SCHOOL OF ECONOMICS AND MANAGEMENT
FACULTY OF SOCIAL SCIENCES
AARHUS UNIVERSITY

CREATES
Center for Research in Econometric Analysis of Time Series

CREATES Research Paper 2010-55

Sign and Quantiles of the Realized Stock-Bond Correlation

Nektarios Aslanidis and Charlotte Christiansen

School of Economics and Management
Aarhus University
Bartholins Allé 10, Building 1322, DK-8000 Aarhus C
Denmark

Sign and Quantiles of the Realized Stock-Bond Correlation*

Nektarios Aslanidis† University Rovira Virgili

Charlotte Christiansen‡ CREATES, Aarhus University

August 31, 2010

*The authors acknowledge support from CREATES funded by the Danish National Research Foundation and from the Danish Council for Independent Research, Social Sciences.

†University Rovira Virgili, Department of Economics, FCEE, Avinguda Universitat 1, 43204 Reus, Catalonia, Spain. Email: nektarios.aslanidis@urv.cat.

‡CREATES, School of Economics and Management, Aarhus University, Bartholins Alle 10, 8000 Aarhus C, Denmark. Email: CChristiansen@creates.au.dk.

Sign and Quantiles of the Realized Stock-Bond Correlation

Abstract: We scrutinize the monthly realized stock-bond correlation based upon high frequency returns. In particular, we use a probit model to track the dynamics of the sign of the correlation relative to its various economic forces. The sign is predictable to a large extent with bond market liquidity being the most important variable. Moreover, stock market volatility, inflation uncertainty, short rate volatility, and bond volatility have significant effects upon the sign. In addition, we use quantile regressions to pin down the systematic variation of the extreme tails of the realized stock-bond correlation over its economic determinants. We document that the correlation behaves differently when it is large negative (0.10 quantile) as opposed to when it is large positive (0.90 quantile). Nevertheless, the empirical findings are only partially robust to using other, possibly less precise, measures of the stock-bond correlation.

Keywords: Realized stock-bond correlation; Sign; Binary models; Quantile regressions

JEL Classifications: C21; C22; C25; G10; G11; G12

1 Introduction

In recent years there has emerged a growing literature documenting substantial time-variation in the stock-bond correlation. Much of this literature explores various economic forces driving the time-varying stock-bond correlation (see for example, Connolly, Stivers, and Sun (2005), Christiansen and Ranaldo (2007), Baele, Bekaert, and Inghelbrecht (forthcoming), among others). Still, little is known about the dynamics of the sign and of the tails of the distribution of the stock-bond correlation. This paper contributes to this literature by investigating new aspects of the time-variation in the monthly realized stock-bond correlation calculated from high-frequency returns. In particular, we analyze the sign and the extreme quantiles (0.10 and 0.90 corresponding to lower and upper tails, respectively) of the realized stock-bond correlation in relation to its various economic determinants.

The sign of the stock-bond correlation is important when considering optimal portfolio allocation. For instance, the diversification benefits of combined stock-bond holdings tend to be higher during times of negative correlations. Thus, bonds appear to be safe investments during periods of negative correlations, and risky investments during episodes of positive correlations. On the other hand, a negative correlation seems inconsistent with models emphasizing traditional long-term fundamentals as in Campbell and Ammer (1993) and Fama and French (1989). Hence, understanding the time-variation in the sign of the stock-bond correlation is an important goal in financial economics. In practice, we investigate the behavior of the sign of the realized stock-bond correlation by using a probit model.

Ilmanen (2003) contains one of the first explicit empirical discussions of the changing nature of the sign of the stock-bond correlation. On the other hand, Connolly, Stivers, and Sun (2005) ascribe the sustained negative stock-bond correlation observed since 1998 to a “flight-to-safety" phenomenon, where increased stock market uncertainty induces investors to flee stocks in favour of bonds. Further, Aslanidis and Christiansen (2010) show that it is important to account for the sign of the stock-bond correlation when using smooth transition regression (STR) models to describe the realized stock-bond correlation.

The present study takes a step further by adopting a different approach to examine the sign of the stock-bond correlation. In particular, we put forward a binary probit specification inspired by the literature on forecasting the state of the business cycle as represented by the NBER recession dates cf. Estrella and Mishkin (1998) and Hamilton and Kim (2002). The idea of a binary model in the stock-bond correlation literature is also explored by Chiang and Li (2009), although with a different correlation measure: they derive their correlation from a bivariate GARCH model by using daily data from two investment funds. Instead, we use high frequency data to calculate the stock-bond correlation. High frequency data contain as much information as possible and, therefore, may provide a more accurate correlation measure compared to correlations from multivariate GARCH models. We also test the robustness of our results to a variety of correlation measures such as correlations obtained from a dynamic conditional correlation (DCC) model, historical correlations and realized correlations obtained from daily data. Another important difference with Chiang and Li (2009) is that we employ a broader set of explanatory variables than they do. It is also worth mentioning that their analysis is confined to the fairly short period of the recent 12 years, while our sample period covers nearly the last three decades.

The extreme quantiles of the realized stock-bond correlation are related to its sign. In particular, by considering the 0.10 and 0.90 quantiles we can examine the lower and upper distribution tails of the stock-bond correlation, which would correspond to strongly negative and strongly positive correlation, respectively. Therefore, this paper also draws on a quantile regression framework to investigate if and how the dynamics in the realized stock-bond correlation are different at the tails.

In practice, we build on Viceira (forthcoming) who investigates the bond risk, represented by the realized bond beta from the standard CAPM. The realized bond beta is equal to the realized stock-bond correlation scaled with the fraction of realized stock volatility to the realized bond volatility. Viceira (forthcoming) finds that the short-term interest rate and the yield spread are positively related to the realized bond beta. We extend the analysis of Viceira (forthcoming) by focusing on the sign and tails of the realized stock-bond correlation and by employing several explanatory variables in excess of those used by Viceira (forthcoming).

Our work is also related to Pedersen (2010) who applies bivariate quantile regressions to model the joint stock-bond return distribution using daily data. So, in this analysis the stock-bond correlation is a latent variable. In contrast, our paper treats the realized stock-bond correlation as an observable variable calculated from high frequency data, which is in line with recent studies on realized volatility as seen in e.g. Andersen, Bollerslev, Diebold, and Vega (2004). The use of realized second moments has been reinvigorated recently with the theoretical work of Andersen, Bollerslev, Diebold, and Labys (2003) and Barndorff-Nielsen and Sheppard (2004), among others.

Our results are summarized as follows. Firstly, the sign of the realized stock-bond correlation is highly predictable with bond market liquidity being the most important explanatory variable. In addition, various volatility measures are significant in explaining the sign, namely the volatilities of the stock market volatility, the short rate, the bond market as well as that of inflation. Secondly, we find that the behavior of the realized stock-bond correlation differs when the correlation is large negative (0.10 quantile) as opposed to when it is large positive (0.90 quantile). At the lowest quantile only the industrial production volatility and the bond volatility turn out to be significant. At the highest quantile, the volatilities of the bond market, inflation and the stock market are all significant explanatory variables. Thirdly, we find that our results are to some extend robust to using other possibly less precise measures of the stock-bond correlation. Thus, using high-frequency data is of vast importance for obtaining valid results.

