investment horizons. The long-term correlation, relevant for investors with a long-term horizon, can be different from the short-term correlation due, for example, to short-term frictions (Dimic et al. 2016). The fact that long-term correlation differ from short-term correlation has already been highlighted by Conlon et al. (2018), among others.

As the frequency/investment horizon changes, the underlying driving factors of the correlations' movement change. Intuitively, longer-term correlations capture a more persistent relationship between stocks and bonds which could result from either the behaviour of longer-term investors or from persistent patterns in the behaviour of shorter-term investors. If the determinants of correlations vary in function of its frequency, investors, who are not all interested in the same frequency of correlation, have to focus on a different set of determinants to make portfolio investment decisions (Kiviaho et al. 2014). It is thus relevant to investigate the frequency-variation of potential determinants of stock-bond correlation. However, to the best of our knowledge, a detailed comparison of correlation determinants at different time horizons remains overlooked by the literature. Our paper fills this gap by estimating multiple-horizons correlation via an extension of the Mixed Frequencies - Dynamic Correlation Component (DCC-MIDAS) model developed by Colacito et al. (2011)[1].

The DCC-MIDAS model exploits the richness of high-frequency data to estimate a lower and a higher frequency correlation component. Moreover, it incorporates the intuitive economic notion that the high-frequency component wanders around the low-frequency component. Being intuitively appealing, the DCC-MIDAS is commonly used to model asset correlations (see Conrad et al. (2014) and Virk & Javed (2017), among others) and stock-bond correlations in particular (see Asgharian et al. (2015), Asgharian et al. (2016), Fang et al. (2017), and Perego & Vermeulen (2016), among others).

In the current paper, we build upon their insights and extend the two-component DCC-MIDAS model to include a third component. By doing so, we can analyse, in an integrated framework, which factors drive the short-term, medium-term and long-term components of stock-bond correlations. We propose an estimation strategy that ensures internal consistency between the three different frequency components. In particular, in a first step, we obtain the short- and long-term components of stock-bond correlations. In a second step, we estimate the medium-term component, conditional upon the previously determined long-term component of correlations. The shorter-term components are modelled such that they wander around the long-term component. With this estimation strategy, we can study the daily, monthly and yearly components, which allows for a complete and detailed analysis, over time and frequency, of the determinants of correlation. These three frequencies are chosen to be quite distinct from each other, and our long-term component is set such that a sufficient number of observations is available for the analysis.

By applying our methodology to U.S. stock-bond correlations, we find that accounting for the different frequencies is important to get a better insight into the complex dynamics of time-varying correlations. Our results show that the high frequency component that captures fast moving and short-lived variations of correlations is influenced primarily by uncertainty variables and financial market factors. The medium-term component is more driven by slower-moving, fundamental macroeconomic variables. For this component, the financial market variables, which are important in explaining short-term correlation movements, lose their importance. Finally, the long-term component is driven by monetary policy and economic policy uncertainty. The microstructure of the stock market as well as the balance sheet of financial intermediaries are also found to matter for this long-term correlation component. These results are relevant to investors as they show, for three dif-

[1]Recently Dimic et al. (2016) and Lin et al. (2017) use a wavelet approach to extract correlations at various frequencies and find that, depending on the frequency, different variables have a different impact on correlations. However, both studies focus their analysis on a few set of correlation determinants, mainly linked to uncertainty, inflation, industrial production and interbank interest rate. We also differentiate from these studies by using an approach that extract correlations by taking into account the time-variation of volatilities. Forbes & Rigobon (2002) show that if one does not take into account the impact of time-varying volatilities on correlations, then correlation estimates in turbulent periods are biased.

ferent investment horizons, which macroeconomic and financial variables determine the variation in correlation. There are also relevant to policy makers as it provides them with a more refined picture of financial markets.

The remainder of this paper is as follows. In the next section, we introduce the DCC-MIDAS model and motivate why we need to extend this model with a third frequency component. This section also describes the estimation strategy developed to include this third frequency component. Afterwards, we study the determinants of correlations at each time-frequency: section three presents the methodology and section four analyses which fundamental factors explain the different frequency components of correlation. Finally, section five concludes.

2 A three-component DCC-MIDAS specification

Colacito et al. (2011) introduced a two-component DCC-MIDAS model that combines the DCC model of Engle (2002) with the GARCH-MIDAS approach of Engle et al. (2008) to exploit the abundance of information contained in high-frequency data in order to uncover lower frequency dynamics.

In our paper, we aim at disentangling between more components. An obvious solution would be to estimate the DCC-MIDAS model twice: for example, a first time to obtain a daily component and a yearly component and a second time to obtain a daily component and a monthly component. By doing this, we would end up with four components: two daily ones, a monthly one and a yearly one. However, as can be seen from Figure 1, the two daily components are different.

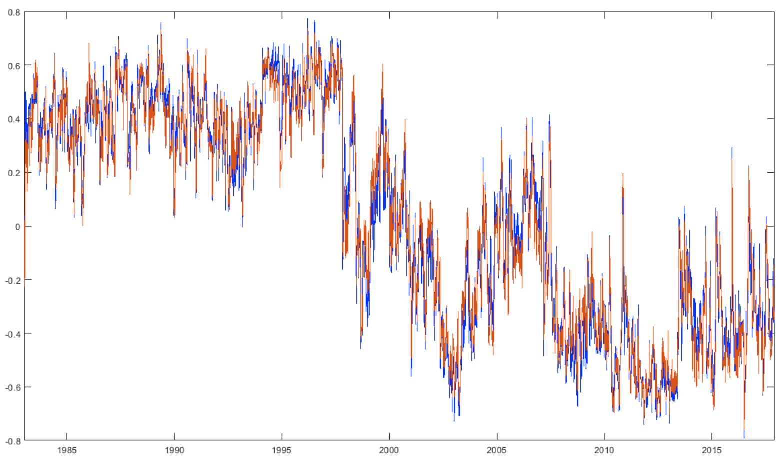


Figure 1: Difference in daily correlation components. This figure shows the daily component obtained from a daily-monthly DCC-MIDAS model (in blue) and the daily component obtained from a daily-yearly DCC-MIDAS model (in red)

Therefore, the question arises as to which of these two different daily components we should choose? This question does not have a good answer: both daily components are correctly estimated with a DCC-MIDAS model. Their difference is due to the fact that each daily component has a different anchor. The daily component obtained from the daily-yearly DCC-MIDAS model is anchored to a yearly component and the daily component obtained from the daily-monthly DCC-MIDAS model is anchored to the monthly component. Because of this anchoring issue, estimating a DCC-MIDAS model twice is not a solution to obtain three frequency components of correlation.

The approach we take in this paper is to develop an estimation strategy that avoids differences in anchoring and ensures that the different frequency components are interrelated in a economically intuitive manner. That is, we want that the short-run (daily) component varies around a long-run (yearly) component and that, similarly, the medium-run (monthly) component wanders around the same long-run component. Both the short-run and the medium-run components would then be anchored to the *same* long-run component. This makes sense as it is very likely that different shorter-term components share the same long-term behaviour. This estimation strategy is developed in the next section[2].

