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Abstract: This paper adopts quantile regressions to scrutinize the realized stock-bond correlation based upon high frequency returns. The paper provides in-sample and out-of-sample analysis and considers a large number of macro-finance predictors well-know from the return predictability literature. Strong in-sample predictability is obtained from quantile models with factor-augmented predictors, particularly at the lower to median quantiles. Out-of-sample the quantile factor model works best at the median to upper quantiles.

Keywords: Realized stock-bond correlation; Quantile regressions; Macro-finance variables; Factor analysis.

JEL Classifications: C22; G11; G12

1 Introduction

Understanding and predicting the correlation between stock and bond returns has key relevance in areas within financial economics such as asset allocation, risk analysis, and hedging. In recent years the literature documents substantial time-variation in the comovement between stocks and bonds. For instance, until the mid 1990s the average US stock-bond correlation is strongly positive, only to drop to extremely large negative levels by the early 2000s. Authors explore different economic forces driving this time-varying structure of the stock-bond correlation; see for example, Pastor and Stambaugh (2003), Connolly, Stivers, and Sun (2005), Christiansen and Ranaldo (2007), Yang, Zhou, and Wang (2009), Baele, Bekaert, and Inghelbrecht (2010), Bansal, Connolly, and Stivers (2010), Aslanidis and Christiansen (2012), and Viceira (2012), among others. In line with this intuition, Campbell, Sunderam, and Viceira (2009) propose an affine term structure model that allows for stock-bond covariances that can move over time and change sign. They assign a latent variable to capture the covariance between nominal variables and the real economy, which, in turn, helps to produce negative comovements between stock and bond returns.

However, the literature almost exclusively focuses on the conditional mean and variance, and thus, ignores other parts of the stock-bond distribution. Yet, there is now ample empirical evidence showing that investors' interest in asset returns goes well beyond the conditional mean and variance. For example, Harvey and Diddique (2000) and Dittmar (2002) consider higher order-moment CAPM models and show that beta describes the cross-sectional variation in US expected stock returns well. Further, in risk analysis, the focus is usually on the lower tails of the return distribution.

We adopt the methodology of quantile regression to investigate the tails of the realized stock-bond correlation. The quantile regression approach can provide a more complete picture of the correlation distribution compared to conditional mean and variance models. In the financial economics literature, the quantile regression is mainly applied to value-at-risk (VaR) calculations starting with Engle and Manganelli (2004). The extreme quantiles of the correlation, say the 0.1 and 0.9 quantiles, correspond to strongly negative and strongly positive correlation, respectively. We also examine a sufficiently fine grid of quantiles to understand how far from the mean we have to be until the behavior of the stock-bond correlation is different and how macro-finance state variables help us understand the correlation dynamics. Moreover, we provide comprehensive in-sample as well as out-of-sample analysis of the predictability of the extreme quantiles by considering a large number of potential predictors well known from the return predictability literature (the Goyal and Welch (2008) data set, the VIX index and the Cochrane and Piazzesi (2005) forward-rate factor). It is likely that a macro-finance variable is a relatively good forecaster of, for example, the lower tail of the distribution, while it is a relatively bad forecaster of the upper tail. Likewise, it is possible that the relative forecast accuracy is very different across the tails and the centre of the distribution. We also explore a principal components factor approach to extract three factors from the macro-finance state variables. The factors then concisely encompass information from many macro-finance variables. These factors are then used as explanatory variables.

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 are particularly high during times of extreme negative correlations. On the other hand, the VaR of a combined stock-bond portfolio is largest when the stock-bond correlation is large positive (the portfolio's standard deviation is at its maximum). A large VaR is a disadvantage to the investor as it expensive due to higher capital requirements. Further, from an asset allocation point of view, a large positive correlation would imply a higher allocation to stocks, given that bonds generally have lower expected returns.

Viceira (2012) shows that the short rate and the yield spread are positively related to the realized (monthly) bond CAPM beta and bond Consumption CAPM beta calculated from daily returns. These are normalized measures of the stock-bond covariance similar to the stock-bond correlation. The author argues that the yield spread appears to proxy for business conditions, while the short rate seems to reflect inflation and economic uncertainty. By using regime switching models, Aslanidis and Christiansen (2012) also argue for the role of these two variables (and the VIX index) in determining correlation regimes. We extend the analysis of Viceira (2012) and Aslanidis and Christiansen (2012) by examining predictability of the entire stock-bond correlation distribution and by considering a larger set of predictive variables.

Ilmanen (2003) contains one of the first explicit empirical discussions of the changing nature of the sign of the stock-bond correlation. The author finds that during periods of high inflation, changes in the discount rates dominate in cash flows expectations, thereby inducing a positive stock-bond correlation. Further, Connolly, Stivers, and Sun (2005) ascribe the sustained negative stock-bond correlation observed since late 1990s to a "flight-to safety" phenomenon, where increased stock market uncertainty induces investors to flee stocks in favour of bonds. Our work is also related to Pedersen (2010) that 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. Instead, we first obtain monthly correlations from high-frequency data and treat the realized correlation as the dependent variable in a univariate quantile regression. This is in line with recent studies on realized volatility e.g. Andersen, Bollerslev, Diebold, and Vega (2004), Andersen, Bollerslev, Diebold, and Labys (2003), and Barndorff-Nielsen and Sheppard (2004). Methodologically, an attractive feature of keeping the realized correlation in the left side of the regression equation is that this facilitates exploring the impact of economic variables on its time series.

The present paper also draws on recent approaches in the financial literature that use information in large sets of macro-finance data to predict asset returns. For example, Goyal and Welch (2008) shows that a long list of US equity premium predictors from the literature is unable to outperform a simple forecast based on the historical average out-of-sample. Interestingly, Ludvigson and Ng (2007) and Ludvigson and Ng (2009) use dynamic factor analysis to study the ability of a large set of macroeconomic indicators to explain equity and bond risk premia, respectively. As shown by Stock and Watson (2002) and others, a large amount of economic information is summarized by few estimated factors. Ludvigson and Ng (2009) and Ludvigson and Ng (2009) find that the factors have important forecasting power for both equity and bond risk premia. In line with this research, we adopt a quantile regression with factor-augmented predictors similar to Ando and Tsay (2011).

Our empirical results are summarized as follows. The autoregressive component of the realized correlation is sizeable at all quantiles. In-sample results show that macro-finance variables are significant at the lower quantiles (up to the median) of the realized correlation. Even better results are obtained by using a factor model. The in-sample predictability is strongest at the lower to median quantiles. Out-of-sample analysis shows that the factor model delivers more accurate forecasts than individual macro-finance predictors, particularly at the upper and median quantiles.

2 Quantiles Regression Model

Why do we need the quantile regression model? Suppose that we are interested in the tails of the realized stock-bond correlation. The ordinary least squares (OLS) method would come to the conclusion that in spite of different correlation levels, the various economic forces affect the correlation in exactly the *same* way. However, if there is variability in the effects across the distribution it will not be captured by the OLS method. For example, the median is a quantile of particular importance that allows for direct comparison to the OLS regression. It is well known that outliers may have a much larger effect on the mean of a distribution than on the median. Hence, the quantile approach can provide more robust results than OLS regressions even for the middle of the distribution.

In the quantile regression for the correlation, the two extreme quantiles 0.1 and 0.9 correspond to large negative and large positive realized stock-bond correlations. In addition, we analyze the median quantile 0.5. To obtain a sufficiently detailed picture of the correlation dynamics, we analyze a grid of quantiles, namely the following quantiles $\tau = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$. This is to understand how far from the mean we have to be until the behavior of the stock-bond correlation is different.

