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Nektarios Aslanidis
Charlotte Christiansen

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Universitat Rovira i Virgili
Facultat de Ciències Econòmiques i Empresarials
Avgda. de la Universitat, 1
43204 Reus
Tel.: +34 977 759 811
Fax: +34 977 300 661
Email: sde@urv.cat

CREIP
www.urv.cat/creip
Universitat Rovira i Virgili
Departament d'Economia
Avgda. de la Universitat, 1
43204 Reus
Tel.: +34 977 558 936
Email: creip@urv.cat

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Quantiles of the Realized Stock-Bond Correlation*

Nektarios Aslanidis†
Universitat Rovira i Virgili, CREIP

Charlotte Christiansen‡
CREATES, Aarhus University

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†Universitat Rovira i Virgili, CREIP, 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.

Quantiles of the Realized Stock-Bond Correlation

Abstract: We scrutinize the realized stock-bond correlation based upon high frequency returns. We use quantile regressions to pin down the systematic variation of the extreme tails over their economic determinants. The correlation dependence behaves differently when the correlation is large negative and large positive. The important explanatory variables at the extreme low quantile are the short rate, the yield spread, and the volatility index. At the extreme high quantile the bond market liquidity is also important. The empirical findings are only partially robust to using less precise measures of the stock-bond correlation. The results are not caused by the recent financial crisis.

Keywords: Extreme returns; Financial crisis; Realized stock-bond correlation; Quantile regressions; VIX

JEL Classifications: C22; G01; 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), Bansal, Connolly, and Stivers (forthcoming), and Aslanidis and Christiansen (2010), among others). Still, little is known about the dynamics 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 realized stock-bond correlation. In particular, we analyze the extreme quantiles of the realized stock-bond correlation in relation to its various economic determinants.

The tails of the distribution of the stock-bond correlation are important when considering optimal portfolio allocation. For instance, the diversification benefits of combined stock-bond holdings tend to be particularly high during times of extreme negative correlations. Thus, bonds appear to be safe investments during periods of extreme negative correlations, and risky investments during episodes of extreme positive correlations. On the other hand, in general 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 lower and upper tails of the stock-bond correlation is an important goal in financial economics.

Ilmanen (2003) contains one of the first explicit empirical discussions of the changing nature of the sign of the stock-bond correlation. 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.

The present study takes a step further by adopting a different approach to examine the sign of the stock-bond correlation. First, by considering the 0.10 and 0.90 quantiles we can examine the lower and upper distribution tails of the stock-bond correlation, which correspond to strongly negative and strongly positive correlation, respectively. Therefore, this paper draws on a quantile regression framework to investigate if and how the dynamics in the realized stock-bond correlation are different at the tails. Second, we use high frequency data to calculate the realized stock-bond correlation. High frequency data contain as much information as possible and, therefore provide a more accurate correlation measure compared to correlations from daily or lower frequency data. 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.

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 tails of the realized stock-bond correlation and by employing several explanatory variables in excess of those used by Viceira (forthcoming). Moreover, we extend the analysis of Bansal, Connolly, and Stivers (forthcoming) who finds that the CBOE volatility index is highly important for the stock-bond correlation using a regime-switching model.

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. This 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 invigorated 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. 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). Moreover, the behavior of the realized stock-bond correlation at both extreme quantiles are also different from the median. The short rate and the yield spread have strong positive influences upon the realized stock-bond correlation at both tails. Similarly, the volatility index has strong negative effects at both quantiles. At the upper tail, the bond market liquidity is an additional important determinant of the realized stock-bond correlation.

We find that our results are only 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 results are robust to leaving out the period covering the recent financial crisis. This implies, that our findings are not caused by unusual events during that period.

The remaining part of the paper is structured as follows. First, we introduce the data in Section 2. In Section 3 we discuss the quantile regression model.

The empirical findings are discussed in Section 4. Finally, Section 5 concludes.

2 Data

We use monthly data over the period 1986M07 - 2009M06 which gives rise to 276 observations.

2.1 Stock-Bond Correlation

The US stock market is represented by the futures contract on the SP500, traded on 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 data are obtained from TickData. The reason for using futures instead of spot prices is that futures on the SP500 and the Treasury Notes are highly liquid assets. Moreover, these futures contracts have also been 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. 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.