2.1 Basic DCC-MIDAS set-up

Assume a vector of stock (e) and bond (b) returns $r_{t_h} = [r_{e,t_h}, r_{b,t_h}]'$, measured on an horizon h, that is governed by the following dynamics:

$$r_{t_h} \sim N(\mu_h, H_{t_h}) \tag{1}$$

$$H_{t_h} = D_{t_h} R_{t_h} D_{t_h} \tag{2}$$

where μ_h is the (2×1) vector of unconditional stock and bond mean returns and H_{t_h} is the (2×2) conditional covariance matrix of returns, with D_{t_h} a diagonal (2×2) matrix of conditional standard deviations, and R_{t_h} the (2×2) matrix of conditional correlations, with the stock-bond correlation ρ equal to the off-diagonal element.

Moreover, define $\xi_{t_h} = D_{t_h}^{-1}(r_{t_h} - \mu_h)$ as the volatility adjusted residuals, such that the conditional correlation matrix can be expressed in terms of the conditional correlation between the volatility adjusted residuals:

$$R_{t_h} = E_{t_h-1}\left(\xi_{t_h}\xi_{t_h}'\right) \tag{3}$$

As Colacito et al. (2011) show, this model can conveniently be estimated in a two-step procedure. In a first step, the conditional standard deviations of D_{t_h} are estimated, and in a second step, the conditional correlation matrix R_{t_h} is estimated.

[2] Another possibility could be to estimate the DCC model (Engle 2002) three times to obtain, each time, a given frequency of correlation. For example, we could estimate first a DCC model on daily returns, then another DCC model on monthly returns and, finally, another DCC model on yearly returns. By doing this, the problem of obtaining different short-term components is solved. However, another problem arises: each frequency of correlation carries redundant information and is, therefore, not a real *component*. Moreover, the three frequencies are not related to each other, intuitively. Indeed, the DCC model is not able to distinguish between different frequencies and, hence, different frequency components. Therefore, estimating three times a DCC model is also not a solution.

To obtain three correlation components, we apply this estimation procedure twice. In a first round, we obtain estimates for the short- and long-run components of correlation. The short-term component follows a DCC scheme and varies around a long-run component, estimated using a MIDAS weighting scheme. In a second round, we estimate the medium-run component by feeding the DCC-MIDAS with the long-run component obtained in the first round. Therefore, the medium-run component also follows a DCC scheme and wanders around the same long-run component as the previously estimated short-run component.

2.2 DCC-MIDAS short- and long-run correlation components

To obtain estimates of the short- and long-run correlation components, we start from a vector of stock and bond returns r_{t_s} measured at the short-run horizon s. Following the specification of Colacito et al. (2011), we assume that returns follow a GARCH-MIDAS process:

$$r_{i,t_s} = \nu_i + \sqrt{\sigma^2_{i,t_s} \times \sigma^2_{i,t_l}}\xi_{i,t_s} \qquad i = e, b \text{ and } t_s = n_l + 1, ..., n_l + N_l \tag{4}$$

where N_l is the number of short-run periods in the long-run period l and where $n_l = \sum_{q=1}^{l-1} N_q$ is the number of short-run periods[3] before period l. In this model σ^2_{i,t_s} and σ^2_{i,t_l} are the two frequency variance components of the short-run returns; σ^2_{i,t_s} varies at the short-run frequency and represents short-lived fluctuations, whereas σ^2_{i,t_l} varies at the long-run frequency and represents more persistent variations, for example associated with the state of the economy. The intuition behind the multiplication of these two components ($\sigma^2_{i,t_s} \times \sigma^2_{i,t_l}$) is that the impact of news will differ between economic expansions and contractions (Engle et al. 2008). In addition, the short-run variance component σ^2_{i,t_s} is governed by a GARCH(1,1) process:

$$\sigma^2_{i,t_s} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t_s-1} - \nu_i)^2}{\sigma^2_{i,t_l}} + \beta_i \sigma^2_{i,t_s-1} \tag{5}$$

where the standard GARCH(1,1) model is adapted to include a trend related to the long-run variance component (Engle et al. 2008). Finally, this long-run variance component is a weighted sum of K_i lagged realised variances over the long-run frequency l. This weighted sum is similar to a MIDAS filtering specification:

$$\sigma^2_{i,t_l} = \sigma^2_{i,t_l} + \theta_i \sum_{k=1}^{K_i} \varphi_k(\omega_i) RV_{i,t_l-k} \tag{6}$$

[3] Using calendar-time, the number of short-run observations in a fixed long-run horizon can vary per long-run horizon. In the empirical application, we choose a daily short-run frequency and a yearly long-run frequency. In this case, n_l is the total number of days in the sample before year l and N_l is the number of days in year l. Using a varying number of days for each given period differs from Colacito et al. (2011) who use fixed numbers of days.

with the long-run realised variance defined as the sum of N_l squared returns measured at the short-run frequency:

$$RV_{i,t_l} = \sum_{t_s=n_l+1}^{n_l+N_l} r_{i,t_s}^2 \tag{7}$$

and with so called Beta weights (Engle et al. 2008):

$$\varphi_k(\omega_i) = \frac{\left(1-\frac{k}{K_i}\right)^{\omega_i-1}}{\sum_{k=1}^{K_i}\left(1-\frac{k}{K_i}\right)^{\omega_i-1}} \tag{8}$$

Once the two conditional variance components are estimated, we can use the standardised residuals ξ_{i,t_s} obtained from equation 4 in a DCC-MIDAS specification to estimate the short- and long-run components of the stock-bond correlation. In particular, from the standardised residuals ξ_{t_s} we obtain a (2×2) matrix Q_{t_s} that follows a DCC(1,1) scheme with elements q_{i,j,t_s} defined as:

$$q_{i,j,t_s} = \rho_{i,j,t_l}(1-a-b) + a\xi_{i,t_s-1}\xi_{j,t_s-1} + bq_{i,j,t_s-1} \qquad i,j = e,b \tag{9}$$

with the long-run correlation component defined as:

$$\rho_{i,j,t_l} = \sum_{p=1}^{P} \varphi_t(\Omega)\, c_{i,j,t_l-p} \tag{10}$$

$$c_{i,j,t_l} = \frac{\sum_{t_s=n_l+1}^{n_l+N_l}\xi_{i,t_s}\xi_{j,t_s}}{\sqrt{\sum_{t_s=n_l+1}^{n_l+N_l}\xi_{i,t_s}^2}\sqrt{\sum_{t_s=n_l+1}^{n_l+N_l}\xi_{j,t_s}^2}} \tag{11}$$

where $\varphi_t(\Omega)$ are Beta weights defined in a similar way as in equation 8 above. Finally, the short-run correlation component is computed as:

$$\rho_{i,j,t_s} = \frac{q_{i,j,t_s}}{\sqrt{q_{i,i,t_s}}\sqrt{q_{j,j,t_s}}} \tag{12}$$

where q_{i,i,t_s} and q_{j,j,t_s} are the diagonal elements of Q_{t_s}. To make clear the intuitive property of the model that the short-run correlation component moves around a slow-moving long-run correlation component, we follow Colacito et al. (2011) and rewrite equation 9 as:

$$q_{i,j,t_s} - \rho_{i,j,t_l} = a\left(\xi_{i,t_s-1}\xi_{j,t_s-1} - \rho_{i,j,t_l}\right) + b\left(q_{i,j,t_s-1} - \rho_{i,j,t_l}\right) \tag{13}$$