The 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 and ε_t^τ is the error term, which is allowed to have a different distribution across the quantiles. Note that the local effect X_t' on the τ-quantile is assumed to be linear. However, since the slope coefficient vector β^{τ} too differs across quantiles, the model can be seen as a flexible non-linear specification for the stock-bond correlation. To obtain estimates of the conditional quantile function, we solve

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

The quantile function is estimated by minimizing a weighted sum of absolute residuals, where the weights are functions of the quantile of interest. The coefficient estimates are computed by using linear programming methods (for more details, see Koenker (2005)). We use bootstrap to compute standard errors of the estimates.

Note that the effects from a given explanatory variable are very different at the two tails due to the distinctive features of the correlation variable. At the lower quantile (0.1) the realized correlation is large negative and at the upper quantile (0.9) it is large positive. A positive effect from variable i at the left tail ($\widehat{\beta}_i^{0.1} > 0$) implies that the greater variable i is, the weaker 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 ($\widehat{\beta}_i^{0.9} > 0$) from variable i implies that the realized stock-bond correlation is stronger the larger variable i is. Similar properties hold for negative effects from variable j. At the left tail, a negative effect ($\widehat{\beta}_j^{0.1} < 0$) implies stronger correlation when variable j increases and at the right tail $\widehat{\beta}_j^{0.9} < 0$ it implies weaker correlation.

3 Data

Our empirical analysis uses monthly data over the period $1983M02-2010M12$, which gives rise to 335 observations.[1] This relatively long sample is important in order to get precise estimates in the tails of the stock-bond distribution.

3.1 Realized 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 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 are used in the literature by

[1] The beginning of sample is when the Treasury Note futures start trading.

Ranaldo and Söderlind (2010), Christiansen, Ranaldo, and Söderlind (2011), and Bansal, Connolly, and Stivers (2010).

More specifically, 5-minute returns are used to calculate the monthly realized stock-bond correlation. We use the Fisher transformation of the correlation that is not bounded between -1 and 1; $C_t = \frac{1}{2}\ln\left(\frac{1+cor_t}{1-cor_t}\right)$, where cor_t is the realized 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 shows the summary statistics of the realized stock-bond correlation. The mean is close to zero (0.03) which is caused by variations of large negative and large positive stock-bond correlations. Nevertheless, the correlation is often negative as indicated by the negative skewness of -0.45. The time series plot of the correlation is shown in Figure 1. Figure 1 displays a great deal of high-frequency variation, with its sign changing several times during the observed period. But it also shows substantial low-frequency movements, with values averaging around 0.4 in the 1980s, a spike in the early mid-1990s, and negative average values in the 2000s. During the two downturns of 2001-2003 and 2008-2009, the average realized stock-bond correlation is about -0.5. Thus from peak to trough, the realized correlation on average declines by about 0.9 and changes its sign.

3.2 Explanatory Variables

In Table 2 we list the explanatory variables and their associated symbols. The explanatory variables are mainly the ones used in Goyal and Welch (2008).[2] In addition, we use the Cochrane and Piazzesi (2005) forward-rate factor and the VIX volatility index.[3] Details regarding the variables are provided in the Appendix. All variables are standardized to have zero mean and unit variance. This set of state variables is previously used in the literature on predictability of asset returns. For example, Goyal and Welch (2008) provide a comprehensive study of these variables' ability to predict the equity premium. Cenesizoglu and Timmermann (2011) employ the Goyal and Welch (2008) variables to examine predictability of the entire stock return distribution. Pedersen (2010) uses a similar set of state variables to predict

[2] We are most grateful that the data are publicly available at the home page of Goyal.

[3] The volatility index (symbol VXO at CBOE) based upon SP100 options is only available from $1986M07$. So for this explanatory variable the sample period is somewhat shorter. The now more popular volatility index based upon SP500 options (symbol VIX on CBOE) is available in an even shorter period beginning $1990M02$.

stock and bond returns in a multivariate framework using quantile regressions. Christiansen, Schrimpf, and Schmeling (forthcoming) use these (and further variables) to predict financial (including stock and bond) volatility.

[Insert Table 2 about here]

The predictor variables contain valuation ratios (DP, DY, EP, and BM), corporate finance variables (DE and $NTIS$), bond yield measures (TBL, LTY, LTR, TMS, DFY, DRF, and CP), and inflation ($INFL$) as a broad macroeconomic indicator. $SVAR$ is a measure of current stock market volatility while the VIX index is a measure of expected future volatility.

4 Empirical Findings

First, we show the in-sample results using simple model specifications and second using a factor model specification. Third, we provide out-of-sample analysis. Fourth, we investigate the recent financial crisis.

4.1 Simple Models

Initially, we consider the explanatory power of each macro-finance variable one at a time in what we call the simple models. The lagged correlation is added to account for any autoregressive component which it is important to account for when considering predictability of financial volatility, cf. Christiansen, Schrimpf, and Schmeling (forthcoming) and Paye (forthcoming). As benchmarks we consider the time-invariant quantile model - known as the prevailing quantile (PQ) model - as well as a quantile AR(1) specification where the only explanatory variable is the lagged realized correlation. Table 3 holds the results.

[Insert Table 3 about here]

The estimated constants and lagged realized correlation coefficients are about the same for all models. For instance, for the DP-model, the estimated constant varies from -0.20 at the lowest quantile to 0.19 at the highest quantile. The coefficients on the lagged realized correlation are highly significant and show strong autoregressive dynamics, particularly at the lower quantiles.

Interestingly, most macro-finance variables are only significant in explaining the behavior of the lower quantiles (up to the median) of the realized correlation. For the upper quantiles most of the state variables provide little information about the stock-bond correlation. Thus, fundamentals are more important when the stock-bond correlation is negative, that is when diversification benefits are high.

On the other hand, some variables are not significant at any of the quantiles, namely the dividend payout ratio (DE), net equity expansion ($NTIS$), term spread (TMS), default yield spread (DFY), inflation ($INFL$), Cochrane-Piazzesi factor (CP), and the volatility index (VIX). For the term spread and the VIX index this result is surprising, given their prominence in the literature on means predictability, e.g. Aslanidis and Christiansen (2012), and Viceira (2012).

Focusing on the significant regressors, the dividend price ratio (DP) has a positive effect upon the correlation with the effect being stronger at the lower quantiles (up to the median). This implies that lower dividend price ratios are associated with more extreme (negative) correlations. The same behavior holds true for the three other valuation ratios, that is, the dividend yield (DY), the earnings price ratio (EP), and the book to market ratio (BM). Similar results apply to some bond yield measures such as the T-bill rate (TBL), the long term yield (LTY), and the default return spread (DFR). The latter finding is consistent with the findings of Viceira (2012) and Aslanidis and Christiansen (2012).

In contrast to the strong evidence of predictability in the lower to medium quantiles there is little evidence of predictability at the upper quantiles. Only the long term return (LTR) is significant at the upper quantiles (from the median to the 0.8 quantile). Here the effect is negative suggesting that higher long term interest rates are associated with a weaker stock-bond correlation.

Stock market volatility ($SVAR$) generally has a significant and negative effect at the middle quantiles (0.4 and 0.5).

The explanatory power of the quantile regressions is relatively high but this is mainly due to the autoregressive component. For instance, for the dividend yield (DY) at the 0.1 quantile the pseudo R-squared value is 0.57 which compares to 0.54 obtained using the quantile AR(1) model. Similarly, for the rest of the quantiles the pseudo R-squared value increases only little once we include the additional regressor. The fit of the models is highest at the middle quantiles ($\tau = \{0.3, .., 0.6\}$) and lowest at the extreme quantiles.