The remaining part of the paper is structured as follows. First, we introduce the data in Section 2. In Section 3 we discuss the econometric models. The main empirical findings are discussed in Section 4. Section 5 contains some robustness analysis. Finally, Section 6 concludes.

2 Data

Table 1 provides detailed information about the data. We use monthly data over the period $1983M02$ - $2009M06$ which gives rise to 317 observations.

2.1 Stock-Bond Correlations

The US stock market is represented by the futures contract on the SP500, traded in the Chicago Mercantile Exchange (CME). For the bond market we use the futures contract on the 10-year Treasury Note, which is traded on the Chicago Board of Trade (CBOT). The symbols used are SP and TY, respectively. The reason for using futures instead of spot prices is that futures on the SP500 and the Treasury Notes are highly liquid assets. Moreover, futures have been also used in the literature by Ranaldo and Söderlind (forthcoming), Christiansen, Ranaldo, and Söderlind (forthcoming), and Bansal, Connolly, and Stivers (forthcoming).

More specifically, 5-minute returns are used to calculate the monthly realized stock-bond correlation. The data are obtained from TickData. We use the Fisher transformation of the correlation, $C_t = \frac{1}{2}\ln\left(\frac{1+cor_t}{1-cor_t}\right)$, where cor_t is the correlation at month t. Thus, similar to studies on realized volatility (e.g., Andersen, Bollerslev, Diebold, and Vega (2004)) we treat the realized stock-bond correlation as an observable variable.

Table 2 (first column) shows the summary statistics of the realized stock-bond correlation. As seen, the mean is close to zero (0.06). Most often the correlation takes on positive values (for example, it is positive for 59% of the observations). The distribution seems left skewed and platykurtic. Also, the correlation shown in Figure 1 provides information on its temporal patterns. The series is highly erratic with its sign changing several times during the observed period.

2.2 Explanatory variables

Below we list the explanatory variables employed and their associated symbols.

Symbol	**Description**
IP_t	Industrial production growth
VIP_t	Industrial production volatility
IF_t	Inflation
VIF_t	Inflation uncertainty
R_t	Short rate
VR_t	Short rate volatility
SPR_t	Yield spread
VSP_t	Stock volatility
VTY_t	Bond volatility
LSP_t	Stock liquidity
LTY_t	Bond liquidity

Details regarding the calculations of the explanatory variables are provided in Table 1. All variables have been standardized to have zero mean and unit variance. This will ease the interpretation of the results by making the size of the different coefficients comparable. For the short rate we use log changes of the 1-month CD rate as the series appears to be non-stationary in levels. This is in contrast with both Baele, Bekaert, and Inghelbrecht (forthcoming) and Viceira (forthcoming) who use short rates in levels (log-short rates in the case of Viceira (forthcoming)). We define the yield spread as the difference between the 10-year Treasury Bond yield and the 3-month Treasury Bill rate. Notice also that Viceira (forthcoming) uses a survey based inflation uncertainty measure, whereas we use the time series inflation volatility.

The set of variables is sufficiently broad to reflect the general state of the economy as well as the business cycle and monetary policy influences. Viceira (forthcoming) shows that the short rate, the yield spread, and inflation uncertainty are important determinants for the stock-bond correlation. We extend the analysis of Viceira (forthcoming) by considering a broader set of explanatory variables. Also, for the industrial production growth, inflation, and the short rate we use an AR(1)-GARCH(1,1) model to calculate the time series of volatilities. This is in line with the recent literature on modelling output growth and inflation uncertainty by using GARCH specifications (for instance, Grier and Perry (2000), Grier, Henry, Olekalns, and Shields (2004), and Fountas and Karanasos (2007)). Further, the stock and bond volatilities calculated from 5-minute returns are also expected to influence the realized correlation. Finally, we believe that the liquidity of the stock and bond markets have a bearing upon the realized stock-bond correlation. We measure liquidity by the traded volume of the relevant futures contracts.

3 Econometric Framework

First we present the probit model that is used to describe the sign of the realized stock-bond correlation. Second, the quantile regression model is laid forward.

3.1 Sign of Stock-Bond Correlation

Let S_t be an indicator function for the sign of the realized stock-bond correlation. S_t can take two values, 1 if the correlation is positive or 0 if it is negative:

$$S_t = \begin{cases} 1 & \text{if} \quad C_t \geq 0 \\ 0 & \text{if} \quad C_t < 0 \end{cases} \tag{1}$$

The probit model for the sign of the correlation is given by

$$S_t = \Phi(\beta X_t') + \varepsilon_t \tag{2}$$

or

$$\Pr(S_t > 0) = \Phi(\beta X_t') \tag{3}$$

where β is is the parameter vector, X_t is the vector of explanatory variables, ε_t is the error term, and $\Phi(.)$ is the cumulative distribution function of the standard normal distribution. This equation states that that the probability of a positive correlation is equal to a function of the explanatory variables. If the probability is above (below) 50%, a positive (negative) correlation is more likely.

3.2 Quantiles of Stock-Bond Correlation

The quantile regression approach is an important econometric tool as it provides a more complete picture of a given relationship compared to the ordinary least squares (OLS) estimation of the conditional mean function. In the financial economics literature, the quantile regression has mainly been applied to value-at-risk calculations starting with Engle and Manganelli (2004). The two extreme quantiles 0.10 and 0.90 correspond to large negative and large positive realized stock-bond correlations. In this sense, examining the extreme quantiles can be seen as a direct extension of the binary outcome analysis. The general quantile regression takes the linear form

$$C_t = X_t' \beta^\tau + \varepsilon_t^\tau \tag{4}$$

where C_t is still the realized stock-bond correlation and X_t the vector of predictor variables. β^τ is the parameter vector associated with the τ^{th} quantile. The flexibility of the quantile regression is seen in the error term ε_t^τ, which is allowed to have a different distribution across the quantiles. Thus, the quantile regression allows for the effects of the predictor variables to change at different points in the conditional distribution of the stock-bond correlation. It is in this way that quantile regressions allow for parameter heterogeneity across different types of regressors. To obtain estimates of the conditional quantile function, we solve

$$\min_{\beta \in \mathbb{R}} \left[\sum_{t \in \{t: C_t \geq X_t' \beta\}} \tau |C_t - X_t' \beta^\tau| + \sum_{t \in \{t: C_t < X_t' \beta\}} (1-\tau) |C_t - X_t' \beta^\tau| \right] \tag{5}$$

The quantile function is a weighted sum of the absolute value of the residuals and can be solved by linear programming methods, see Koenker (2005) for more details).