2.3 DCC-MIDAS medium-run correlation component

Once the short- and long-run correlation components are estimated, the medium-run correlation component is also estimated as moving around the long-run component obtained above. To this end, we start from a vector of stock and bond returns r_{t_m} measured at the medium-run horizon m. In line with equation 4, we assume that the medium-run returns follow a GARCH-MIDAS process:

$$r_{i,t_m} = \mu_i + \sqrt{\sigma_{i,t_m}^2 \times \hat{\sigma}_{i,t_l}^2}\,\xi_{i,t_s} \qquad i = e,b \text{ and } t_m = g_l+1,...,g_l+G_l \tag{14}$$

where G_l is the number of medium-run periods for which the long-run period is fixed and $g_l = \sum_{q=1}^{l-1} G_q$ is the number of medium-run periods[4] before period l. The long-run variance component σ^2_{i,t_l} is estimated earlier via equation 6. The medium-run variance of the stock and bond returns σ^2_{i,t_m} also follows a simple GARCH(1,1) process:

$$\sigma^2_{i,t_m} = (1 - \gamma_i - \delta_i) + \gamma_i \frac{\left(r_{i,t_m-1} - \mu_i\right)^2}{\hat{\sigma}^2_{i,t_l}} + \delta_i \sigma^2_{i,t_m-1} \tag{15}$$

Finally, we use the standardised residuals ξ_{i,t_m} obtained from equation 14 in a DCC-MIDAS specification to estimate the medium-run component of the stock-bond correlation. Similarly to equation 13, we obtain a (2×2) matrix Q_{t_m} that follows a DCC(1,1) scheme with elements q_{i,j,t_m} defined as:

$$q_{i,j,t_m} - \hat{\rho}_{i,j,t_l} = c\left(\xi_{i,t_m-1}\xi_{j,t_m-1} - \hat{\rho}_{i,j,t_l}\right) + d\left(q_{i,j,t_m-1} - \hat{\rho}_{i,j,t_l}\right) \tag{16}$$

with the long-run correlation component ρ_{i,j,t_l} estimated earlier via equation 10. The medium-run correlation component is then computed as:

$$\rho_{i,j,t_m} = \frac{q_{i,j,t_m}}{\sqrt{q_{i,i,t_m}}\sqrt{q_{j,j,t_m}}} \tag{17}$$

3 Finding the determinants of correlation

Once the three correlation components are estimated, we regress each component on variables obtained at the corresponding horizon h. We estimate the following regression:

$$\rho_{i,j,t_h} = \vartheta + \phi\rho_{i,j,t_h-1} + \Omega' X_{t_h-1} + \epsilon_{i,j,t_h} \tag{18}$$

where, for each h, ρ_{i,j,t_h} is the correlation component, X_{t_h-1} are a set of one-period-lagged explanatory variables, and ϵ_{i,j,t_h} is an error term. For the medium- and short-run horizon, the correlation component ρ_{i,j,t_h} is the difference between the long-run correlation component and the medium- and short-run correlation component, respectively. Taking the difference with respect to the long-run component[5] allows to extract the medium- or short-run correlation detrended from the long-run movement, such that we can exclusively focus on the shorter-term movements in correlation[6]. Finally, to control for a possible high persistence of the correlation component, we follow Perego & Vermeulen (2016) and include the lagged dependent variable ρ_{i,j,t_h-1} in our regression. This lagged dependent variable is orthogonalised with respect to the explanatory variables X_{t_h-1}.

Table 1 reports the macroeconomic and financial explanatory variables and their summary statistics are reported in Table 2[7]. We divide these variables in six different subgroups.

A first subgroup is composed of indicators of economic condition (ADS and UNEM). The state of the economy is often investigated to explain time-variation in stock-bond

[4] In line with footnote 3, we also use calendar-time here. In the empirical application we choose the medium-run frequency as the monthly horizon. In this case, g_l is the total number of months before year

Table 1: Macro-finance variables

This table presents the macroeconomic and financial variables used as predictors of correlations. Note that it is sometimes needed to compute the first-difference in order to make a variable stationary, as this is also done in Asgharian et al. (2016), among others.

Factor	Description	Frequency	Source
Economic condition			
ADS	Index composed of economic indicators to track real business conditions	Daily	Aruoba et al. (2009)
UNEM	Civilian unemployment rate computed by the U.S. Bureau of Labor Statistics	Monthly	Fed. St. Louis
Inflation and interest rate			
PCE	First-difference in the inflation rate computed as the percent change from year ago of the trimmed mean personal consumption expenditures of the Federal Reserve Bank of Dallas	Monthly	Fed. St. Louis
SIR	First-difference in the 3-month London Interbank Offered Rate (LIBOR) computed by the ICE Benchmark Administration Limited (IBA)	Daily	Fed. St. Louis
YSPR	First-difference in the yield spread between the Moody's AAA corporate bond and the 3-month Treasury Bill rates	Daily	Fed. St. Louis
TED	First-difference in the spread between the 3-month LIBOR and 3-month Treasury Bill	Daily	Fed. St. Louis
Business condition			
RS	Log return of the Datastream U.S. stock market index	Daily	Datastream
CAPE	Cyclically adjusted price earning ratio	Monthly	Shiller (2016)
Uncertainty			
VXO	Chicago Board Options Exchange S&P 100 Volatility Index	Daily	Fed. St. Louis
EPU	Index of economic policy uncertainty based on U.S. newspapers coverage frequency	Daily	Baker et al. (2016)
Forecast			
INPF	Annual average projection for the following year of the industrial production index computed by the Survey of Professional Forecasters	Quarterly	Philadelphia Fed.
CPIF	First-difference in the annual average projection for the following year of the CPI inflation (annual) rate computed by the Survey of Professional Forecasters	Quarterly	Philadelphia Fed.
Funding opportunities			
LIQ	Liquidity factor computed by Pastor and Stambaugh (2003) using data from the New York Stock Exchange and American Stock Exchange	Monthly	Pastor & Stambaugh (2003)
BDLEV	Logarithm of the security broker-dealer leverage computed as the ratio of Total Financial Assets over the difference between Total Financial Assets and Total Liabilities	Quarterly	Fed. St. Louis

Table 2: Summary statistics of macro-finance variables

This table reports the summary statistics for the macroeconomic and financial variables for the longest available period (1987-2016). The summary statistics are computed for the highest frequency available for each variable.