We perform the Wald test proposed by Koenker and Basset (1982) that test for the equality of the slope coefficients at the median and the two extreme quantiles $\tau = \{0.1, 0.5, 0.9\}$. The χ^2 statistics are generally significant at conventional test levels. Thus, we conclude there are significant differences between the behavior at the median and the two extreme quantiles. Thereby, quantile regressions provide additional information compared to only considering predictability of conditional means within an OLS regression framework.

4.2 Constructing Factors

We use factor analysis to consider the joint effect of the macro-finance state variables. Recent empirical research advocates the use of dynamic factor models to study the ability of a large set of economic indicators to explain equity and bond risk premia (e.g. Ludvigson and Ng (2007) and Ludvigson and Ng (2009)). Therefore, we adopt a quantile regression with factor-augmented predictors.

The estimation of factors is carried out by principal components analysis using all the macro-finance variables except for those that are not significant in any of the quantile regressions in Table 2. Furthermore, we only include DP and not DY due to their very strong correlation (above 0.99). Thus, we construct the principal components from the following variables: DP, EP, $SVAR$, BM, TBL, LTY, LTR, and DFR. We follow Ludvigson and Ng (2009) and use the observations for the entire sample period to form the principal components for the in-sample analysis, while for the out-of-sample analysis we re-estimate the factors recursively each period.

We focus on the first three factors that explain 81% of the total variation in macro-finance variables during the entire sample period, cf. the Appendix. We denote the first three factors $PC1$, $PC2$, and $PC3$.

[Insert Table 4 about here]

[Insert Figure 2 about here]

Table 4 shows the factor loadings for the first three principal components. The first factor has large positive loadings on the dividend price ratio, the earnings price ratio, the book to market ratio, the T-bill rate, and the long term yield. The second factor has a large positive loading on the long term return and a large negative loading on the default return spread. The third principal component loads most heavily on the stock variance. So, all the variables enter strongly into either of the first three principal components. Although any labeling of the factors is imperfect, nevertheless our three factors capture relevant macro-finance information. The first factor represents the joint stock and bond market, the second factor represents the bond market, and the third factor represents the market uncertainty.

Figure 2 shows the time series of the three factors. The first factor shows low frequency patterns whereas the second and third factors show high frequency time variation.

4.3 Factor Model Analysis

[Insert Table 5 about here]

Table 5 shows the results from estimating the factor model for each of the quantiles as well as the OLS regression. The explanatory power of the quantile model improves compared to the simple models. The pseudo R-squared values range from 0.52 to 0.66. Thus, using a collection of macro-finance state variables implies an economically larger degree of predictability of the stock-bond correlation distribution than using just one of the macro-finance variables. Moreover, the autoregressive dynamics are weaker in the factor models compared to the individual models. This is also an indication that combining information in the macro-finance variables is important in explaining the future realized stock-bond correlation.

[Insert Figure 3 about here]

Figure 3 shows the coefficient estimates with confidence intervals (based on bootstrap standard errors) across quantiles for the factor model.

The first factor ($PC1$) is significant at the lower and middle quantiles (0.1 to 0.7). The estimated coefficients to $PC1$ are positive at all quantiles. So, for large negative correlations, the larger the first factor is, the less strong is the correlation. Thus, at the lower quantiles, the joint stock and bond market factor has a dampening effect on the stock-bond correlation.

The second factor ($PC2$) is significant at the same quantiles as the first factor (0.1 to 0.7). The estimated coefficients to $PC2$ are negative at all quantiles. So, for large negative correlations, the larger the second factor is, the more extreme negative is the correlation. $PC1$ and $PC2$ thereby have opposite effects. At the lower quantiles, the bond market factor has a strengthening effect on the stock-bond correlation, which makes bonds even better hedges against stocks.

The third factor ($PC3$) is only significant at the quantiles below the median (0.1 to 0.4). The estimated coefficients to $PC3$ are always negative. Thus, the third factor works in a similar manner to the second factor. Again, at the lower quantiles, the stock market uncertainty has a strengthening effect on the stock-bond correlation, which shows "flight-to safety" behavior, e.g. Connolly, Stivers, and Sun (2005).

For the lower quantiles, the realized correlation has the largest factor loadings for $PC2$, while $PC3$ has somewhat stronger factor loadings than $PC1$. This means that at the lower quantiles (0.1 to 0.7) the bond market as represented by the second factor has the strongest influence on the stock-bond correlation. Market uncertainty as represented by the third factor has slightly stronger influence on the stock-bond correlation at the 0.1 to 0.4 quantiles than the joint stock and bond market as represented by the first factor.

At the upper quantiles (0.8 to 0.9) neither of the factors are significant. Thus, at the upper quantiles, only the autoregressive component explains the stock-bond correlation. The macro-finance factors have no influence upon the stock-bond correlation when it is strongly positive. This is similar to the findings from the simple models and the factor model does not provide any improvements here.

The behavior at the median quantile is quite similar to that obtained from the OLS regression.

4.4 Out-of-Sample Results

We conduct out-of-sample analysis using an expanding window, where all parameters and factors are estimated recursively. For quantile regressions, a long sample period is essential in order to have enough tail data, and this is best ensured with an expanding window. The initialization period is $1983M02$ - $2002M12$. Then, we produce 1-step ahead quantile forecasts for the realized correlation for the following month $2003M01$. Subsequently, the estimation window is expanded with one further observation and the out-of-sample forecasting is repeated. So, the out-of-sample forecasting period runs from $2003M01$ to $2010M12$, thus providing 96 forecasts for each quantile.

Figure 4 plots the time series of the $0.1, 0.5$ and 0.9 quantile forecasts based on the PQ, the AR(1), and the factor model. At the 0.1 quantile, the AR(1) forecast is typically below the factor model forecast, except for the period around the financial crisis. There is considerable variation over time in the conditional quantiles. Moreover, for the factor model during the recent financial turmoil this variation is much stronger in the lower tail than in the upper tail. This is possibly due to the very high levels of stock market volatility, which turn the lower tail extremely negative; a similar picture is obtained when $SVAR$ is the only predictor (results available upon request).

[Insert Figure 4 about here]

Table 6 reports out-of-sample coverage probabilities for each year in the out-of-sample period as well as for the entire period, cf. the unconditional coverage probabilities in Cenesizoglu and Timmermann (2011).[4] The coverage probability is the proportion of the realized stock-bond correlation that falls below the predicted quantile. If the model performs well out-of-sample, the coverage ratios should be close to their correct values, i.e. roughly 10%

[4]We do not apply the Diebold and Mariano (1995) type of loss differentials analysis as in e.g. Pedersen (2010) because there are too few out-of-sample observations to render this analysis reliable.

of correlations fall below the 0.1 quantile forecasts. Still, there are only 96 out-of-sample observations, so adequate caution should be given when interpreting the results.

The predicted models are not perfect. Nevertheless, all quantile models improve substantially on the PQ model. As expected, the PQ model appears to be highly mispecified.

Focusing on the entire period and at the lower quantile, for most of the simple models the coverage ratios are close to their correct values. The factor and $SVAR$ specifications are not as accurate though, which confirms the result in Figure 4. For the 0.1 quantile it is the case, that the coverage probabilities are too large mainly in the most recent years, that is during and after the financial crisis. However, at the upper and median quantiles the factor model is far more accurate than other candidates providing the best coverage probabilities.

In the out-of-sample analysis, the factor model works best at the median to upper quantiles. This is in opposition to the in-sample results that point towards the factor model being best in the lower to median quantiles.

4.5 Effect of Financial Crisis

We investigate if the results are caused or disturbed by the recent financial crisis. For this, we consider a shorter sample period that ends before the financial crisis, namely $1983M02$ - $2006M12$. The in-sample results are shown in the Appendix. The results are generally similar to those for the full sample. We conclude that the in-sample results are not simply a reflection of the recent turmoil in the capital markets.