[Insert Table 1 about here]
[Insert Figure 1 about here]

Table 1 (first column) shows the summary statistics of the realized stock-bond correlation. As seen, the mean is close to zero (0.02). The realized correlation is almost equally often positive and negative. The distribution is slightly 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. Details regarding the calculations of the explanatory variables are provided in Table 2.

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
VXO_t	Volatility index
LSP_t	Stock liquidity
LTY_t	Bond liquidity

All variables have been standardized to have zero mean and unit variance. 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.

[Insert Table 2 about here]

Viceira (forthcoming) shows that the short rate and the yield spread are important determinants for the stock-bond correlation. We extend the analysis of Viceira (forthcoming) by considering a broader set of explanatory variables. For the short rate we use the 1-month CD rate. We define the yield spread as the difference between the 10-year Treasury Bond yield and the 3-month Treasury Bill rate. 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, we use the CBOE (Chicago Board of Options Exchange) volatility index VXO (previously denoted the VIX) as it plays an important role in describing the relationship between bond and stock returns, cf. Connolly, Stivers, and Sun (2005). The VXO measures the implied volatility of options on the SP100 stock index with 22 trading days until maturity.[1] The CBOE publishes this index and trade derivatives upon it. Finally, we anticipate that the liquidity of the stock and bond markets have a bearing upon the realized stock-bond correlation, cf. Bansal, Connolly, and Stivers (forthcoming). We measure liquidity by the monthly traded volume of the relevant futures contracts.

[1] The VXO was previously denoted the VIX index. Now, the VIX is based upon the SP500 and it is only available since 1993.

3 Quantiles Regression Model

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

$$C_t = X_t' \beta^\tau + \varepsilon_t^\tau \tag{1}$$

where C_t is 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 vary 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

$$\min_{\beta \in \mathbb{R}} \left[\sum_{t \in \{t: C_t \geq X_t' \beta\}} \tau |C_t - X_t' \beta^\tau| + \sum_{t \in \{t: C_t < X_t' \beta\}} (1-\tau) |C_t - X_t' \beta^\tau| \right] \tag{2}$$

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).

The coefficient estimates are computed by solving linear programming methods and their standard errors are obtained by bootstrap resampling.

4 Empirical Findings

Here, we first discuss the main empirical findings and then we consider their economic importance.[2] At last we consider two types of robustness analysis; the effect of using less precise measures of the stock-bond correlation and the effect of the recent financial crisis.

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

4.1 Main Empirical Results

Two models are shown for each of the following quantiles: $\{0.10, 0.50, 0.90\}$. In addition to the extreme tails (0.10 for extreme negative and 0.90 for extreme positive correlations), we also consider the median correlation. Due to the findings in Viceira (forthcoming), model (i) uses only the short rate and the yield spread as explanatory variables. Model (ii) includes all the explanatory variables discussed in Section 2. Table 3 shows the results from estimating the quantile regressions. Panel A shows the parameter estimates and Panel B shows the slope equality tests.

[Insert Table 3 about here]

The explanatory power of model (i) is fairly low (the R^2 values range from 0.19 to 0.33). We gain a lot of information by including the full set of explanatory variables that we propose in this study. Firstly, with model (ii) we are able to explain between 0.34 and 0.48 of the variation in the correlation across the different quantiles. Thus, the explanatory power of model (ii) is much greater than for model (i). The explanatory power is lowest at the extreme high quantile (the R^2 value is 0.34) and highest at the median and extreme low quantiles (R^2 values of 0.48 and 0.47 respectively). The improvement in explanatory power is greatest at the extreme low quantile.

In Panel B of Table 3 we report results for the slope equality tests. In model (i) these tests deliver no evidence of differences between the quantiles. However, for model (ii), the estimated coefficients at the extreme quantiles are significantly different from each other.[3] Thus, model (ii) also improves our understanding of the realized stock-bond correlation by providing evidence that the behavior is different for extreme negative and extreme positive values. 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.