4 Empirical Findings

This section discusses the results. First we present results for the sign of the realized stock-bond correlation and then the results for its quantiles.[1] In the text we use a 5% level of significance whereas in the tables ***/**/* indicate significance at the %/5%/10% level.

[1] The estimation is conducted using the software package EViews.

4.1 Sign of Stock-Bond Correlation

In Table 3 we report the results from estimating a probit model for the sign of the realized stock-bond correlation as well as the marginal effects of the explanatory variables. The latter are evaluated at their sample means. Three models are shown. Similar to Viceira (forthcoming), model (i) uses only inflation uncertainty (VIF), the short rate (R), and the yield spread (SPR) as explanatory variables. Model (ii) includes all explanatory variables discussed in Section 2. Finally, model (iii) uses a subset of these variables, namely those that are jointly significant in model (ii).

Notice that model (i) has a much lower explanatory power than model (ii). This is seen in both the McFadden R^2 and log-likelihood values. More importantly, the information criteria also indicates that model (ii) is preferable to model (i). We therefore conclude that employing only the three explanatory variables that Viceira (forthcoming) uses for the realized bond beta is not sufficient to explain the sign of the realized stock-bond correlation. Thus, it is important to include additional variables that reflect broader macroeconomic and financial conditions, as we do here.

In model (ii) the individual t-tests imply that industrial production (IP), inflation (IF), the short rate (R), the yield spread (SPR) and stock market liquidity (LSP) are not important for the sign of the correlation. Indeed, the Wald test statistic of 0.83 clearly shows that all the aforementioned variables are jointly insignificant. The remaining explanatory variables are significant. Thus, it is not the industrial production growth itself but rather its volatility that is of importance. Similarly, the inflation rate is not important but the inflation uncertainty is.

In model (iii) we only retain the significant variables from model (ii). This hardly changes the results (marginal effects remain almost the same) from model (ii). Interestingly, bond market liquidity (LTY) has the strongest effect upon the sign of the realized stock-bond correlation. Its marginal effect is -0.92 implying that the more liquid the bond market is the more likely is that the correlation is negative. Thus, an investor obtains the best diversification benefit from investing in both stocks and bonds when the bond market is liquid. On the other hand, when liquidity is low it is actually the time when it is most important to hold diversified portfolios, so in this sense the influence of liquidity is not helpful. Apparently, stock market liquidity (LSP) is not informative (insignificant) in this respect.

Next, stock market volatility (VSP) has the second largest impact upon the sign of the realized stock-bond correlation (-0.78). As before, the marginal effect is negative. Inflation uncertainty (VIF) and short rate volatility (VR) also have negative marginal effects, although much smaller in magnitude (both -0.22). On the other hand, bond market volatility (VTY) has a positive effect upon the sign of the correlation (the marginal effect amounts to 0.24) and the effect of industrial production volatility is also positive but much weaker.

For the most part, the volatility variables have negative marginal effects implying the more uncertainty, the more likely is that the correlation is negative. This is actually good news, because when there is uncertainty in the markets, then the two most important asset classes provide good hedges against each other. So, in times of large uncertainty, stock and bond returns tend to move in opposite directions, which is consistent with a flight to quality phenomenon. There are two exceptions: industrial production volatility and bond market volatility both have a positive on the sign of the correlation. So, in addition to the flight to quality phenomenon, there is evidence that uncertainty in the economy affects stock and bond returns in the same direction. Nevertheless, all in all the positive marginal effects are much smaller than the negative marginal effects.

The fit in model (ii) in quite good; the McFadden R^2 is 0.43. So, the sign of the realized stock-bond correlation is to a large extent predictable by the variables we put forward.

4.2 Quantiles of Stock-Bond Correlation

Table 4 shows the results from estimating quantile regressions for the following quantiles: $\{0.10, 0.25, 0.50, 0.75, 0.90\}$. The coefficient estimates are computed by solving linear programming methods and their standard errors are obtained by bootstrap resampling. Our main interest lies in the tails, that is, in the 0.10 quantile for large negative and in the 0.90 quantile for large positive observations of the realized stock-bond correlation.

As before, we estimate three models: model (i) with the Viceira (forthcoming) explanatory variables, model (ii) with all explanatory variables, and model (iii) with only the significant variables resulting from model (ii).

The results show that in all quantiles the explanatory power of model (i) is extremely low (the R^2 values range from 0.01 to 0.08). Except for the intercept and, in some quantiles, inflation uncertainty none of the regressors is actually significant. In this light, we conclude that model (i) is not an adequate specification for the realized stock-bond correlation. On the other hand, we gain a lot of information by including the full set of explanatory variables that we propose in this study. For instance, with model (ii) we are able to explain between 18% and 25% of the variation in the correlation across the different quantiles. Still, there are some explanatory variables that are not significant in any of the quantiles (for example, IP, IF, R, VR, SPR). This can be also confirmed by the Wald test statistic of 5.57 that jointly tests the significance of these variables.[2] These are almost the same variables that have no explanatory power for the sign of the correlation using the probit model. Only short rate volatility (VR) is now insignificant taking the place of stock market liquidity (LSP) above. The polished model (iii) shows that excluding the insignificant variables does not change overall results of the model.

In Panel B of Table 4 we report results for the slope equality tests. As seen, for model (iii), the coefficients of the lowest (0.10) and highest (0.90) quantiles are (jointly) significantly different from each other and from those of the 0.50 quantile (median). Therefore, the effect of the explanatory variables is distinct across the three quantile under consideration. This implies that it is important to use quantile regression methods rather than rely on a standard regression (conditional) mean model. In contrast, for model (i) the coefficients are not significantly different across the quantiles, which is not surprising given that the included regressors are generally not significant. Note also that the slope coefficients have the same sign for the low and high quantiles implying that the differences in the slope coefficients are with respect to their sizes.

At the lowest quantile (0.10) only two variables turn out to be significant in explaining it, namely industrial production volatility (VIP) and bond market volatility (VTY). Their effects are positive, which means that the larger these volatilities are the less negative is the realized stock-bond correlation. Thus, increased macroeconomic uncertainty would imply that stocks and bonds become closer to being perfectly negatively correlated, which implies larger portfolio diversification opportunities. The pseudo R^2 amounts to 0.22 indicating a relatively good degree of predictability of the left tails of the correlation distribution.

At the highest quantile (0.90) four variables come into play. As before bond market volatility (VTY) has a positive influence on the correlation. However, there are also significantly negative effects arising from inflation uncertainty (VIF), stock market volatility (VSP) and bond market liquidity (LTY). The explanatory power of the model drops compared to the lower quantile (compare the R^2 value of 0.17 with 0.22). Interestingly, it is only bond market volatility that is significant in both low and high quantile regressions.