Based on the previous coverage probabilities, however, at the lower quantile the out-of-sample predictability appears to be somewhat worsened during and after the financial crisis.

5 Conclusion

This study looks further into the unexplored properties of the realized stock-bond correlation based upon high-frequency returns. First, we use quantile regressions to analyze the tails of the correlation. The behavior of the correlation at the median and the two extreme quantiles is significantly different, and quantile regressions are therefore preferable to conditional mean models. Second, we construct factors from the macro-finance variables using principal components in a quantile framework. Hereby, the explanatory power of the macro-finance variables improves. Third, factor models deliver more accurate out-of-sample forecasts that the single macro-finance predictors, particularly at the upper and median quantiles.

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A Data Description

[Insert Table A1 about here]

B Additional Results

[Insert Table A2 about here]

[Insert Table A3 about here]

[Insert Table A4 about here]

Table 1: Realized Stock-Bond Correlation Descriptive Statistics

	Correlation	Fisher transform
Mean	0.03	0.03
Max	0.67	0.81
Min	-0.77	-1.01
Standard deviation	0.37	0.41
Skewness	-0.39	-0.45
Kurtosis	1.90	2.17
Percent negative	43.6	43.6

The table shows summary statistics for the realized stock-bond correlation and its Fisher transform. The sample period is 1983M03-2010M12.

Table 2: Data Overview

Symbol	Name
DP	Dividend price ratio
DY	Dividend yield
EP	Earnings price ratio
DE	Dividend payout ratio
SVAR	Stock variance
BM	Book to market ratio
NTIS	Net equity expansion
TBL	T-bill rate
LTY	Long term yield
LTR	Long term return
TMS	Term spread
DFY	Default yield spread
DFR	Default return spread
INFL	Inflation
CP	Cochrane-Piazzesi factor
VIX	Volatility index

Table 3: In-Sample Quantile Regressions for Individual Models

	Q	cons	AR(1)	DP	DY	EP	DE	SVAR	BM	NTIS
cons	0.1	-0.569 ***	-0.197 ***	-0.199 ***	-0.203 ***	-0.189 ***	-0.207 ***	-0.200 ***	-0.198 ***	-0.196 ***
	0.2	-0.374 ***	-0.112 ***	-0.112 ***	-0.107 ***	-0.107 ***	-0.119 ***	-0.115 ***	-0.109 ***	-0.120 ***
	0.3	-0.209 ***	-0.064 ***	-0.066 ***	-0.066 ***	-0.059 ***	-0.059 ***	-0.063 ***	-0.066 ***	-0.061 ***
	0.4	-0.055	-0.027 ***	-0.026 **	-0.029 **	-0.027 ***	-0.027 ***	-0.032 ***	-0.025 **	0.028 ***
	0.5	0.138 ***	0.012	0.010	0.009	0.010	0.014	-0.002	0.009	0.013
	0.6	0.254 ***	0.061 ***	0.055 ***	0.049 ***	0.046 ***	0.054 ***	0.054 ***	0.051 ***	0.065 ***
	0.7	0.327 ***	0.096 ***	0.097 ***	0.096 ***	0.095 ***	0.095 ***	0.091 ***	0.094 ***	0.093 ***
	0.8	0.392 ***	0.132 ***	0.133 ***	0.133 ***	0.133 ***	0.134 ***	0.134 ***	0.135 ***	0.137 ***
	0.9	0.481 ***	0.185 ***	0.189 ***	0.189 ***	0.188 ***	0.186 ***	0.190 ***	0.190 ***	0.184 ***
C lagged	0.1		0.994 ***	0.923 ***	0.874 ***	0.980 ***	0.977 ***	0.889 ***	0.941 ***	0.978 ***
	0.2		0.983 ***	0.934 ***	0.920 ***	0.935 ***	1.003 ***	0.934 ***	0.970 ***	1.003 ***
	0.3		0.981 ***	0.918 ***	0.912 ***	0.916 ***	0.981 ***	0.926 ***	0.951 ***	0.982 ***
	0.4		0.957 ***	0.905 ***	0.885 **	0.915 ***	0.958 ***	0.914 ***	0.925 ***	0.956 ***
	0.5		0.928 ***	0.896 ***	0.889	0.881 ***	0.930 ***	0.907 ***	0.908 ***	0.936 ***
	0.6		0.865 ***	0.854 ***	0.843 ***	0.856 ***	0.882 ***	0.859 ***	0.881 ***	0.869 ***
	0.7		0.836 ***	0.817 ***	0.815 ***	0.816 ***	0.835 ***	0.821 ***	0.835 ***	0.839 ***
	0.8		0.856 ***	0.844 ***	0.843 ***	0.849 ***	0.856 ***	0.858 ***	0.864 ***	0.844 ***
	0.9		0.839 ***	0.829 ***	0.829 ***	0.833 ***	0.838 ***	0.832 ***	0.851 ***	0.814 ***
X lagged	0.1			0.058 ***	0.078 ***	0.021	0.022 *	-0.173 *	0.053 **	0.005
	0.2			0.046 ***	0.054 ***	0.034 **	0.006	-0.081	0.029 **	-0.017
	0.3			0.042 ***	0.049 ***	0.033 ***	-0.007	-0.065 *	0.031 ***	-0.010
	0.4			0.031 **	0.039 ***	0.034 ***	-0.012	-0.068 **	0.023 ***	-0.002
	0.5			0.028 ***	0.031 ***	0.035 ***	-0.009	-0.070 **	0.021 ***	-0.008
	0.6			0.016	0.024 *	0.025 **	-0.019	-0.028	0.009	0.014
	0.7			0.011	0.012	0.011	-0.004	-0.030	0.004	0.011
	0.8			0.006	0.007	0.003	0.006	0.006	-0.007	0.019 *
	0.9			0.006	0.006	0.006	-0.003	-0.001	-0.015	0.012
Pseudo	0.1		0.54	0.56	0.57	0.54	0.54	0.58	0.55	0.54
R-squared	0.2		0.60	0.62	0.62	0.61	0.60	0.63	0.61	0.61
	0.3		0.63	0.64	0.64	0.64	0.63	0.65	0.64	0.63
	0.4		0.64	0.64	0.65	0.65	0.64	0.65	0.64	0.64
	0.5		0.63	0.64	0.64	0.64	0.63	0.64	0.63	0.63
	0.6		0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61
	0.7		0.58	0.59	0.59	0.59	0.58	0.59	0.59	0.59
	0.8		0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
	0.9		0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.52
Slope equality test			9.3 ***	13.8 ***	15.7 ***	11.0 **	13.5 ***	12.0 **	25.4 ***	13.1 **