	Freq.	N.	Mean	Std.Dv.	Min.	Max.	Skew.	Kurt.
Economic condition								
ADS	daily	7,107	−0.166	0.702	−4.082	1.889	−2.015	10.458
UNEM	monthly	349	6.001	1.501	3.800	10.000	1.001	3.224
Inflation and interest rate								
PCE	monthly	349	−0.005	0.078	−0.290	0.240	−0.073	3.434
SIR	daily	7,107	−0.001	0.039	−0.688	0.570	−1.643	43.298
YSPR	daily	7,107	−0.000	0.065	−0.519	0.894	1.023	20.813
TED	daily	7,107	−0.000	0.059	−0.800	0.990	0.193	38.102
Business condition								
RS	daily	7,107	0.039	1.104	−9.396	9.676	−0.431	10.515
CAPE	monthly	349	24.641	6.857	13.324	44.198	0.993	3.857
Uncertainty								
VXO	daily	7,107	20.204	8.449	8.510	87.240	1.963	9.960
EPU	daily	7,107	95.481	66.859	3.320	719.070	2.093	10.905
Forecast								
INPF	yearly	30	117.316	14.781	94.636	145.538	0.400	2.163
CPIF	yearly	30	−0.036	0.331	−0.925	1.000	0.467	5.849
Funding opportunities								
LIQ	monthly	349	−0.023	0.063	−0.308	0.198	−1.216	6.730
BDLEV	yearly	30	3.087	0.235	2.667	3.508	−0.180	2.169

correlations and is many times found to be an important driver (Asgharian et al. 2015, 2016, Ilmanen 2003). However, its sign can vary. According to the flight-to-quality phenomenon (Baur & Lucey 2009), when the economy is in a bad state, investors are looking for safety and rebalance their portfolios from relatively riskier stocks to relatively safer bonds (they fly from riskier to safer assets); while, when the economy is doing well, no flight occurs and investors are willing to hold a diversified portfolio composed of both bonds and stocks. In this setting, the relationship between stock-bond correlations and the state of the economy is expected to be positive (Asgharian et al. 2015, 2016). However, other dynamics may be at work. As is well known, the price of stocks and bonds should be equal to their discounted expected future cash flows. During phases of economic expansion, dividends increase while fixed coupons do not. At the same time, discount rates might be impacted by economic growth and increase. Therefore, an improvement in

l and G_l is the number of months in year l (which is equal to 12).

[5]The Fisher transformation $\frac{1}{2} \times \ln(\frac{1+\rho_{i,j,t_h}}{1-\rho_{i,j,t_h}})$ is applied to the correlation components in order to unbound them (Perego & Vermeulen 2016).

[6]These pure movements of correlation can also be understood as correlation innovations. This terminology will be used interchangeably throughout the paper.

[7]These variables have been tested for stationarity.

business conditions can also be associated with an increase in stock prices and a decrease in bond values, creating a decoupling between stocks and bonds (Ilmanen 2003). In this paper, we use a low-frequency indicator of the state of the economy (UNEM) as well as a high-frequency one (ADS). As such, we can also investigate the impact of the state of the economy on the short-run correlation component.

A second subgroup relates to the inflation and interest rates/spreads (PCE, SIR, YSPR and TED). Results tend to show that they are potential factors explaining stock-bond correlations (Aslanidis & Christiansen 2012, Ilmanen 2003, Lin et al. 2017). As regards inflation, the expected sign of its impact on correlations is not straightforward. An increase in inflation rates is expected to decrease bond values through an increase in the nominal discount factor (Christiansen & Ranaldo 2007). However, the effect is more ambiguous for equity instruments. Indeed, inflation would not have any impact on stock prices if cash flow growth rate increases with inflation (Ilmanen 2003). Therefore, depending on whether inflation has a bigger impact on cash flows or on discount rates, stock values are expected to increase or decrease, thereby inducing a negative or positive stock-bond correlation, respectively. For short-term interest rates (SIR), a positive impact on correlation is expected: an increase in the general level of interest rates raises the discount factor and thus decreases both stock and bond prices. Their correlation will then increase (Christiansen & Ranaldo 2007). This is consistent with previous literature (Aslanidis & Christiansen 2012, Viceira 2012). The yield spread (YSPR) is also expected to have a positive impact on stock-bond correlations. The reason is that an increase in this spread indicates better business conditions in the future and is therefore expected to have a positive impact on correlations (Aslanidis & Christiansen 2012)[8]. Finally, the TED spread, which measures the short-term liquidity in the credit market and is also a proxy for credit risk in interbank lending, is expected to be negative according to the flight-to-quality explanation (Chiang et al. 2015). A higher TED spread means that liquidity is drying up or that credit risk increases. In this context, investors might be more uncertain and thus they might fly from stocks to bonds.

A third subgroup gathers proxies for business condition (RS and CAPE). This is motivated by the findings in Chiang et al. (2015) from which it follows that the return on the stock market determines the stock-bond return correlations in six advanced markets, including the U.S.. As a better state of the firms could proxy for better investment sentiment, investors might be more willing to hold portfolios including both stocks and bonds (Chiang et al. 2015). This relates to the flight-to-quality explanation.

A fourth category includes variables related to uncertainty (VXO, EPU) which is undoubtedly reported to have a negative impact on correlations (Andersson et al. 2008, Asgharian et al. 2015, 2016, Chiang et al. 2015, Connolly et al. 2005). In periods of un-

[8] Aslanidis & Christiansen (2012) use a government bond yield spread. Our interest rate spread is slightly different and has been chosen to mainly capture the behaviour of investors who are looking for better investment opportunities and, who, therefore, consider the spectrum of relatively safe bonds, going from 3-month Treasury Bill to Moody's AAA corporate bond. However, we do not expect the result of the yield spread to be significantly different than in Aslanidis & Christiansen (2012).

certainty, investors are looking for more safety and will therefore rebalance their portfolio to hold more bonds and less stocks, according to the flight-to-quality phenomenon.

A fifth subgroup includes forecasts (CPIF and INPF) which are also found to be relevant (Andersson et al. 2008, Asgharian et al. 2016). Given that stock and bond values reflect expected future cahsflows, such forecasts are indeed potentially important (Andersson et al. 2008). In line with this, Asgharian et al. (2016) find an impact of expected inflation on correlations, while not of historical inflation.

Finally, the sixth category is related to funding opportunities in the economy. This subgroup contains the liquidity of the financial markets (LIQ) and the balance sheet of intermediaries proxied by the broker-dealer leverage (BDLEV). Baele et al. (2010) highlight the predominant importance of liquidity in explaining long-term stock-bond correlations. They find a positive impact of liquidity on correlations. One of the reasons is related to flight-to-liquidity. When liquidity in the stock market dries up, investors start looking for more liquid assets (government bonds) instead of illiquid stocks. This flight induces an increase in bond prices and a decrease in stock prices, thereby creating a decreasing stock-bond correlation (Baele et al. 2010). As regards the broker-dealer leverage, **?** explain that the effective risk aversion of market based financial intermediaries (such as brokers-dealers) can be proxied by the growth of their balance sheet. These intermediaries face balance sheet constraints and when the constraints are lower, their risk appetite is stronger. This results in an increase in the size of the balance sheet and in lower asset returns, due to a decrease in risk premia. **?** find that financial intermediary balance sheet growth is associated with lower stock returns and lower bond returns in the next quarter[9]. Therefore, the broker-dealer leverage is expected to have a positive impact on stock-bond correlations.