At the median (0.50 quantile) a different picture emerges. Notice that with the exception of VIP all variables are now highly significant. Thus, by only

[2] This a Fisher-type test combining p-values from Wald tests applied to the different quantiles (0.1, 0.25, 0.5, 0.75, 0.9). The statistic is $\chi^2(10)$ distributed. The critical value is 18.30.

considering the median of the distribution the number of significant variables is larger than at the left and right tails of the distribution. The explanatory power of the quantile regression at the median is of the same size (0.22) as in the left end. Thus, it is more difficult to explain the large positive than the median and large negative observations of the realized stock-bond correlation.

5 Alternative Stock-Bond Correlation Measures

So far, we have calculated the monthly realized stock-bond correlation using high frequency data. This is similar to Christiansen and Ranaldo (2007). In this section we investigate whether our results are robust to using alternative stock-bond correlation measures.

We use the following alternative correlation measures. First, we employ daily data to calculate the monthly realized stock-bond correlation and denote this series by CD_t. Next, we use monthly data to calculate historical monthly correlations based upon overlapping windows of 36 months, denoted by CH_t. This measure is similar to Ilmanen (2003) who also uses a rolling window of historical correlations. From the monthly data we also calculate the stock-bond correlation using the dynamic conditional correlation (DCC) model of Engle (2002), DCC_t.[3] This is related to Scruggs and Glabadanidis (2003) who use bivariate GARCH models to describe the monthly stock and bond returns. Their results reject the hypothesis of a constant conditional stock-bond correlation. Note that we denote the realized correlation calculated from high frequency data by CH_t.

In summary, $C_t = \{CH_t, CD_t, CM_t, DCC_t\}$ is the stock-bond correlation at time t and they are defined as follows.

Symbol	**Description**
CH_t	Realized stock-bond correlation based on 5-minute returns
CD_t	Realized stock-bond correlation based on daily returns
CM_t	Rolling-window stock-bond correlation based on monthly returns
DCC_t	DCC stock-bond correlation based on monthly returns

Table 2 contains summary statistics for the four correlation measures while Figure 1 plots them. As seen, the stock-bond correlation is very much depen-

[3] The DCC model allows correlations to vary over time with the dynamics driven by past correlations, $q_{12,t} = \bar{\rho}_{12}(1-\alpha-\beta)+\alpha\varepsilon_{1,t-1}\varepsilon_{2,t-1}+\beta q_{12,t-1}$, where $\bar{\rho}_{12}$is the unconditional correlation between $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ (standardized stock and bond returns, respectively), and α and β are the news and decay parameters, respectively. The quantity $q_{12,t}$ is typically rescaled using $\rho_t = q_{12,t}/\sqrt{q_{11,t}q_{22,t}}$ to constrain the conditional correlation ρ_t to lie between -1 and +1.

dent upon the frequency at which the underlying returns are recorded. The daily correlation is fairly close to the high-frequency correlation in many respects. Yet, it is more variable as seen from its standard deviation as well as from the time series plot of the data. In contrast the monthly correlation (CM_t) and the DCC one are very different from CH_t. For example, the CM_t is close to being symmetric and has lower kurtosis than CH_t. Also, the monthly correlation is less variable. This is expected since the CM_t is a moving average measure which tends to smooth out extreme observations. Interestingly, the DCC_t correlation has the fewest negative observations and is the least variable correlation measure.

5.1 Sign of Stock-Bond Correlation

Table 5 (Panels A and B) shows the results (only marginal effects) from estimating the probit models (i) and (ii) for each of the four measures of the stock-bond correlation. The empirical findings can be interpreted as follows. First, the full model (ii) with all explanatory variables improves substantially on model (i) that includes only the variables from Viceira (forthcoming). This holds for all four correlation measures and is consistent with our previous results. In particular, in terms of R^2 the improvement from model (i) to (ii) is 0.33, 0.16, 0.18, and 0.09 for CH_t, CD_t, CM_t, DCC_t, respectively. Notice also that in model (i) the only important variable is inflation uncertainty having a negative effect on the correlation. Second, using the high-frequency correlation (CH_t) yields by far the best fit of the model. In particular, the explanatory power of model (ii) is 0.43 when using CH_t, drops to 0.33 when using the historical correlation CM_t, while the worse fit (0.11) is obtained when using the DCC_t. Finally, the variables that are significant in explaining CH_t and CM_t are identical and the effects have the same sign. Thus, the two correlation measures which are best explained by the model provide us with identical conclusions as to which effects are important. On the other hand, the significant explanatory variables differ somehow for CD_t and DCC_t compared to CH_t.

Overall, we conclude that the findings regarding the systematic variation in the sign of the high-frequency realized stock-bond correlation (CH_t) are robust to using historical rolling window correlations (CM_t). In contrast, there are some differences between the CH_t and the realized correlation based upon daily data (CD_t) or the DCC_t correlation.

5.2 Quantiles of Stock-Bond Correlation

Tables 6 and 7 show the results from estimating the quantile regressions (i) and (ii) for each of the four correlation measures. The results can be summarized as follows. Once again, model (i) is inadequate in explaining the quantiles of the stock-bond correlation. Similar to above, the highest explanatory power is achieved by the high-frequency correlation (CH_t). The other three correlation measures have about the same explanatory power. Moreover, it is not the same explanatory variables that are significant in explaining the quantiles for each of the four correlation measures. Still, for all four correlation measures we find that the two extreme quantiles are significantly different (panel B of Table 7).

Overall, the results for the quantiles of the stock-bond correlation are only to some extend robust to using correlations based upon returns recorded at different frequencies than the 5-minute returns.

6 Conclusion

This study looks further into the properties of the realized stock-bond correlation based upon high-frequency returns. In particular, we investigate three features of the stock-bond correlation that has so far been left unexplored. First, we look at the dynamics of the sign of the correlation relative to its various economic forces. The sign is predictable to a large extent with bond market liquidity being the most important variable. Second, we use quantile regressions to analyze the tails of the correlation. The lower quantile (lower tail), that is, when the realized stock-bond correlation is large negative is more predictable than the upper quantile (upper tail), when the realized stock-bond correlation is large positive. The behavior of the correlation at the two extreme quantiles is significantly different, and quantile regressions are preferable to conditional mean models. Finally, we investigate if the results are robust to using less finely recorded returns than high-frequency returns to calculate the stock-bond correlation. The results are only partially robust to using the other possibly less precise measures of the stock-bond correlation pointing out the importance of using high-frequency data to make correct assessments.

References

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2003): "Modeling and Forecasting Realized Volatility," *Econometrica*, 71, 529–626.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2004): "Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets," Working paper, University of Pennsylvania.

Aslanidis, N., and C. Christiansen (2010): "Smooth Transition Patterns in the Realized Stock-Bond Correlation," Working paper, CREATES.

Baele, L., G. Bekaert, and K. Inghelbrecht (forthcoming): "The Determinants of Stock and Bond Return Comovements," *Review of Financial Studies*.

Bansal, N., R. A. Connolly, and C. Stivers (forthcoming): "Regime-Switching in Stock and T-bond Futures Returns and Measures of Stock Market Stress," *Journal of Futures Markets*.