	Q	TBL	LTY	LTR	TMS	DFY	DFR	INFL	CP	VIX
cons	0.1	-0.200 ***	-0.203 ***	-0.187 ***	-0.214 ***	-0.190 ***	-0.204 ***	-0.188 ***	-0.195 ***	-0.209 ***
	0.2	-0.109 ***	-0.110 ***	-0.113 ***	-0.109 ***	-0.116 ***	-0.114 ***	-0.115 ***	-0.118 ***	-0.131 ***
	0.3	-0.059 ***	-0.062 ***	-0.065 ***	-0.065 ***	-0.065 ***	-0.062 ***	-0.065 ***	-0.063 ***	-0.072 ***
	0.4	-0.024 **	-0.029 ***	-0.024 ***	-0.028 ***	-0.025 ***	-0.027 ***	-0.025 ***	-0.027 ***	-0.031 ***
	0.5	0.012	0.009	0.013	0.012	0.010	0.006	0.007	0.011	0.003
	0.6	0.055 ***	0.052 ***	0.055 ***	0.051 ***	0.060 ***	0.049 ***	0.053 ***	0.060 ***	0.055 ***
	0.7	0.090 ***	0.094 ***	0.092 ***	0.092 ***	0.094 ***	0.092 ***	0.094 ***	0.096 ***	0.089 ***
	0.8	0.131 ***	0.132 ***	0.133 ***	0.132 ***	0.133 ***	0.128 ***	0.130 ***	0.132 ***	0.137 ***
	0.9	0.189 ***	0.192 ***	0.189 ***	0.189 ***	0.189 ***	0.190 ***	0.192 ***	0.187 ***	0.207 ***
C lagged	0.1	0.994 ***	0.855 ***	0.998 ***	1.021 ***	1.010 ***	0.966 ***	0.984 ***	0.991 ***	0.973 ***
	0.2	0.943 ***	0.893 ***	0.974 ***	0.984 ***	1.000 ***	0.961 ***	0.991 ***	0.966 ***	0.984 ***
	0.3	0.908 ***	0.916 ***	0.967 ***	0.983 ***	0.985 ***	0.951 ***	0.983 ***	0.963 ***	0.953 ***
	0.4	0.898 ***	0.910 ***	0.953 ***	0.959 ***	0.960 ***	0.966 ***	0.954 ***	0.955 ***	0.948 ***
	0.5	0.852 ***	0.871 ***	0.927 ***	0.927 ***	0.935 ***	0.945 ***	0.933 ***	0.926 ***	0.914 ***
	0.6	0.819 ***	0.839 ***	0.910 ***	0.882 ***	0.865 ***	0.902 ***	0.896 ***	0.865 ***	0.880 ***
	0.7	0.825 ***	0.810 ***	0.850 ***	0.838 ***	0.838 ***	0.850 ***	0.869 ***	0.839 ***	0.845 ***
	0.8	0.830 ***	0.838 ***	0.845 ***	0.855 ***	0.853 ***	0.864 ***	0.857 ***	0.859 ***	0.863 ***
	0.9	0.823 ***	0.798 ***	0.823 ***	0.837 ***	0.830 ***	0.848 ***	0.826 ***	0.842 ***	0.882 ***
X lagged	0.1	-0.005	0.073 **	-0.016	0.037 *	0.014	0.060 **	-0.018	0.038 *	0.002
	0.2	0.036 **	0.051 ***	-0.034 *	0.004	0.005	0.044 ***	-0.008	0.024	0.010
	0.3	0.036 ***	0.036 ***	-0.019	0.002	0.002	0.034 ***	0.000	0.013	-0.010
	0.4	0.030 **	0.029 ***	-0.014	-0.003	0.005	0.029 ***	-0.005	0.001	-0.002
	0.5	0.038 ***	0.031 ***	-0.023 **	-0.001	0.012	0.032 **	-0.008	0.003	-0.003
	0.6	0.028 ***	0.025 **	-0.028 **	-0.006	0.001	0.041 ***	-0.016	0.000	0.009
	0.7	0.015	0.017 *	-0.016 *	-0.004	-0.007	0.022	-0.019	0.002	0.008
	0.8	0.013	0.012	-0.028 ***	-0.003	-0.005	0.028	-0.013	0.004	0.012
	0.9	0.013	0.029	-0.030 *	-0.004	-0.003	0.017	0.006	-0.006	0.022
Pseudo	0.1	0.54	0.55	0.54	0.55	0.54	0.55	0.54	0.55	0.50
R-squared	0.2	0.61	0.61	0.61	0.60	0.60	0.62	0.61	0.61	0.58
	0.3	0.64	0.64	0.63	0.63	0.63	0.64	0.63	0.63	0.61
	0.4	0.64	0.65	0.64	0.64	0.64	0.65	0.64	0.64	0.62
	0.5	0.64	0.64	0.63	0.63	0.63	0.64	0.63	0.63	0.63
	0.6	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61
	0.7	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.58	0.59
	0.8	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
	0.9	0.52	0.52	0.52	0.51	0.51	0.52	0.52	0.51	0.52
Slope equality test		9.8 **	10.6 **	14.8 ***	19.1 ***	13.9 ***	8.3 *	14.4 ***	20.2 ***	5.1

The table shows the results from estimating quantile regressions for each of the explanatory variables (X). With the exception of the VIX model (1986M08-2010M12), estimation period is 1983M03-2010M12. The slope equality test statistic compares the 0.1, 0.5, and 0.9 quantiles. ***/**/* indicates that the variable is significant at the 1%/5%/10% level (based on bootstrapped standard errors).

Table 4: Factor Loadings for Principal Components

	PC1	PC2	PC3
DP	0.43	0.02	0.35
EP	0.41	0.04	-0.25
SVAR	-0.12	0.32	0.80
BM	0.46	0.01	0.25
TBL	0.43	0.00	-0.17
LTY	0.48	-0.06	0.05
LTR	0.05	0.66	-0.15
DFR	-0.02	-0.67	0.23

The table shows the factor loadings for the first three principal components for the sample period 1983M3-2010M12.

Table 5: In-Sample Quantile Regressions for Factor Models

Q	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	OLS
cons	-0.193 ***	-0.109 ***	-0.067 ***	-0.030 ***	0.002	0.045 ***	0.089 ***	0.132 ***	0.189 ***	0.006
C lagged	0.768 ***	0.854 ***	0.860 ***	0.868 ***	0.833 ***	0.826 ***	0.814 ***	0.841 ***	0.841 ***	0.815 ***
PC1(-1)	0.040 ***	0.029 ***	0.028 ***	0.023 ***	0.023 ***	0.019 ***	0.015 **	0.004	0.004	0.024 ***
PC2(-1)	-0.087 ***	-0.053 ***	-0.050 ***	-0.030 ***	-0.032 ***	-0.039 ***	-0.028 **	-0.021 *	-0.024	-0.039 ***
PC3(-1)	-0.069 **	-0.040 **	-0.048 ***	-0.039 **	-0.046 *	-0.027	-0.006	0.013	0.008	-0.010
Pseudo R-squared	0.60	0.64	0.66	0.66	0.65	0.62	0.60	0.57	0.52	0.84
Slope equility test					22.8 ***					

The table shows the results from estimating quantile and OLS regressions for the factor models for the sample period 1983M03-2010M12. The slope equality test statistic compares the 0.1, 0.5, and 0.9 quantiles. ***/**/* indicates that the variable is significant at the 1%/5%/10% level (based on bootstrapped standard errors).

Table 6: Out-of-Sample Analysis: Coverage Probabilities

0.1 Quantile

	2003	2004	2005	2006	2007	2008	2009	2010	2003-2010
PQ	0.500	0.083	0.000	0.000	0.417	0.917	0.000	0.250	0.271
AR(1)	0.000	0.167	0.083	0.083	0.250	0.083	0.083	0.167	0.115
DP	0.000	0.000	0.083	0.083	0.250	0.167	0.250	0.167	0.125
DY	0.000	0.083	0.083	0.083	0.333	0.333	0.250	0.250	0.177
EP	0.000	0.167	0.083	0.083	0.417	0.167	0.000	0.333	0.156
DE	0.000	0.000	0.083	0.083	0.167	0.083	0.500	0.167	0.135
SVAR	0.167	0.333	0.167	0.250	0.333	0.000	0.000	0.250	0.188
BM	0.000	0.083	0.083	0.083	0.250	0.167	0.000	0.167	0.104
NTIS	0.000	0.083	0.083	0.083	0.250	0.000	0.000	0.167	0.083
TBL	0.000	0.167	0.083	0.083	0.250	0.083	0.083	0.167	0.115
LTY	0.000	0.000	0.083	0.083	0.250	0.000	0.000	0.167	0.073
LTR	0.000	0.167	0.083	0.083	0.250	0.167	0.167	0.167	0.135
TMS	0.000	0.167	0.083	0.083	0.250	0.000	0.083	0.167	0.104
DFY	0.000	0.000	0.083	0.083	0.250	0.167	0.250	0.167	0.125
DFR	0.000	0.083	0.083	0.083	0.250	0.000	0.167	0.167	0.104
INFL	0.000	0.167	0.083	0.083	0.333	0.083	0.083	0.167	0.125
CP	0.000	0.000	0.083	0.083	0.250	0.000	0.000	0.167	0.073
VIX	0.000	0.167	0.083	0.083	0.333	0.167	0.000	0.167	0.125
Factor Model	0.250	0.333	0.083	0.083	0.250	0.250	0.000	0.250	0.187