Some explanatory variables are not significant in any of the quantiles, namely the industrial production, the industrial production volatility, and the inflation volatility. This is also confirmed by the Wald test statistic of 5.43 that jointly tests the significance of these variables.[4] Surprisingly, the business cycle variables industrial production and industrial production volatility have no bearings

[3] The Wald test statistic for slope equality for quantiles 0.50 and 0.90 is just not significant with a p-value of 10.2%.

[4] This a Fisher-type test combining p-values from Wald tests applied to the different quantiles (0.10, 0.50, 0.90). The statistic is $\chi^2(10)$ distributed. The critical value at the 5% level is 18.30.

upon the realized stock-bond correlation, neither at the tails nor at the median. So, the business cycle as measured by the industrial production is not a determinant of the realized stock-bond correlation. Viceira (forthcoming) also finds that the inflation volatility is insignificant for the bond beta, once the short rate and the yield spread are taken into account.

The significant slope coefficients have the same sign for the low, median, and high quantiles implying that the differences in the slope coefficients are with respect to their sizes.

Three variables are economically important determinants of the realized stock-bond correlation at all three quantiles, namely the short rate, the volatility index, and the yield spread. The size of these slope coefficients vary across quantiles, whereas the sign is identical across quantiles.

It is important to notice that the effects from a given variable are still very different at the two tails. For instance, a positive effect from, say, the short rate implies that at the left tail, the greater the short rate is the less extreme is the realized stock-bond correlation (a negative stock-bond correlation becoming larger implies that it is smaller in absolute measures). At the right tail, a positive effect implies that the realized stock-bond correlation becomes more extreme (a positive stock-bond correlation becoming larger implies that it becomes stronger in absolute terms). The opposite applies for the negative effect from the volatility index. At the left tail, the effect from the volatility index implies a stronger correlation and at the right tail a weaker correlation.

At the extreme low quantile (0.10), we observe a large positive effect from the term structure variables; the short rate and the yield spread which have estimated slope coefficients of 0.50 and 0.29, respectively. This implies that when the realized stock-bond correlation is large negative, there is a positive effect from the term structure variables; the smaller the short rate or the yield spread is, the more negative the stock-bond correlation tends to be. In contrast, there is a large negative effect from the volatility index, where the slope coefficient amounts to -0.35. Thus, the more variable the market conditions are, the more negative the realized stock-bond correlation tends to be. In addition, there are smaller positive effects from the short rate volatility, and the stock market liquidity, and a small negative effect from the inflation upon the realized stock-bond correlation at the extreme low quantile.

At the extreme high quantile (0.90), the effect from the short rate and the yield spread are of about the same magnitude as at the extreme low quantile (slope coefficients are 0.49 and 0.24). At the 0.90 quantile, this implies that the larger these term structure variables are, the stronger is the realized stock-bond correlation. The negative effect from the volatility index is somewhat weaker than at the extreme low quantile. So, market uncertainly is not so important for the realized stock-bond correlation when considering large positive correlations. Then, at the extreme high quantile, the liquidity variables are also important. In particular, the bond market liquidity has a large and positive effect the realized stock-bond correlation. The more liquid the bond market is, the larger is the correlation. The effect from the stock market liquidity is smaller but it is still significant. Thus, when markets are liquid, stocks and bonds are more likely to be substitutes.

At the median, only the short rate, the yield spread, and the volatility index have any significant effects upon the realized stock-bond correlation. Thus, only considering the median gives you less information about which variables are important for the behavior of the realized stock-bond correlation compared to the information available from the extreme quantiles. The most important variable is the short rate, for which the effect is still smaller than at the extreme quantiles. The effect from the yield spread and the volatility are of about the same size and are both smaller than at the extreme tails.

4.2 Economic Importance

Figure 2 shows the slope coefficients from model (ii) together with their 95% confidence band. We have plotted the slope coefficients for 20 different equally spaced quantiles (instead of only the three tabulated above). Remember that the explanatory variables are all standardized, so that we can get useful information about the economic importance of the variables by comparing the size of the slope coefficients.

[Insert Figure 2 about here]

As we saw above, the short rate, the yield spread, the volatility index, and the bond market liquidity are the most interesting variables as these have the biggest slope coefficients that are also significant.

The slope coefficients for the short rate follows a smile pattern, which implies that it has the biggest impact in the tails and the least impact in the median. The slope coefficients of the yield spread also follows a smile pattern but with a drop at the right hand side tail. This implies that the effect of the short rate and the yield spread upon the realized stock-bond correlation is underrated when considering only OLS regressions.