Barndorff-Nielsen, O. E., and N. Sheppard (2004): "Econometric Analysis of Realized Covariation: High Frequency Based Covariance, Regression, and Correlation in Financial Economics," *Econometrica*, 72, 885–925.

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.

Chiang, T. C., and J. Li (2009): "The Dynamic Correlation between Stock and Bond Returns: Evidence from the U.S. Market," Working paper, SSRN.

Christiansen, C., and A. Ranaldo (2007): "Realized Bond-Stock Correlation: Macroeconomic Announcement Effects," *Journal of Futures Markets*, 27(5), 439–469.

Christiansen, C., A. Ranaldo, and P. Söderlind (forthcoming): "The Time-Varying Systematic Risk of Carry Trade Strategies," *Journal of Financial and Quantitative Analysis*.

Connolly, R., C. Stivers, and L. Sun (2005): "Stock Market Uncertainty and the Stock-Bond Return Relation," *Journal of Financial and Quantitative Analysis*, 40(1), 161–194.

Engle, R. (2002): "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models," *Journal of Business & Economic Statistics*, 20(3), 339–350.

Engle, R. F., and S. Manganelli (2004): "CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles," *Journal of Business and Economic Statistics*, 22, 367–381.

Estrella, A., and F. S. Mishkin (1998): "Predicting U.S. Recessions: Financial Variables as Leading Indicators," *Review of Economics and Statistics*, 80, 45–61.

Fama, E., and K. French (1989): "Business Conditions and Expected Returns on Stocks and Bonds," *Journal of Financial Economics*, 25, 23–49.

Fountas, S., and M. Karanasos (2007): "Inflation, Output Growth and Nominal and Real Uncertainty: Empirical Evidence for the G7," *Journal of International Money and Finance*, 26, 229–250.

Grier, K., O. Henry, N. Olekalns, and K. Shields (2004): "The asymmetric Effects of Uncertainty on Inflation and Output Growth," *Journal of Applied Econometrics*, 19, 551–565.

Grier, K., and M. Perry (2000): "The Effects of Real and Nominal Uncertainty on Inflation and Output Growth: Some GARCH-M Evidence," *Journal of Applied Econometrics*, 15, 45–58.

Ilmanen, A. (2003): "Stock-Bond Correlations," *Journal of Fixed Income*, 13(2), 55–66.

Koenker, R. (2005): *Quantile Regression*. Cambridge University Press.

Pedersen, T. Q. (2010): "Predictable Return Distributions," Working paper, CREATES.

Ranaldo, A., and P. Söderlind (forthcoming): "Safe haven currencies," *Review of Finance*.

Scruggs, J. T., and P. Glabadanidis (2003): "Risk Premia and the Dynamic Covariance between Stock and Bond Returns," *Journal of Financial and Quantitative Analysis*, 38(2), 295–316.

Viceira, L. M. (forthcoming): "Bond Risk, Bond Return Volatility, and the Term Structure of Interest Rates," *International Journal of Forecasting*.

Table 1: Data Overview

	Name	Description	Symbol	Source
HSP	High frequency stock return	5-minute ln-returns	SP	TickData
HTY	High frequency bond return	5-minute ln-returns	TY	TickData
DSP	Daily stock return	Daily ln-returns	ISPCS00	DataStream
DTY	Daily bond return	Daily ln-returns	CTYCS00	DataStream
MSP	Monthly stock return	Monthly ln-returns	ISPCS00	DataStream
MTY	Monthly bond returns	Monthly ln-returns	CTYCS00	DataStream
IP	Industrial production growth	Ln-returns of IP index	INDPRO	FRED
VIP	Industrial production volatility	AR(1)-GARCH(1,1) volatility	INDPRO	FRED
IF	Inflation	Ln-changes of CPI index	CPIAUCSL	FRED
VIF	Inflation uncertainty	AR(1)-GARCH(1,1) volatility	CPIAUCSL	FRED
R	Log short rate changes	1-month certificate of deposit rate	CD1M	FRED
VR	Short rate volatility	AR(1)-GARCH(1,1) volatility	CD1M	FRED
SPR	Yield spread	10-year Treasury Constant Maturity Rate -	GS10	FRED
		3-month Treasury Bill secondary market rate	TB3MS	FRED
VSP	Stock volatility	Realized volatility from 5-minute stock returns	ISPCS00	DataStream
VTY	Bond volatility	Realized volatility from 5-minute bond returns	CTYCS00	DataStream
LSP	Stock liquidity	SP500 monthly volume	ISPCS00	DataStream
LTY	Bond liquidity	TY monthly volume	CTYCS00	DataStream

Table 2: Stock-Bond Correlation Descriptive Statistics

	CH	CD	CM	DCC
Mean	0.06	0.15	0.12	0.11
Standard deviation	0.40	0.46	0.34	0.21
Skewness	-0.55	-0.44	0.04	-0.27
Kurtosis	2.29	2.75	1.79	2.55
Percent negative	41%	35%	42%	29%
Observations	317	317	289	317

The table shows summary statistics for the stock-bond correlation (Fisher transform) based upon high-frequency data (CH), daily data (CD), monthly data (CM), and the DCC model.

Table 3: Probit Model

	(i) Marg.	(i) Coef.	(i) Std.err.	(ii) Marg.	(ii) Coef.	(ii) Std.err.	(iii) Marg.	(iii) Coef.	(iii) Std.err.
Cons		0.21 ***	(0.08)		-0.72 ***	(0.20)		-0.74 ***	(0.17)
IP				0.03	0.09	(0.12)			
VIP				0.10	0.32 **	(0.16)	0.10	0.33 **	(0.15)
IF				0.00	-0.01	(0.12)			
VIF	-0.19	-0.49 ***	(0.10)	-0.23	-0.73 ***	(0.15)	-0.22	-0.73 ***	(0.14)
R	0.06	0.16	(0.12)	0.01	0.02	(0.18)			
VR				-0.22	-0.73 **	(0.35)	-0.22	-0.73 **	(0.32)
SPR	0.07	0.17 **	(0.08)	0.00	-0.01	(0.13)			
VSP				-0.79	-2.56 ***	(0.61)	-0.80	-2.63 ***	(0.57)
VTY				0.24	0.78 ***	(0.22)	0.24	0.78 ***	(0.19)
LSP				-0.01	-0.05	(0.12)			
LTY				-0.91	-2.95 ***	(0.57)	-0.92	-3.04 ***	(0.48)
McFadden R-squared		0.10			0.43			0.43	
Akaike criterion		1.24			0.84			0.81	
Schwarz criterion		1.29			0.99			0.90	
Log likelihood		-192.63			-121.59			-122.00	
Wald test statistic (IP, IF, R, SPR, LSP)					0.83				

The table shows the results from estimating probit models where the explained variable is the sign of the realized stock-bond correlation. The explanatory variables are listed in the text. The marginal effects of the explanatory variables are evaluated at their sample means. ***/**/* indicates that the parameter is significant at the 1%/5%/10% level.