0.5 Quantile

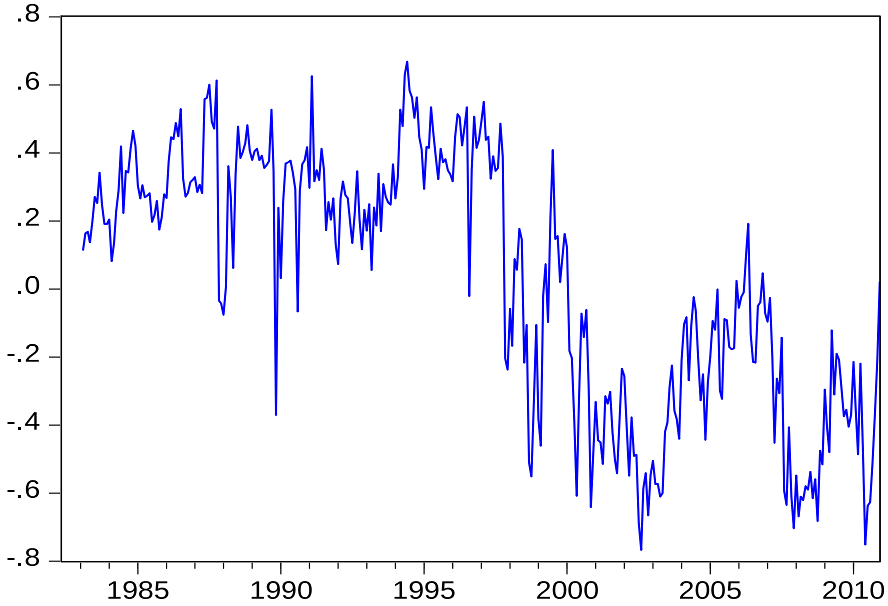
	2003	2004	2005	2006	2007	2008	2009	2010	2003-2010
PQ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
AR(1)	0.917	0.583	0.667	0.667	0.667	0.833	0.750	0.500	0.698
DP	0.750	0.417	0.583	0.500	0.667	0.833	0.750	0.417	0.615
DY	0.750	0.417	0.583	0.500	0.667	0.833	0.750	0.417	0.615
EP	0.750	0.583	0.583	0.667	0.667	0.833	0.500	0.583	0.646
DE	0.917	0.583	0.667	0.667	0.750	0.833	0.750	0.583	0.719
SVAR	0.833	0.583	0.667	0.667	0.667	0.750	0.750	0.417	0.667
BM	0.750	0.417	0.583	0.583	0.667	0.833	0.750	0.417	0.625
NTIS	0.833	0.583	0.667	0.667	0.750	0.833	0.750	0.417	0.688
TBL	0.583	0.417	0.583	0.583	0.667	0.583	0.583	0.417	0.552
LTY	0.750	0.417	0.583	0.417	0.667	0.833	0.750	0.417	0.604
LTR	0.917	0.500	0.583	0.667	0.667	0.833	0.750	0.417	0.667
TMS	0.750	0.500	0.583	0.667	0.750	0.833	0.750	0.417	0.656
DFY	0.833	0.500	0.583	0.667	0.667	0.833	0.833	0.417	0.667
DFR	0.833	0.500	0.583	0.583	0.667	0.750	0.833	0.417	0.646
INFL	0.917	0.667	0.583	0.667	0.750	0.833	0.750	0.500	0.708
CP	0.833	0.583	0.667	0.667	0.750	0.833	0.750	0.417	0.688
VIX	0.750	0.500	0.583	0.667	0.667	0.833	0.750	0.417	0.646
Factor Model	0.750	0.417	0.583	0.500	0.667	0.417	0.417	0.417	0.521

0.9 Quantile

	2003	2004	2005	2006	2007	2008	2009	2010	2003-2010
PQ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
AR(1)	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
DP	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
DY	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
EP	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
DE	1.000	1.000	1.000	1.000	1.000	1.000	0.833	1.000	0.979
SVAR	1.000	1.000	1.000	1.000	1.000	0.833	0.833	1.000	0.958
BM	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
NTIS	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
TBL	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
LTY	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
LTR	1.000	1.000	1.000	1.000	1.000	1.000	0.833	1.000	0.979
TMS	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
DFY	1.000	1.000	1.000	1.000	1.000	1.000	0.833	1.000	0.979
DFR	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
INFL	1.000	1.000	0.917	1.000	1.000	1.000	0.833	1.000	0.969
CP	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
VIX	1.000	1.000	1.000	1.000	1.000	1.000	0.917	1.000	0.990
Factor Model	1.000	1.000	0.917	1.000	1.000	0.917	0.833	1.000	0.958

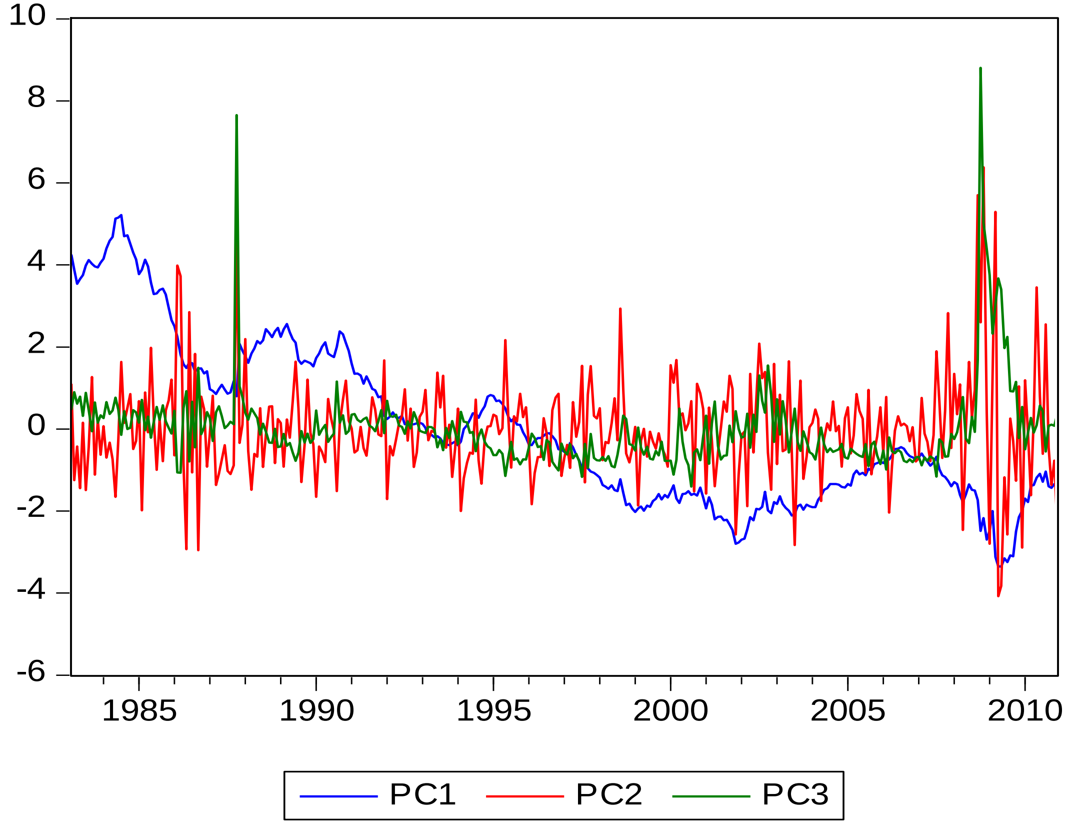
This table reports the proportion of realized stock-bond correlations for each year as well as for the entire out-of-sample period (2003M01 -2010M12) that falls below the predicted quantile. PQ indicates the prevailing quantile model.