The slope coefficient of the volatility index shows an inverted U-shaped pattern. In particular, it increases rapidly up to quantile 0.40 after which it drops for a while and stays at the same level up to the right tail. The volatility index provides a measure of the economy wide uncertainty. When the realized stock-bond correlation is large negative (left tail) then the economic uncertainty is highly important whereas when the realized stock bond correlation is positive then the economic uncertainty is not so important.

The slope coefficients of the bond market liquidity are increasing across the quantiles though with an increasing confidence band. At the lower quantiles $(0.15 - 0.40)$ the slope coefficients are significantly negative and at the higher quantiles $(0.70 - 0.95)$ the slope coefficients are significantly positive. However, the slope coefficients are only large in absolute size at the upper quantiles. Thus, the economic impact of the bond market liquidity is only sizeable when the realized stock-bond correlation is fairly large and positive. So, in this case the more liquid the bond market is the even stronger the stock-bond correlation.

4.3 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.[5] 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. Now 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.

[5] The DCC model allows correlations to vary over time with the dynamics driven by past correlations, $q_{12,t} = \overline{\rho}_{12}(1-\alpha-\beta)+\alpha\varepsilon_{1,t-1}\varepsilon_{2,t-1}+\beta q_{12,t-1}$, where $\overline{\rho}_{12}$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.

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 1 contains summary statistics for the four correlation measures while Figure 1 plots them. As seen, the stock-bond correlation is very much dependent 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 and the DCC one are very different from CH_t. For example, the CM_t 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.

[Insert Table 4 about here]

Tables 4 shows the results from estimating the quantile regressions (ii) for each of the four correlation measures. Model (i) (results not tabulated) is inadequate in explaining the quantiles of the stock-bond correlation as the explanatory power is much greater in model (ii) across all correlation measures.

The highest explanatory power is achieved by the high-frequency correlation. The other three correlation measures have about the same explanatory power. Still, for the CM_t and DCC_t we find that the two extreme quantiles are significantly different, however, for the CD_t the quantiles are not significantly different. Moreover, it is not the same explanatory variables that are significant in explaining the quantiles for each of the four correlation measures. The short rate is an important determinant no matter which correlation measure is used. The daily correlation has coefficients not too different from the high frequency correlation. In contrast, the yield spread is not significant in explaining the stock-bond correlation at the extreme low tail when measured by CM_t and DCC_t. For the monthly correlation the inflation uncertainty is important at the right tail whereas the yield spread and the volatility index are not.

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. Thus, using the appropriate measure of the stock-bond correlation is highly important for the empirical findings obtained.

4.4 Effect of Financial Crisis

We investigate if the results are caused by or disturbed by the recent financial crisis. We do this by considering a shorter sample period that ends before the financial crisis, namely $1986M07$ - $2006M12$. The results are shown in Table 5.

[Insert Table 5 about here]

The results only change slightly when excluding the most recent period. Thus, it is safe to conclude that the empirical findings are not caused by the recent financial crisis, and the results are thereby robust to taking into account any unusual events during the financial crisis.

5 Conclusion

This study looks further into the properties of the realized stock-bond correlation based upon high-frequency returns. In particular, we investigate features of the stock-bond correlation that has so far been left unexplored. First, we use quantile regressions to analyze the tails of the correlation. The lower quantile, that is, when the realized stock-bond correlation is large negative is more predictable than the upper quantile, 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 therefore preferable to conditional mean models. Second, 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. Finally, the results are robust to leaving out the period covering the recent financial crisis. Thus, the unusual period during the recent financial crisis is not the cause of the results.