Table 4: Quantile Regressions

Panel A: Regression results

		(i)		(ii)		(iii)	
	Q	Coef.	Std.err.	Coef.	Std.err.	Coef.	Std.err.
Cons	0.10	-0.54 ***	-0.06	-0.41 ***	(0.03)	-0.42 ***	(0.04)
	0.25	-0.22 ***	-0.04	-0.18 ***	(0.04)	-0.17 ***	(0.03)
	0.50	0.15 ***	-0.03	0.09 ***	(0.02)	0.09 ***	(0.02)
	0.75	0.32 ***	-0.03	0.26 ***	(0.02)	0.26 ***	(0.02)
	0.90	0.47 ***	-0.03	0.40 ***	(0.02)	0.40 ***	(0.02)
IP	0.10			0.00	(0.05)		
	0.25			0.02	(0.03)		
	0.50			0.00	(0.03)		
	0.75			0.03	(0.02)		
	0.90			0.00	(0.02)		
VIP	0.10			0.09 ***	(0.03)	0.10 ***	(0.04)
	0.25			0.05	(0.05)	0.04	(0.04)
	0.50			0.01	(0.02)	0.00	(0.02)
	0.75			0.05	(0.05)	0.02	(0.03)
	0.90			0.04	(0.04)	0.04	(0.04)
IF	0.10			0.01	(0.04)		
	0.25			-0.01	(0.03)		
	0.50			0.00	(0.02)		
	0.75			0.00	(0.02)		
	0.90			0.00	(0.04)		
VIF	0.10	-0.05	(0.10)	-0.08	(0.09)	-0.08	(0.11)
	0.25	-0.09	(0.06)	-0.10	(0.09)	-0.07	(0.05)
	0.50	-0.11 ***	(0.03)	-0.12 ***	(0.03)	-0.08 ***	(0.02)
	0.75	-0.11 ***	(0.02)	-0.11 ***	(0.03)	-0.10 ***	(0.02)
	0.90	-0.08 *	(0.05)	-0.11 ***	(0.03)	-0.10 ***	(0.02)
R	0.10	0.03	(0.06)	0.07	(0.06)		
	0.25	0.08	(0.07)	0.02	(0.09)		
	0.50	0.03	(0.03)	-0.02	(0.02)		
	0.75	0.01	(0.03)	0.00	(0.02)		
	0.90	0.03	(0.03)	0.01	(0.04)		
VR	0.10			-0.04	(0.14)		
	0.25			0.04	(0.11)		
	0.50			0.02	(0.03)		
	0.75			0.00	(0.02)		
	0.90			0.04	(0.04)		
SPR	0.10	-0.01	(0.04)	-0.06 *	(0.03)		
	0.25	0.03	(0.04)	-0.04	(0.05)		
	0.50	0.03	(0.03)	-0.06 *	(0.03)		
	0.75	-0.02	(0.03)	-0.05 *	(0.03)		
	0.90	0.02	(0.04)	0.00	(0.04)		
VSP	0.10			-0.57	(0.39)	-0.56	(0.49)
	0.25			-0.36	(0.69)	-0.33	(0.60)
	0.50			-0.07 ***	(0.01)	-0.06 ***	(0.01)
	0.75			-0.08 ***	(0.02)	-0.07 ***	(0.01)
	0.90			-0.08 ***	(0.02)	-0.08 ***	(0.02)
VTY	0.10			0.18 ***	(0.03)	0.14 ***	(0.05)
	0.25			0.14 ***	(0.04)	0.14 ***	(0.03)
	0.50			0.13 ***	(0.02)	0.10 ***	(0.02)
	0.75			0.12 ***	(0.03)	0.11 ***	(0.03)
	0.90			0.10 **	(0.04)	0.10 **	(0.04)
LSP	0.10			-0.07 *	(0.04)	-0.07 *	(0.04)
	0.25			-0.10 *	(0.05)	-0.10 *	(0.06)
	0.50			-0.09 ***	(0.03)	-0.07 ***	(0.03)
	0.75			-0.06 **	(0.03)	-0.05 *	(0.03)
	0.90			0.03	(0.05)	0.03	(0.05)
LTY	0.10			-0.19	(0.15)	-0.21	(0.15)
	0.25			-0.20 ***	(0.07)	-0.16 **	(0.07)
	0.50			-0.18 ***	(0.02)	-0.18 ***	(0.02)
	0.75			-0.17 ***	(0.02)	-0.19 ***	(0.02)
	0.90			-0.20 ***	(0.02)	-0.16 **	(0.06)
Pseudo R-squared	0.10	0.01		0.24		0.22	
	0.25	0.04		0.25		0.24	
	0.50	0.08		0.23		0.22	
	0.75	0.06		0.19		0.17	
	0.90	0.05		0.18		0.17	
Wald test statistic (IP, IF, R, VR,SPR)				5.57			

Panel B: Slope equality tests

Quantiles	(i)	(ii)	(iii)
0.10; 0.50	0.82	42.34 ***	19.37 ***
0.50; 0.90	0.63	16.85	12.79 **
0.10; 0.90	0.35	31.58 ***	14.89 **

Panel A shows the results from estimating quantile regressions for the realized stock-bond correlation. Panel B shows the Wald test statistics of the slope equililty tests. ***/**/* indicates that the variable is significant at the 1%/5%/10% level.

Table 5: Probit Model for Various Correlations

Panel A: Model (i)

	CH	CD	CM	DCC
VIF	-0.19 ***	-0.14 ***	-0.31 ***	-0.07
R	0.06	0.11 **	0.05	-0.01 *
SPR	0.07 **	0.02	0.02	-0.02
McFadden R-squared	0.10	0.07	0.15	0.02

Panel B: Model (ii)

	CH	CD	CM	DCC
IP	0.03	-0.01	0.06	0.02
VIP	0.10 **	0.04	0.10 *	0.08 *
IF	0.00	0.06	-0.04	-0.01
VIF	-0.23 ***	-0.14 ***	-0.35 ***	-0.08 **
R	0.01	0.11 **	0.04	-0.02
VR	-0.22 **	-0.09	-0.27 **	-0.01
SPR	0.00	-0.03	0.00	-0.06 *
VSP	-0.79 ***	-0.09 **	-0.10 **	-0.04
VTY	0.24 ***	0.19 ***	0.21 ***	0.10 **
LSP	-0.01	-0.14 ***	0.02	-0.09 ***
LTY	-0.91 ***	-0.21 ***	-0.88 ***	-0.16 ***
McFadden R-squared	0.43	0.23	0.33	0.11

The table shows the marginal effects from a probit model where the explained variable is the sign of the stock-bond correlation based on high-frequency data (CH), daily data (CD), monthly data (CM), and the DCC model. The explanatory variables are listed in the text. The marginal effects of the explanatory variables are evaluated at their sample means. ***/**/* indicates that the parameter is significant at the 1%/5%/10% level.