Figure 1: Realized Stock-Bond Correlation



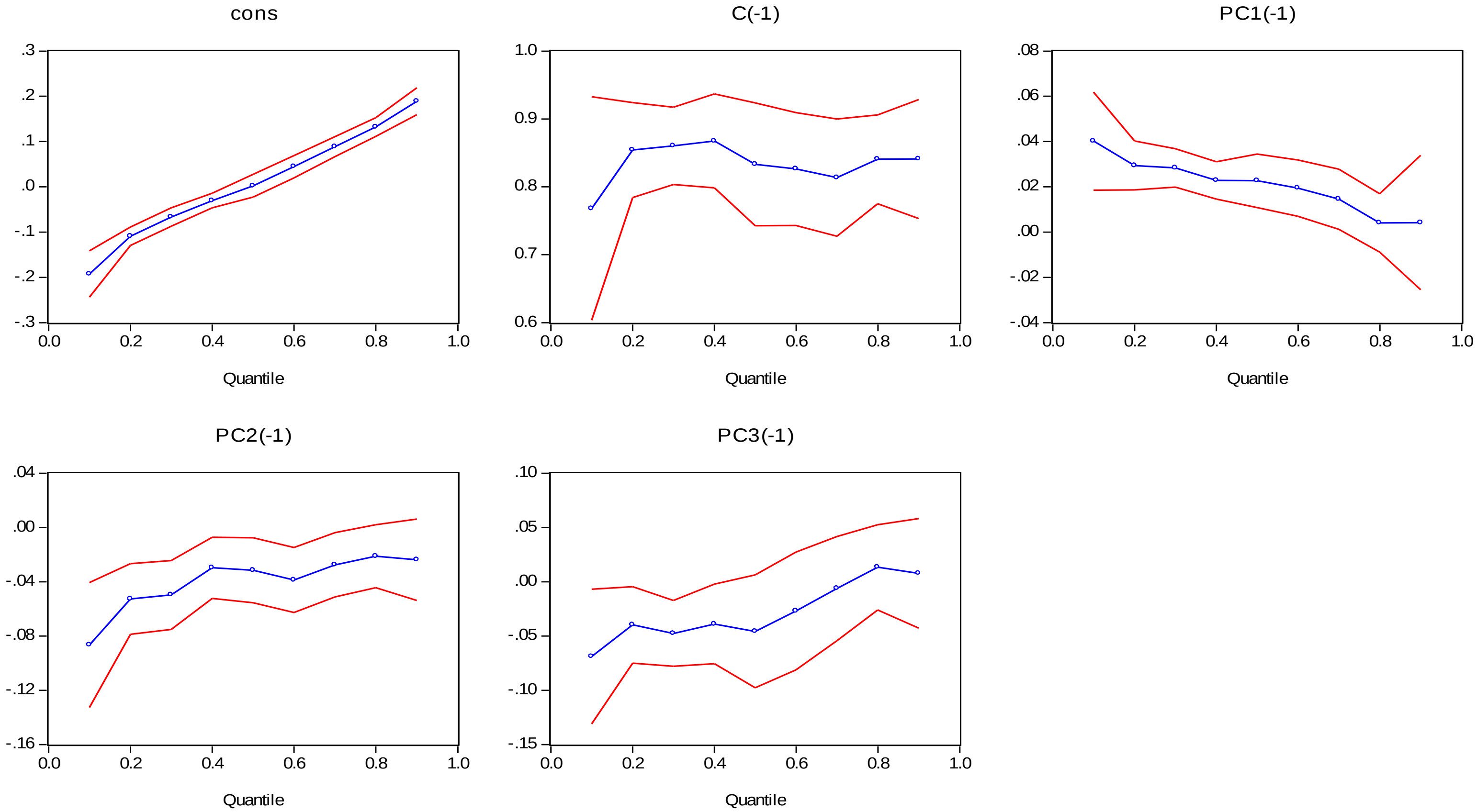
Notes: The figure shows the time series of the realized stock-bond correlation.

Figure 2: Time Series of Principal Components Factors



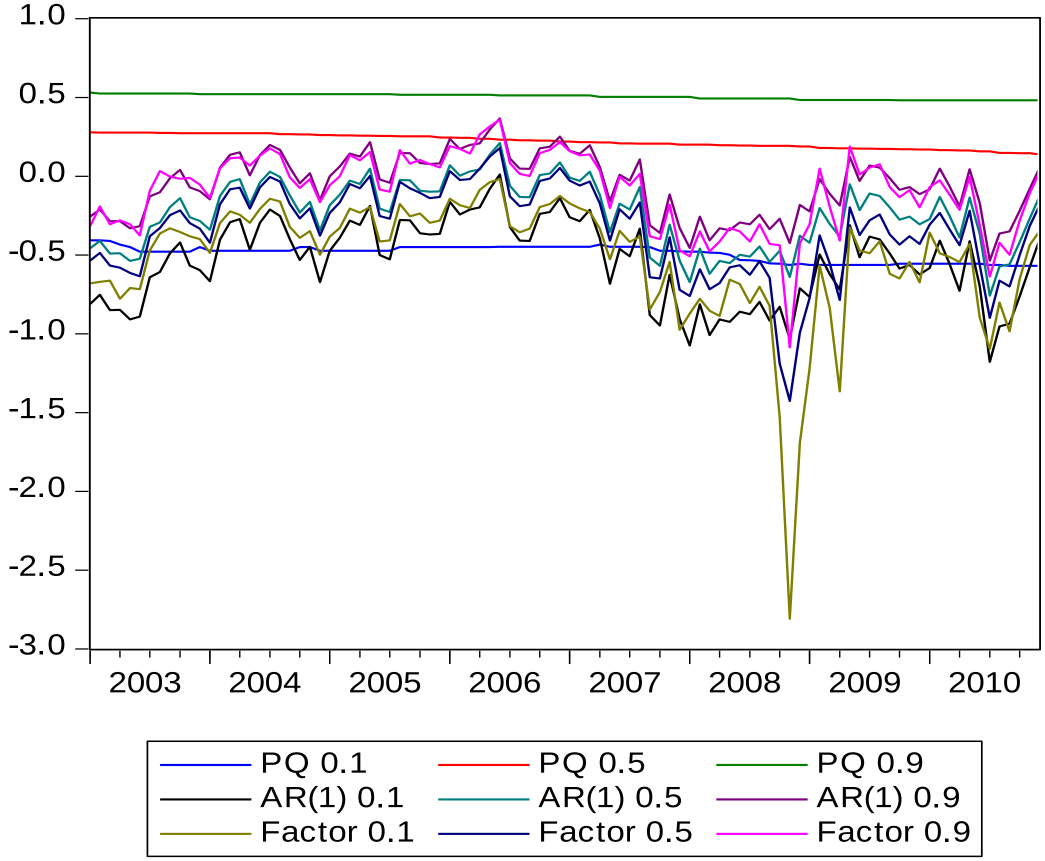
The figure shows the time series of the three factors.