Seven of these macroeconomic and financial variables are available at a daily frequency and are aggregated to a monthly and yearly frequency by taking the mean over the corresponding period. For the stock return (RS), the aggregation is performed by taking the log difference between the last observation of the corresponding period and the last observation of the preceding period[10]. Four other variables are available at a monthly frequency. Their aggregation to a lower frequency (yearly) is also performed by taking the average over the year. Finally, three additional variables are available at quarterly frequency and their mean over the year is used in the regression for the yearly component of correlations.

Due to the small number of yearly observations, we perform the yearly regression in two

[9] **?** do not use the broker-dealer leverage to predict treasury bond returns because it never passes the variable selection method (LAR). Therefore, they decide to never test its impact. However, they find a negative impact of the shadow bank asset growth on Treasury bond returns. Given that asset growth in shadow bank and leverage growth in security brokers-dealers are both synonyms for an increase in market based financial intermediary balance sheet, we can conclude that this balance sheet has a positive impact on stock-bond correlation.

[10] For example, the stock return over February 1995 is computed by taking the log difference between the price on the last day of February 1995 and the price on the last day of January 1995.

steps. By means of a subset selection method, we select the best predictors among all the possible variables (available at a daily, monthly or yearly frequency) and a trend[11]. We use the Least Angle Regression (LAR) method developed by Efron et al. (2004) which has also been used by **?**, among others. Once the best predictors are selected, an OLS regression is run.

In the literature, DCC-MIDAS models are mainly used to investigate the impact of low-frequency (for example monthly or quarterly) variables on daily correlations (Asgharian et al. 2016, Conrad & Loch 2016) and these low-frequency explanatory variables are directly included in the DCC-MIDAS model. However, in this paper, we opt for a two-stage estimation procedure where, in a first stage, we estimate the correlation components and then, in a second stage, we run an OLS regression. Two reasons explain this choice. First, we aim to investigate the explanatory power of a large amount of macroeconomic and financial variables at the same time. In a one-stage estimation procedure, it is difficult, not to say impossible, to include as many explanatory variables as in a two-stage procedure. Second, our analysis has a different purpose than those using a one-stage DCC-MIDAS. Indeed, we do not want to look at the impact of low-frequency variables on a high-frequency correlation. Instead, we want to estimate three correlation components (daily, monthly and yearly) and investigate the determinants of each of these components to see whether they differ between components. Using a one-stage analysis for this purpose would greatly increase the complexity of the model so that it becomes infeasible. This strategy of estimating, in a first step, the correlation components and, in a second step, the regression is also used in Perego & Vermeulen (2016).

4 Estimation results

The empirical analysis is performed on U.S. data, which allows to study stock-bond correlations for a long period of time. Stock returns are computed as log returns of the U.S. total market index constructed by Datastream and bond returns are calculated as implied returns from the 10-year maturity Treasury note zero-coupon yield estimated by Gürkaynak et al. (2007)[12]. Our stock and bond data covers the period from January 2, 1973 to November 30, 2017. The summary statistics are detailed in Table 3.

4.1 Estimation of daily, monthly and yearly correlation components

We estimate three U.S. stock-bond correlation components: a daily component, a monthly component and a yearly component. The number of lags of realised variance and realised

[11] The trend is necessary because the long-run correlation is trend-stationary.

[12] The correlation between zero-coupon notes and coupon-bearing notes is 0.999. Therefore, using one or the other should not matter.

Table 3: Summary statistics of stock and bond returns

This table reports the summary statistics for daily U.S. stock and bond returns over the period January 2, 1973 to November 30, 2017.

	Stock return (%)	Bond return (%)
N.	11342	11342
Mean	0.040	0.003
Std. Deviation	1.064	0.663
Minimum	-20.691	-5.372
Maximum	10.913	7.647
Skewness	-0.860	0.072
Kurtosis	23.170	9.395

correlation is set to K=P=10.[13] The estimation results are available in Table A1 in the appendix. The resulting three components of correlation as well as the short- and medium-run innovation in correlations (difference between the shorter-run component and the long-run component) are plotted in Figure 2[14]. In Panel (a), we can see that these correlation components show a clear downward trend, which is consistent with previous literature (Asgharian et al. 2016, Ohmi & Okimoto 2016). Panel (a) also shows that the short- and medium-run components wander around the long-run component, as modelled in the DCC-MIDAS.

Table 4 reports the summary statistics of these three different correlation components. We see that the daily component has a smaller mean than the two other components. This is probably explained by its dynamics during the second half of the 00's decade when it is reaching positive values while the monthly and yearly components mostly stay under zero. It also has a slightly higher standard deviation, a lower minimum and higher maximum than the two other components.

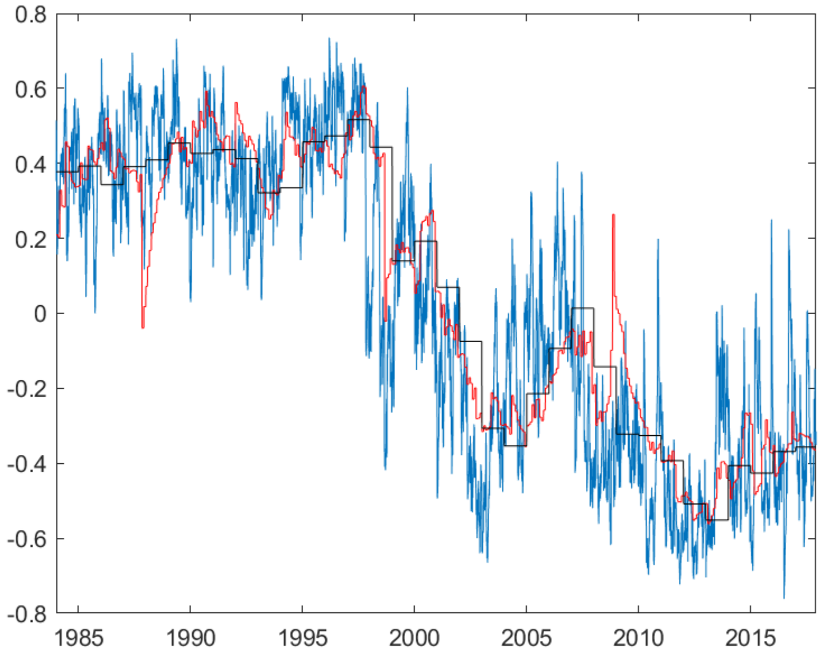
Panel (b) of Figure 2 provides information on the movements of correlations as it represents the short- and medium-run correlations detrended using the long-run correlation. We can see that these two detrended correlation components do not always behave similarly. For example, the period around 1987 features a monthly innovation close to its minimum value while the daily innovation is more volatile and turns positive. This highlights the importance and the interest in studying different frequency components of correlation.