Table 6: Quantile Regressions (i) for Various Correlations

Panel A: Regression results

	Q	CH	CD	CM	DCC
Cons	0.10	-0.54 ***	-0.52 ***	-0.33 ***	-0.19 ***
	0.25	-0.22 ***	-0.13 ***	-0.14 ***	-0.04 *
	0.50	0.15 ***	0.22 ***	0.14 ***	0.11 ***
	0.75	0.32 ***	0.43 ***	0.36 ***	0.27 ***
	0.90	0.47 ***	0.68 ***	0.53 ***	0.37 ***
VIF	0.10	-0.05	-0.03	-0.05	0.02 *
	0.25	-0.09	-0.10 **	-0.08 **	-0.03 *
	0.50	-0.11 ***	-0.11 ***	-0.11 ***	-0.05 ***
	0.75	-0.11 ***	-0.11 ***	-0.17 ***	-0.05
	0.90	-0.08 *	-0.15 ***	-0.13 ***	0.00
R	0.10	0.03	0.01	-0.02	0.02 *
	0.25	0.08	0.09	-0.02	0.01
	0.50	0.03	0.01	-0.01	-0.01
	0.75	0.01	0.01	-0.02	0.00
	0.90	0.03	-0.02	-0.09 **	0.04 **
SPR	0.10	-0.01	0.02	-0.10 ***	-0.06 ***
	0.25	0.03	0.03	-0.06 *	-0.02
	0.50	0.03	0.01	0.06 **	-0.01
	0.75	-0.02	0.01	0.03	0.00
	0.90	0.02	-0.03	-0.01	0.00
Pseudo	0.10	0.01	0.00	0.09	0.04
R-squared	0.25	0.04	0.02	0.05	0.02
	0.50	0.08	0.05	0.09	0.03
	0.75	0.06	0.05	0.14	0.02
	0.90	0.05	0.04	0.07	0.01

Panel B: Slope equality tests

Quantiles	CH	CD	CM	DCC
0.10; 0.50	0.82	2.27	45.99 ***	30.39 ***
0.50; 0.90	0.63	1.94	9.47 **	6.63 *
0.10; 0.90	0.35	5.49	9.23 **	10.34 **

Panel A of the table shows the results from estimating quantile regressions for the stock-bond correlation using high-frequency data (CH), daily data (CD), monthly data (CM), and the DCC model. Panel B shows the Wald test statistics of the slope equililty tests. ***/**/* indicates that the variable is significant at the 1%/5%/10% level.

Table 7: Quantile Regressions (ii) for Various Correlations

Panel A: Regression results

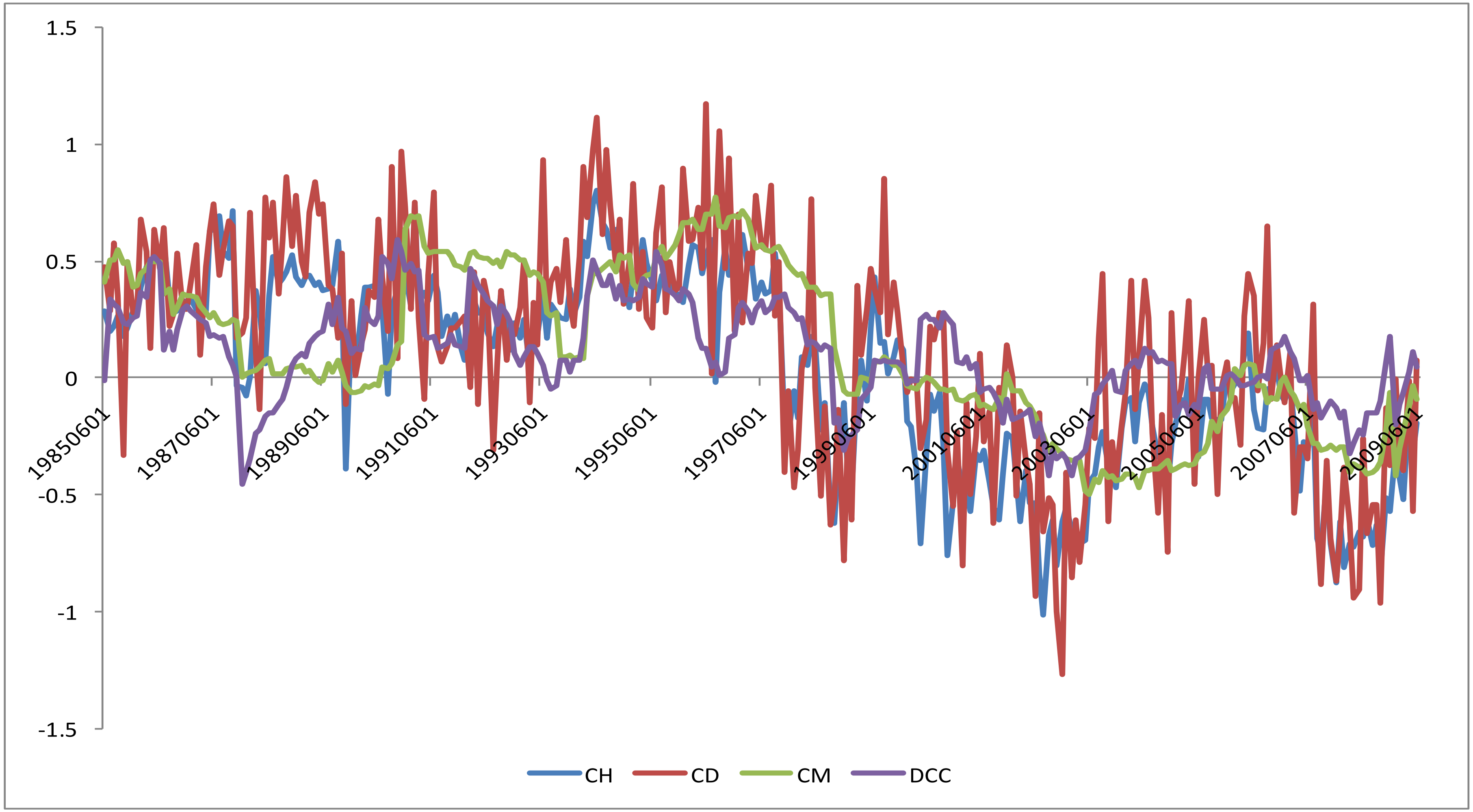
	Q	CH	CD	CM	DCC
Cons	0.10	-0.41 ***	-0.39 ***	-0.31 ***	-0.16 ***
	0.25	-0.18 ***	-0.11 **	-0.10 **	-0.04
	0.50	0.09 ***	0.17 ***	0.15 ***	0.10 ***
	0.75	0.26 ***	0.42 ***	0.35 ***	0.24 ***
	0.90	0.40 ***	0.62 ***	0.47 ***	0.35 ***
IP	0.10	0.00	0.04	-0.02	0.00
	0.25	0.02	0.00	0.02	-0.01
	0.50	0.00	0.02	0.01	0.01
	0.75	0.03	0.02	0.03	0.02
	0.90	0.00	0.02	0.01	0.00
VIP	0.10	0.09 ***	0.02	0.03	0.08 **
	0.25	0.05	0.00	-0.01	0.08 ***
	0.50	0.01	-0.04	0.06	0.05 **
	0.75	0.05	0.01	0.05	0.02
	0.90	0.04	0.01	0.09 **	0.01
IF	0.10	0.01	0.08	0.00	0.01
	0.25	-0.01	0.00	-0.01	0.01
	0.50	0.00	-0.01	-0.04	-0.01
	0.75	0.00	-0.02	-0.08 **	-0.03
	0.90	0.00	-0.01	-0.10 ***	0.00
VIF	0.10	-0.08	-0.01	-0.10 *	-0.03
	0.25	-0.10	-0.09	-0.05 **	-0.04 *
	0.50	-0.12 ***	-0.08 **	-0.14 ***	-0.06 **
	0.75	-0.11 ***	-0.14 ***	-0.19 ***	-0.06 **
	0.90	-0.11 ***	-0.11	-0.16 ***	-0.03
R	0.10	0.07	0.07	0.01	0.00
	0.25	0.02	0.06	0.00	0.01
	0.50	-0.02	0.00	0.00	0.01
	0.75	0.00	-0.01	-0.01	0.00
	0.90	0.01	-0.01	-0.08 **	-0.01
VR	0.10	-0.04	0.00	0.01	-0.10
	0.25	0.04	0.02	0.00	-0.01
	0.50	0.02	0.02	0.01	-0.02
	0.75	0.00	0.06	0.03	0.03
	0.90	0.04	0.03	0.01	0.03
SPR	0.10	-0.06 *	-0.05	-0.14 ***	-0.03
	0.25	-0.04	-0.06	-0.05	-0.04
	0.50	-0.06 *	-0.02	0.05	-0.04 **
	0.75	-0.05 *	-0.06	0.02	-0.06 **
	0.90	0.00	-0.01	0.00	-0.03
VSP	0.10	-0.57	-0.27	-0.01	-0.28
	0.25	-0.36	-0.17	-0.01	-0.17
	0.50	-0.07 ***	-0.05 ***	-0.03 *	-0.05 ***
	0.75	-0.08 ***	-0.06 ***	-0.03 **	-0.05 ***
	0.90	-0.08 ***	-0.04	-0.04 *	-0.05 ***
VTY	0.10	0.18 ***	0.18 ***	0.11 ***	0.04 *
	0.25	0.14 ***	0.15 ***	0.08 ***	0.06
	0.50	0.13 ***	0.12 ***	0.05 *	0.08 ***
	0.75	0.12 ***	0.10 **	0.01	0.08 **
	0.90	0.10 **	0.05	0.02	0.06 *
LSP	0.10	-0.07 *	-0.02	-0.01	-0.03
	0.25	-0.10 *	-0.12 **	-0.02	-0.03
	0.50	-0.09 ***	-0.11 ***	-0.02	-0.05 ***
	0.75	-0.06 **	-0.07 *	-0.02	-0.05 **
	0.90	0.03	-0.07	0.01	-0.04
LTY	0.10	-0.19	-0.17 ***	-0.09	-0.04
	0.25	-0.20 ***	-0.17 **	-0.07 ***	-0.07 **
	0.50	-0.18 ***	-0.18 ***	-0.10 ***	-0.07 ***
	0.75	-0.17 ***	-0.14 ***	-0.09 ***	-0.05
	0.90	-0.20 ***	-0.17 ***	-0.11 ***	-0.11 ***
Pseudo R-squared	0.10	0.24	0.16	0.15	0.17
	0.25	0.25	0.17	0.12	0.13
	0.50	0.23	0.15	0.15	0.14
	0.75	0.19	0.13	0.22	0.11
	0.90	0.18	0.09	0.15	0.12