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Table 1: Stock-Bond Correlation Descriptive Statistics

	CH	CD	CM	DCC
Mean	0.02	0.13	0.10	0.09
Standard deviation	0.41	0.48	0.34	0.21
Skewness	-0.36	-0.34	0.14	-0.11
Kurtosis	2.06	2.59	1.85	2.56
Percent negative	47%	37%	44%	33%

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 2: 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
VXO	Volatility index	SP100 volatility index	VXO	CBOE
LSP	Stock liquidity	SP500 monthly volume	ISPCS00	DataStream
LTY	Bond liquidity	TY monthly volume	CTYCS00	DataStream

Table 3: Quantile Regressions

Panel A: Regression results

	Q	(i) Coef.		(i) Std.err.	(ii) Coef.		(ii) Std.err.
Cons	0.10	-0.29	***	(0.07)	-0.16	***	(0.03)
	0.50	0.15	***	(0.02)	0.10	***	(0.03)
	0.90	0.54	***	(0.03)	0.44	***	(0.03)
IP	0.10				0.01		(0.03)
	0.50				0.02		(0.02)
	0.90				0.04		(0.03)
VIP	0.10				-0.02		(0.04)
	0.50				0.03		(0.04)
	0.90				0.07	*	(0.04)
IF	0.10				-0.07	**	(0.03)
	0.50				-0.02		(0.03)
	0.90				-0.03		(0.03)
VIF	0.10				0.03		(0.06)
	0.50				0.02		(0.04)
	0.90				0.03		(0.04)
R	0.10	0.40	***	(0.08)	0.50	***	(0.04)
	0.50	0.38	***	(0.02)	0.41	***	(0.04)
	0.90	0.46	***	(0.06)	0.49	***	(0.07)
VR	0.10				0.08	**	(0.03)
	0.50				-0.03		(0.04)
	0.90				-0.02		(0.05)
SPR	0.10	0.20	***	(0.07)	0.29	***	(0.04)
	0.50	0.20	***	(0.02)	0.22	***	(0.03)
	0.90	0.23	***	(0.03)	0.24	***	(0.05)
VXO	0.10				-0.35	***	(0.05)
	0.50				-0.19	***	(0.03)
	0.90				-0.22	***	(0.04)
LSP	0.10				0.06	**	(0.03)
	0.50				0.04		(0.03)
	0.90				0.06	**	(0.03)
LTY	0.10				-0.04		(0.03)
	0.50				-0.07		(0.05)
	0.90				0.21	**	(0.10)
Pseudo	0.10	0.19			0.47		
R-squared	0.50	0.33			0.48		
	0.90	0.21			0.34		
Wald test statistic (IP, VIP, VIF)					5.43		

Panel B: Slope equality tests

Quantiles	(i)	(ii)
0.10; 0.50	0.12	35.56 ***
0.50; 0.90	2.58	15.92
0.10; 0.90	0.39	45.71 ***

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, $\chi^2(3)$ and $\chi 2(10)$distributed. ***/**/* indicates that the variable is significant at the 1%/5%/10% level.

Table 4: Quantile Regressions (ii)

Panel A: Regression results

	Q	CH	CD	CM	DCC
Cons	0.10	-0.16 ***	-0.16 ***	-0.19 ***	-0.12 ***
	0.50	0.10 ***	0.25 ***	0.19 ***	0.11 ***
	0.90	0.44 ***	0.68 ***	0.49 ***	0.37 ***
IP	0.10	0.01	0.03	0.00	0.00
	0.50	0.02	0.02	0.00	-0.02
	0.90	0.04	0.06	0.02	0.00
VIP	0.10	-0.02	-0.07	-0.01	0.05 *
	0.50	0.03	0.02	0.12 **	0.07 **
	0.90	0.07 *	0.04	0.09 **	0.03
IF	0.10	-0.07 **	-0.06 *	0.00	0.00
	0.50	-0.02	0.01	-0.06 **	0.00
	0.90	-0.03	-0.04	-0.10 *	-0.04 **
VIF	0.10	0.03	0.09 *	0.00	-0.02
	0.50	0.02	0.09	-0.08 *	-0.01
	0.90	0.03	0.04	-0.14 **	-0.01
R	0.10	0.50 ***	0.56 ***	0.20 ***	0.10 ***
	0.50	0.41 ***	0.41 ***	0.30 ***	0.18 ***
	0.90	0.49 ***	0.36 ***	0.18	0.29 ***
VR	0.10	0.08 **	-0.05	0.00	-0.03
	0.50	-0.03	0.01	-0.02	-0.04
	0.90	-0.02	0.01	0.00	-0.02
SPR	0.10	0.29 ***	0.29 ***	0.05 *	0.02
	0.50	0.22 ***	0.23 ***	0.17 ***	0.07 ***
	0.90	0.24 ***	0.24 ***	0.04	0.10 ***
VXO	0.10	-0.35 ***	-0.21 ***	-0.01	-0.13 ***
	0.50	-0.19 ***	-0.17 ***	-0.14 ***	-0.08 **
	0.90	-0.22 ***	-0.22 ***	-0.06	-0.07 **
LSP	0.10	0.06 **	0.05	0.04 *	0.02
	0.50	0.04	0.04	0.06 **	0.02
	0.90	0.06 **	0.05	-0.03	-0.02
LTY	0.10	-0.04	0.00	-0.02	-0.01
	0.50	-0.07	-0.03	-0.02	-0.01
	0.90	0.21 **	0.05	0.06	0.10 *
Pseudo	0.10	0.47	0.36	0.29	0.32
R-squared	0.50	0.48	0.28	0.24	0.20
	0.90	0.34	0.18	0.21	0.26