4.2 Macro-finance determinants of correlation

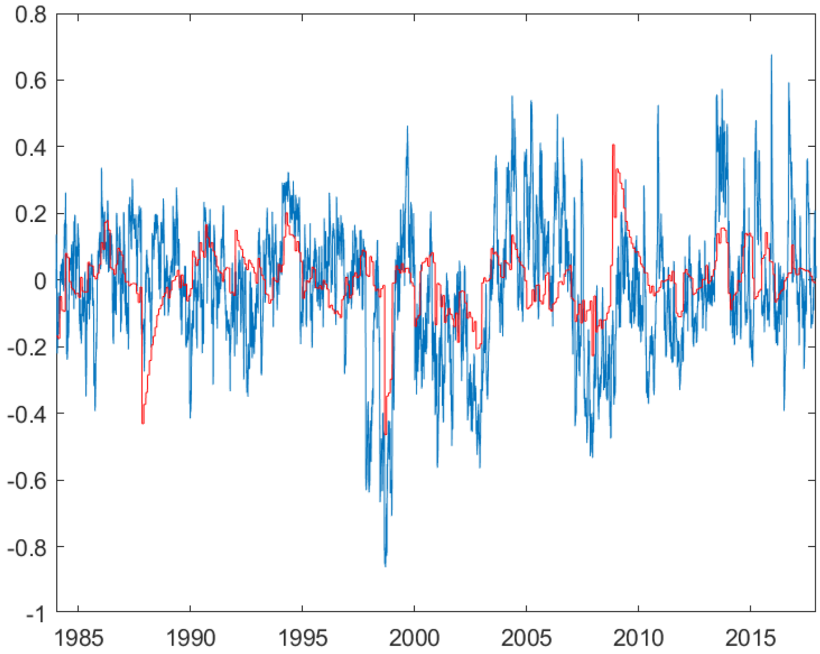
In order to show that each correlation component matters and is impacted by different variables, we regress each of the three correlation components on a set of well-known

[13] In order to make sure that our results are not driven by the choice of parameters K and P, we also replicate the entire analysis of this paper with K=P=8 as well as with K=P=12. Our conclusions are robust to the choice of K and P. Results are available upon request.

[14] As can be noticed on this Figure, our estimation strategy requires a relatively large amount of initial observations. This drawback makes it less desirable to use in a context outside financial markets, in which data are available for a shorter period of time.



(a) Correlation components



(b) Correlation innovations

Figure 2: U.S. stock-bond correlation Panel (a) shows the U.S. stock-bond daily (in blue), monthly (in red) and yearly (in black) correlation components estimated with our strategy to extended the DCC-MIDAS model. Panel (b) shows the movements in correlations (correlation innovations), computed by taking the difference between each shorter-run component and the long-run yearly component.

Table 4: Summary statistics of correlation components

This table reports the summary statistics for the U.S. stock-bond daily, monthly and yearly correlation components estimated with the extended DCC-MIDAS model. These components are represented in Figure 2, panel(a).

	N.	Mean	Std.Dv.	Min.	Max.	Skew.	Kurt.
Daily component	8,561	0.029	0.398	−0.762	0.735	−0.100	1.602
Monthly component	407	0.050	0.359	−0.561	0.607	−0.083	1.432
Yearly component	34	0.052	0.365	−0.552	0.517	−0.207	1.409

determinants that are available at the corresponding frequency. Due to availability of macroeconomic and financial data, our analysis covers the period going from January 1988 to December 2016. Table 5 reports the result of this analysis.

Column (1) of Table 5 reports the results for the daily correlation and shows that all the daily variables are significant determinants of these daily movements in correlation. The two uncertainty variables (EPU and VXO) and the TED spread have a negative impact on daily correlation, which is explained by a flight-to-quality and is consistent with previous literature (Andersson et al. 2008, Asgharian et al. 2015, 2016, Chiang et al. 2015, Connolly et al. 2005).

The impact of the short-term interest rates (SIR) and of the yield spread (YSPR) are also consistent with previous literature (Aslanidis & Christiansen 2012, Viceira 2012). We also find a negative and significant impact of the proxy for business conditions (ADS) which is consistent with the findings of Ilmanen (2003).

The positive impact of the yield spread, which can be seen as a proxy for the future state of the economy, seems to point out that the yield spread and the business conditions index are actually conveying two different types of information for correlations. Indeed, the business condition index is found to have a negative impact on correlation. This suggest that, if the yield spread gives an indication on the future state of the economy (Aslanidis & Christiansen 2012), this is probably with a long horizon perspective, while the business conditions proxy indicates more the current state of the economy.

Finally, an increase in stock returns today (RS) is associated with a decrease in daily stock-bond correlations. Even though a rise in stock returns could correlate with a positive market sentiment and, thus, indicate an increasing demand for stocks and bonds (Chiang et al. 2015), our results point towards a different interpretation. First, increasing stock returns go hand in hand with economic expansions. The signs for ADS and RS are therefore consistent with one another. An alternative explanation could be that an increase in stock returns indicates that the return of investors' portfolios can be increased by seizing this momentum in stock prices and by investing more money in the stock market and less money in the bond market. This would induce a flight-from-quality, associated with a decoupling in stock and bond prices. As we are focusing on the daily correlation component, such search for momentum and the resulting portfolio rebalancing might be particularly important at this short-run daily frequency.

Table 5: Determinants of correlations

This table shows the results of a regression of (1) the Fisher transformation of daily innovations in correlation (difference between daily and yearly components) on lagged determinants, (2) the Fisher transformation of monthly innovations in correlation (difference between monthly and yearly components) on lagged determinants, and (3) the Fisher transformation of yearly correlation components on lagged determinants. The sample period is January 1988 - December 2016. The independent variables are defined in Table 1 and COR is the lagged orthogonalised dependent variable. The independent variables are all standardised. (trend) is a trend term and is also standardised. X means that the variable has not been selected by the Least Angle Regression method as a determinant of the yearly component in correlation. In columns (1) and (2), robust standard errors are reported in parentheses. In column(3), standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Daily Cor	(2) Monthly Cor	(3) Yearly Cor
ADS	−0.0259***	−0.0421***	X
	(0.0007)	(0.0056)	
UNEM		0.0330***	X
		(0.0030)	
PCE		−0.0126***	−0.0340*
		(0.0034)	(0.0166)
SIR	0.0164***	0.0327***	X
	(0.0010)	(0.0073)	
YSPR	0.0048***	0.0123**	X
	(0.0013)	(0.0059)	
TED	−0.0136***	−0.0194***	X
	(0.0014)	(0.0062)	
RS	−0.0136***	−0.0018	X
	(0.0011)	(0.0068)	
CAPE		0.0071*	X
		(0.0038)	
VXO	−0.1089***	−0.0133**	0.0051
	(0.0007)	(0.0052)	(0.0232)
EPU	−0.0104***	−0.0114**	−0.0942***
	(0.0006)	(0.0045)	(0.0183)
INPF			X
CPIF			X
LIQ		0.0046	0.0731***
		(0.0038)	(0.0226)
BDLEV			0.0429**
			(0.0164)
COR	0.1981***	0.0705***	0.0795***
	(0.0006)	(0.0033)	(0.0151)
(trend)			−0.3469***
			(0.0157)
(cons)	−0.0344***	−0.0031	0.0237
	(0.0005)	(0.0030)	(0.0149)
N	7,106	348	29
Adj. R^2	0.9605	0.6968	0.9586
AIC	-23,797	-1,010	-57
VIF	1.51	1.84	1.50