Panel B: Slope equality tests

Quantiles	CH	CD	CM	DCC
0.10; 0.50	42.34 ***	23.12 **	68.07 ***	23.80 **
0.50; 0.90	16.85	5.48	27.10 **	25.14 ***
0.10; 0.90	31.58 ***	20.87 **	72.80 ***	84.91 ***

Panel A of the table shows the results from estimating the quantile regressions for the stock-bond correlation using high-frequency data (CH), daily data (CD), monthly data (CM), and the DCC model. Panel B shows the Wald test statistics of the slope equililty tests. ***/**/* indicates that the variable is significant at the 1%/5%/10% level.

Figure 1: Stock-Bond Correlation



Notes: The figure shows the time series of the Fisher transform of the stock-bond correlation calculated using high-frequency data (CH), daily data (CD), monthly data (CM) and the DCC model.

Research Papers 2010

CREATES
Center for Research in Econometric Analysis of Time Series

2010-41: Ole E. Barndorff-Nielsen, Fred Espen Benth and Almut E. D. Veraart: Modelling electricity forward markets by ambit fields

2010-42: Robinson Kruse and Philipp Sibbertsen: Long memory and changing persistence

2010-43: Dennis Kristensen: Semi-Nonparametric Estimation and Misspecification Testing of Diffusion Models

2010-44: Jeroen V.K. Rombouts and Lars Stentoft: Option Pricing with Asymmetric Heteroskedastic Normal Mixture Models

2010-45: Rasmus Tangsgaard Varneskov and Valeri Voev: The Role of Realized Ex-post Covariance Measures and Dynamic Model Choice on the Quality of Covariance Forecasts

2010-46: Christian Bach and Stig Vinther Møller: Habit-based Asset Pricing with Limited Participation Consumption

2010-47: Christian M. Dahl, Hans Christian Kongsted and Anders Sørensen: ICT and Productivity Growth in the 1990's: Panel Data Evidence on Europe

2010-48: Christian M. Dahl and Emma M. Iglesias: Asymptotic normality of the QMLE in the level-effect ARCH model

2010-49: Christian D. Dick, Maik Schmeling and Andreas Schrimpf: Macro Expectations, Aggregate Uncertainty, and Expected Term Premia

2010-50: Bent Jesper Christensen and Petra Posedel: The Risk-Return Tradeoff and Leverage Effect in a Stochastic Volatility-in-Mean Model

2010-51: Christos Ntantamis: A Duration Hidden Markov Model for the Identification of Regimes in Stock Market Returns

2010-52: Christos Ntantamis: Detecting Structural Breaks using Hidden Markov Models

2010-53: Christos Ntantamis: Detecting Housing Submarkets using Unsupervised Learning of Finite Mixture Models

2010-54: Stefan Holst Bache: Minimax Regression Quantiles

2010-55: Nektarios Aslanidis and Charlotte Christiansen: Sign and Quantiles of the Realized Stock-Bond Correlation