Panel B: Slope equality tests

Quantiles				
0.10; 0.50	35.56 ***	8.89	41.84 ***	20.51 **
0.50; 0.90	15.92	6.90	13.27	34.23 ***
0.10; 0.90	45.71 ***	12.32	23.93 ***	65.69 ***

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, $\chi^2(10)$. ***/**/* indicates that the variable is significant at the 1%/5%/10% level.

Table 5: Quantile Regressions (ii), Sub-Sample 1986-2006

Panel A: Regression results

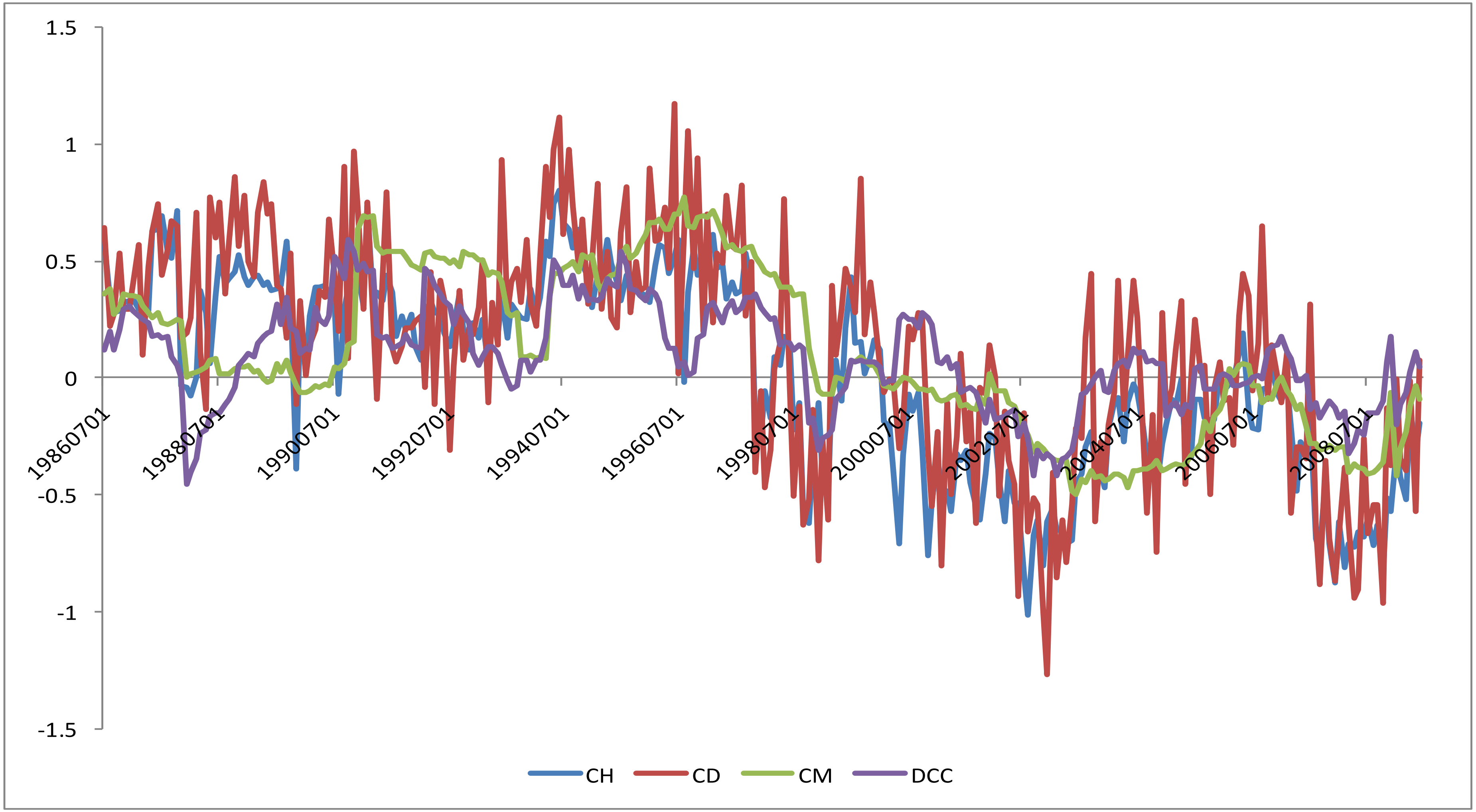
	Q	CH	CD	CM	DCC
Cons	0.10	-0.17 ***	-0.12	-0.14 ***	-0.03
	0.50	0.12 ***	0.33 ***	0.15 ***	0.16 ***
	0.90	0.44 ***	0.81 ***	0.40 ***	0.34 ***
IP	0.10	0.01	0.02	0.00	-0.02
	0.50	0.03	0.03	0.02	-0.03
	0.90	0.06 *	0.04	0.02	-0.01
VIP	0.10	0.03	-0.10	0.02	0.07 **
	0.50	0.01	0.00	0.09 **	0.05 *
	0.90	0.05	-0.04	0.09 ***	0.03
IF	0.10	-0.07 ***	-0.05	-0.01	0.00
	0.50	-0.02	0.03	-0.10 **	0.00
	0.90	-0.02	-0.01	-0.08 **	-0.02
VIF	0.10	-0.06	0.06	-0.04	-0.06 *
	0.50	-0.05 *	0.03	-0.21 ***	-0.02
	0.90	-0.04	-0.10	-0.20 ***	-0.06 ***
R	0.10	0.41 ***	0.57 ***	0.22 ***	0.15 ***
	0.50	0.46 ***	0.49 ***	0.30 ***	0.24 ***