The second column of Table 5 shows the results of the regression of monthly correlations on daily and monthly macroeconomic and financial variables. What is striking is the change in importance of the variables related to the stock market and uncertainty, in comparison to the regression of daily correlations. Indeed, given that the explanatory variables are standardised, we can compare the amplitude of their coefficients. For the monthly correlations, the stock market uncertainty (VXO) and economic policy uncertainty (EPU) are among the determinants with the lowest importance. In particular, stock market uncertainty, which was the most important macro-financial determinant of daily correlations completely loses its predominance among determinants of monthly correlations. Moreover, while the stock market return (RS) was a significant determinant of daily correlations, it is not significant in determining monthly correlations. This strengthens our interpretation of a negative impact of stock returns on daily correlations. If investors induce this negative relationship by trading on momentum, it is reasonable to assume that this relationship disappears at a lower frequency.

In contrast, the business conditions (ADS)[15] and the short-term interest rate (SIR), which are significant determinants of daily correlations, remain important determinants of monthly correlations. Their importance even increases as their coefficients become the largest ones in the monthly regression. This points towards macroeconomic fundamental variables playing a more important role than stock market and uncertainty variables for monthly stock-bond correlations.

This conclusion is reinforced by the significance of two additional variables, which were not available at daily frequency: the unemployment rate (UNEM) and change in inflation rate (PCE). The unemployment rate is even one of the main determinants of stock-bond monthly correlations. The positive sign of unemployment is in line with the negative impact of the business indicator and is, as such, as expected. When the economy is growing, the unemployment rate is decreasing. Since we find a negative impact of business conditions on correlation, we should find a positive impact of unemployment rates. The sign of the change in inflation rates is negative. This finding is not new and has been shown by Campbell & Ammer (1993) and D'Addona & Kind (2006).

The third column of Table 5 shows the impact of all the variables (daily, monthly and yearly) on yearly correlations. A time trend is also added given that the long-run correlation is trend-stationary. Four macro-finance variables are significant. Two of these variables were also significant for other correlation components: the economic policy uncertainty (EPU) and the change in inflation rate (PCE). We can also see that the liquidity of the stock market (LIQ), which was not significant for monthly correlations, now becomes significant. The fact that liquidity turns out to be significant and has one of the largest coefficient of the yearly regression, while other macroeconomic variables (such as the business conditions index[16] and interest rates) lose their significance matches the result that Baele et al. (2010) find with long-run quarterly data. Their results show that

[15] We also perform a regression using other proxies for business condition (the industrial production growth rate and the Chicago Fed National Activity Index) and the conclusions remain the same.

[16] We also perform a regression using other proxies for business condition (the GDP growth rate, the

macroeconomic fundamentals (interest rates, business conditions, etc.) contribute little in explaining stock-bond correlations while market liquidity matters more.

In addition, the significant impact of security broker-dealer leverage (BDLEV) is also interesting. The positive sign is in line with our expectations (?). Moreover, consistent with our results, ? find that none of the expectation variables (for example GDP forecast[17]) are significant when they are jointly accounted for with the broker-dealer leverage in a regression.

As a final remark, we see that the trend is negative and strongly significant for yearly correlations. This finding is consistent with the downward trend in Figure 2 and is in line with Ohmi & Okimoto (2016) who find a negative trend in the stock-bond correlation of many advanced economies. Stronger flight-to-quality behaviour is the explanation for such a finding. As stock markets become increasingly integrated, investors are increasingly exposed to the risk of simultaneous drops in stock prices. Therefore, they need to fly more and more often to the bond market to balance the risk of their portfolio. This results in a negative time trend in correlations (Ohmi & Okimoto 2016). The high significance of the time trend variable also shows that the trend in correlation cannot be fully explained by macroeconomic and financial variables. This result is not new and is also found by Christoffersen et al. (2012) for correlations between equity markets.

If we compare the set of significant variables as well as their importance for each of the correlation components, a clear pattern emerges. While daily correlations are mostly determined by short-lived variables, mainly related to financial market (stress), monthly correlations are much more influenced by fundamental variables such as interest rates and business condition indicators. The stress variables and stock market variables lose their importance at this medium-run frequency. In turn, yearly correlations keep being influenced by fundamental variables (economic and monetary policy (uncertainty)) and are also influenced by the microstructure of the stock market and the health of financial institutions. Clearly, the latter two are also related to fundamental factors as they reflect available funding opportunities to the economy.

The previous investigation was performed by analysing, for each correlation component, all the available macroeconomic and financial determinants at its corresponding frequency. Therefore, each correlation component is regressed on a different set of variables. An alternative is to keep the number of determinants constant across the three correlation component regressions. This is done in Table 6 (regressions using all the daily variables) and in Table 7 (regressions using all the daily and monthly variables).

In Table 6, we see that our previous conclusions remain valid: the daily variables that are significant in column (2) for monthly correlations are also significant in column (2) of Table 5. We also see that the stock market and uncertainty variables lose their importance. For yearly correlations, we see however that two variables that are significant in column (3)

industrial production growth rate and the Chicago Fed National Activity Index) and the conclusions remain the same.

[17]Inflation expectations only turn significant in one of their specifications.

Table 6: Daily determinants of correlations

This table shows the results of a regression of (1) the Fisher transformation of daily innovations in correlation (difference between daily and yearly components) on lagged daily determinants, (2) the Fisher transformation of monthly innovations in correlation (difference between monthly and yearly components) on lagged daily determinants, and (3) the Fisher transformation of yearly correlation components on lagged daily determinants. The sample period is January 1988 - December 2016. The independent variables, all available at a daily frequency, are defined in Table 1 and COR is the lagged orthogonalised dependent variable. The independent variables are all standardised. (trend) is a trend term and is also standardised. X means that the variable has not been selected by the Least Angle Regression method as a determinant of the yearly component in correlation. In columns (1) and (2), robust standard errors are reported in parentheses. In column(3), standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Daily Cor.	(2) Monthly Cor	(3) Yearly Cor.
ADS	-0.0259^{***}	-0.0403^{***}	X
	(0.0007)	(0.0059)	
SIR	0.0164^{***}	0.0347^{***}	X
	(0.0010)	(0.0071)	
YSPR	0.0048^{***}	0.0114^{*}	0.0508^{**}
	(0.0013)	(0.0059)	(0.0218)
TED	-0.0136^{***}	-0.0219^{***}	X
	(0.0014)	(0.0063)	
RS	-0.0136^{***}	0.0027	0.0294
	(0.0011)	(0.0068)	(0.0192)
VXO	-0.1089^{***}	-0.0204^{***}	-0.0627^{***}
	(0.0007)	(0.0055)	(0.0206)
EPU	-0.0104^{***}	0.0111^{***}	-0.0843^{***}
	(0.0006)	(0.0033)	(0.0182)
COR	0.1981^{***}	0.0756^{***}	0.0898^{***}
	(0.0006)	(0.0033)	(0.0160)
(trend)			-0.3480^{***}
			(0.0168)
(cons)	-0.0344^{***}	-0.0031	0.0237
	(0.0005)	(0.0030)	(0.0158)
N	7,106	348	29
Adj. R^2	0.9605	0.6977	0.9536
AIC	-23,797	-1,015	-55
VIF	1.51	1.80	1.39

lose their significance in a regression including additionally monthly and yearly variables. These two variables are the yield spread (YSPR) and the VXO. Their significance could be simply due to the fact that two important determinants of yearly correlations (the liquidity and the broker-dealer leverage) are not available at a daily frequency and therefore not present in this regression. Finally, Table 7 shows that the results also remain similar to those in column (3) of Table 5. The robustness analysis performed in Table 6 and Table 7 therefore confirms our conclusion: the variables that remain important determinants for longer-term correlations tend to proxy for more fundamental factors.

Table 7: Monthly and daily determinants of correlations

This table shows the results of a regression of (1) the Fisher transformation of monthly innovations in correlation (difference between monthly and yearly components) on lagged daily and monthly determinants, and (2) the Fisher transformation of yearly correlation components on lagged daily and monthly determinants. The sample period is January 1988 - December 2016. The independent variables, all available at a daily or at a monthly frequency, are defined in Table 1 and COR is the lagged orthogonalised dependent variable. The independent variables are all standardised. (trend) is a trend term and is also standardised. X means that the variable has not been selected by the Least Angle Regression method as a determinant of the yearly component in correlation. Robust standard errors are reported in parentheses in column (1) and standard errors are reported in parentheses in column (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Monthly Cor.	(2) Yearly Cor.
ADS	-0.0421^{***}	X
	(0.0056)	
UNEM	0.0330^{***}	X
	(0.0030)	
PCE	-0.0126^{***}	-0.0396^{**}
	(0.0034)	(0.0161)
SIR	0.0327^{***}	X
	(0.0073)	
YSPR	0.0123^{**}	X
	(0.0059)	
TED	-0.0194^{***}	X
	(0.0062)	
RS	-0.0018	X
	(0.0068)	
CAPE	0.0071^{*}	X
	(0.0038)	
VXO	-0.0133^{**}	-0.0086
	(0.0052)	(0.0221)
EPU	-0.0114^{**}	-0.0986^{***}
	(0.0045)	(0.0179)
LIQ	0.0046	0.0532^{**}
	(0.0038)	(0.0208)
COR	0.0705^{***}	0.0888^{***}
	(0.0033)	(0.0148)
(trend)		-0.3453^{***}
		(0.0153)
(cons)	-0.0031	0.0237
	(0.0030)	(0.0145)
N	348	29
Adj. R^2	0.6968	0.9605
AIC	-1,010	-59
VIF	1.84	1.49

5 Conclusion

While the time-varying nature of correlations has long been accepted, its frequency-varying component has only recently been acknowledged. However, this frequency-varying aspect is crucial to understand not only the behaviour of correlations but also their determinants. Each frequency reflects a different time horizon and hence a different facet of correlations. Moreover, different investors, with different investment horizons, cannot all rely on the same frequency of correlations to build their investment portfolio: investors need to rely on correlations calculated at the appropriate frequency. In addition, while a higher frequency might be more interesting for risk managers, lower frequency is more important for policy makers, as an indication of the long-term trend in financial markets. The determinants of each correlation frequency might also vary.

In this paper, we therefore investigate both the time-variation and the frequency-variation in correlations. To this end, we develop a strategy to extend the two-frequency DCC-MIDAS model developed by Colacito et al. (2011) in order to estimate three frequency components of correlations: a daily component, a monthly component and a yearly component. Our estimation strategy ensures internal consistency between these three frequency components. In particular, in a first step, we obtain a short- and long-term component of stock-bond correlation. In a second step, we estimate a medium term component, conditional upon the previously determined long-term component of correlations. The shorter-term components are always modelled such that they wander around this long-term component.

Thanks to this framework, we can investigate which macroeconomic and financial factors drive the short-term, medium-term and long-term components of stock-bond correlations. Our analysis focuses on the U.S. market and we find that, while the daily short-lived correlation component is influenced primarily by uncertainty variables and financial market factors, the monthly correlation component is mostly driven by fundamental macroeconomic variables. For monthly correlations, the stock market and uncertainty variables turn out to lose their importance. In addition, the long-term yearly component is mainly influenced by fundamental variables related to inflation, economic policy uncertainty, the microstructure of stock market and the balance sheet of financial intermediaries.

Our results are of great importance to different actors of the financial markets. First, for asset managers, our findings highlight that the frequency of correlation matters and that the macroeconomic and financial determinants do not explain each of these correlation frequencies similarly. Asset managers having different holding period should therefore focus on different factors driving the correlation of assets in their portfolios. Second, our analysis disentangles the broad correlation variable into three frequency components, which allows policy makers to obtain a more refined instrument to monitor the markets. Our results also indicate that, in order to evaluate the impact of a policy tool, the appropriate frequency should be taken into account: there is no *one-frequency-fits-all* in financial markets.

Finally, our strategy to obtain three frequency components of correlation could be used in future research. For example, it could be interesting to study whether the hedging properties of assets (investigated by Ciner et al. (2013), among others) hold across different frequencies or is only limited to some.

6 References

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Appendix

A Estimation of correlation components

Using our new DCC-MIDAS model, we estimate three U.S. stock-bond correlation components: a daily component, a monthly component and a yearly component. The number of lags of realised variance and realised correlation is set to $K = P = 10$. The estimation results are available in Table A1. The sums of $\alpha + \beta$, $a + b$, $\gamma + \delta$ and $c + d$ are always smaller than 1 (even if, sometimes, rounding the coefficients makes it seem that it is equal to 1).

Table A1: Estimation of correlation components

This table presents the results of the estimation of the extended DCC-MIDAS model which estimates three components: a daily, monthly and yearly component for U.S. stock-bond return correlations. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

			Daily-yearly			
	ν	α	β	θ	ω	$\overline{\sigma_l^2}$
Stock	0.071***	0.098***	0.880***	0.037***	11.102***	0.819***
	(0.009)	(0.003)	(0.004)	(0.003)	(3.447)	(0.040)
Bond	0.026***	0.068***	0.932***	0.014***	4.999***	0.010
	(0.005)	(0.003)	(0.002)	(0.002)	(1.712)	(0.377)
	a	b	Ω			
Stock-bond	0.044***	0.933***	5.711***			
	(0.003)	(0.005)	(1.131)			
			Monthly			
	μ	γ	δ			
Stock	0.985***	0.134***	0.839***			
	(0.179)	(0.021)	(0.025)			
Bond	0.164*	0.078***	0.922***			
	(0.096)	(0.007)	(0.008)			
	c	d				
Stock-bond	0.044***	0.787***				
	(0.011)	(0.092)				