	0.90	0.52 ***	0.48 ***	0.29 ***	0.30 ***
VR	0.10	0.04	-0.07	-0.03	-0.02
	0.50	-0.09 *	-0.06	-0.08 *	-0.11 ***
	0.90	-0.07	0.01	-0.07	-0.04
SPR	0.10	0.20 ***	0.28 ***	0.03	0.06 **
	0.50	0.22 ***	0.24 ***	0.11 ***	0.08 ***
	0.90	0.22 ***	0.18 ***	0.06	0.09 ***
VXO	0.10	-0.29 ***	-0.24 ***	0.00	-0.16 ***
	0.50	-0.23 ***	-0.24 ***	-0.14 ***	-0.13 ***
	0.90	-0.22 ***	-0.18 ***	-0.14 ***	-0.09 ***
LSP	0.10	0.03	0.07	0.03	0.02
	0.50	0.05 *	0.00	0.06 *	0.03
	0.90	0.05	-0.05	0.01	-0.01
LTY	0.10	-0.17	0.11	0.18 **	0.24 **
	0.50	0.05	0.41 *	-0.03	0.24 **
	0.90	0.23	0.64 **	-0.11	0.07
Pseudo R-squared	0.10	0.55	0.40	0.35	0.40
	0.50	0.52	0.30	0.30	0.27
	0.90	0.40	0.22	0.28	0.32

Panel B: Slope equality tests

Quantiles	CH	CD	CM	DCC
0.10; 0.50	15.27	9.46	93.67 ***	12.30
0.50; 0.90	8.17	9.77	5.92	33.54 ***
0.10; 0.90	19.97 **	11.85	49.62 ***	51.20 ***

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, $\chi^2(10)$. ***/**/* 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.

Figure 2: Slope Coeffients with 95% Confidence Band