Figure 3: Coeffients with 95% Confidence Intervals for Factor Model



The figure shows the estimated coefficents and their 95% confidence interval (based on bootstrap standard errors) for the factor model for the sample period 1983M03-2010M12.

Figure 4: Time Series of Quantile Forecasts from PQ, AR(1), and Factor Model



The figure shows the time series of the forecasted 0.1, 0.5, and 0.9 conditional quantiles from the PQ, AR(1), and factor model.

Table A1: Data Overview

Symbol	Name	Description
Explained variable		
C	Stock-bond correlation	High-frequency realized stock-bond correlation
Intermediate variables		
D	Dividends	12-month moving dividends at SP500
P	Stock price	SP500 index
E	Earnings	12-month moving earnings at SP500
BAA	BAA yield	BAA corporate bond yield
AAA	AAA yield	AAA corporate bond yield
CORP	Long term corporate bond retu	Long term corporate bond returns from Ibbotson
Explanatory variables		
DP	Dividend price ratio	ln(D) - ln(P)
DY	Dividend yield	ln(D) - ln(P lag)
EP	Earnings price ratio	ln(E)-ln(P)
DE	Dividend payout ratio	ln(D)-ln(E)
SVAR	Stock variance	Sum of squared daily returns on SP500
BM	Book to market ratio	Book to market ratio from Dow Jones Industrial Average
NTIS	Net equity expansion	12-month moving sum of net issues at NYSE divided by the total market value at NYSE
TBL	T-bill rate	3-month Treasury bill secondary market rate
LTY	Long term yield	Long term government bond yield from Ibbotson
LTR	Long term return	Long term government bond return from Ibbotson
TMS	Term spread	LTY-TBL
DFY	Default yield spread	BAA-AAA
DFR	Default return spread	CORP-LTR
INFL	Inflation	Consumer price index (all urban consumers) from Bureau of Labor Statistics
CP	Cochrane-Piazzesi factor	Measure of bond risk premia calculated from the term structure of forward rates
VIX	Volatility index	Volatility index from Chicago Board of Exhange based upon SP100 options (VXO)

Table A2: Explanatory Power for the Principal Components

PC no	Cummulative Prop.
1	0.48
2	0.68
3	0.81
4	0.88
5	0.93
6	0.98
7	0.99
8	1.00

The table shows the cummulative explanatory power for the principal components based on significant variables in Table 2 for the sample period 1983M03-2010M12.

Table A3: In-Sample Quantile Regressions for Individual Models, Sub-Sample 1983-2006

	Q	cons	AR(1)	DP	DY	EP	DE	SVAR	BM	NTIS
cons	0.1	-0.448 ***	-0.185 ***	-0.157 ***	-0.158 ***	-0.163 ***	-0.199 ***	-0.215 ***	-0.171 ***	-0.180 ***
	0.2	-0.220 ***	-0.106 ***	-0.086 ***	-0.088 ***	-0.096 ***	-0.101 ***	-0.112 ***	-0.090 ***	-0.098 ***
	0.3	-0.062	-0.047 ***	-0.057 ***	-0.053 ***	-0.052 ***	-0.047 ***	-0.071 ***	-0.056 ***	-0.046 ***
	0.4	0.117 **	-0.023 **	-0.012	-0.012	-0.023 ***	-0.023 *	-0.034 ***	-0.020 *	-0.017
	0.5	0.221 ***	0.013	0.013	0.012	0.014	0.014	0.001	0.010	0.019
	0.6	0.289 ***	0.067 ***	0.062 ***	0.061 ***	0.059 ***	0.067 ***	0.052 ***	0.065 ***	0.067 ***
	0.7	0.356 ***	0.100 ***	0.101 ***	0.101 ***	0.098 ***	0.097 ***	0.087 ***	0.099 ***	0.098 ***
	0.8	0.412 ***	0.138 ***	0.137 ***	0.136 ***	0.137 ***	0.140 ***	0.126 ***	0.140 ***	0.138 ***
	0.9	0.512 ***	0.190 ***	0.192 ***	0.192 ***	0.189 ***	0.193 ***	0.187 ***	0.189 ***	0.182 ***
C lagged	0.1		0.983 ***	0.819 ***	0.781 ***	0.904 ***	0.983 ***	0.889 ***	0.867 ***	0.978 ***
	0.2		0.980 ***	0.869 ***	0.853 ***	0.889 ***	0.981 ***	0.869 ***	0.933 ***	0.976 ***
	0.3		0.943 ***	0.903 ***	0.887 ***	0.865 ***	0.943 ***	0.875 ***	0.933 ***	0.952 ***
	0.4		0.950 ***	0.859 ***	0.853 ***	0.896 ***	0.950 ***	0.897 ***	0.920 ***	0.935 ***
	0.5		0.926 ***	0.898 ***	0.881 ***	0.860 ***	0.927 ***	0.911 ***	0.911 ***	0.911 ***
	0.6		0.852 ***	0.830 ***	0.825 ***	0.819 ***	0.852 ***	0.843 ***	0.858 ***	0.852 ***
	0.7		0.837 ***	0.805 ***	0.803 ***	0.821 ***	0.836 ***	0.805 ***	0.824 ***	0.825 ***
	0.8		0.846 ***	0.838 ***	0.834 ***	0.845 ***	0.849 ***	0.822 ***	0.860 ***	0.845 ***
	0.9		0.831 ***	0.825 ***	0.826 ***	0.831 ***	0.825 ***	0.809 ***	0.855 ***	0.817 ***
X lagged	0.1			0.075 ***	0.091 ***	0.079 **	0.029	-0.323 ***	0.052 **	-0.008
	0.2			0.056 ***	0.063 ***	0.060 ***	0.017	-0.170 **	0.032 ***	-0.026 *
	0.3			0.046 ***	0.047 ***	0.059 ***	0.007	-0.142 **	0.029 ***	-0.015
	0.4			0.037 ***	0.038 ***	0.044 ***	0.001	-0.107 **	0.021 ***	-0.018 *
	0.5			0.028 ***	0.032 ***	0.042 ***	0.002	-0.071	0.016 **	-0.015 *
	0.6			0.018	0.021	0.026	0.006	-0.071	0.003	0.000
	0.7			0.012	0.012	0.007	0.014	-0.072 *	0.004	0.010
	0.8			0.004	0.007	0.001	0.016	-0.077 *	-0.010	0.019
	0.9			0.006	0.005	0.006	0.006	-0.037	-0.018	0.012
Pseudo	0.1		0.54	0.57	0.57	0.56	0.54	0.62	0.56	0.54
R-squared	0.2		0.60	0.62	0.62	0.61	0.60	0.64	0.61	0.60
	0.3		0.61	0.63	0.63	0.63	0.61	0.64	0.62	0.61
	0.4		0.61	0.62	0.62	0.62	0.61	0.63	0.62	0.61
	0.5		0.59	0.59	0.59	0.59	0.59	0.60	0.59	0.59
	0.6		0.56	0.56	0.56	0.56	0.56	0.57	0.56	0.56
	0.7		0.54	0.54	0.54	0.54	0.54	0.55	0.54	0.54
	0.8		0.50	0.50	0.50	0.50	0.50	0.51	0.51	0.51
	0.9		0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
Slope equality test			6.3 **	8.8 *	9.2 *	9.2 *	8.4 *	18.3 ***	15.0 ***	9.9 **

	Q	TBL	LTY	LTR	TMS	DFY	DFR	INFL	CP	VIX
cons	0.1	-0.185 ***	-0.192 ***	-0.177 ***	-0.194 ***	-0.179 ***	-0.185 ***	-0.182 ***	-0.195 ***	-0.201 ***
	0.2	-0.104 ***	-0.106 ***	-0.104 ***	-0.102 ***	-0.102 ***	-0.112 ***	-0.105 ***	-0.102 ***	-0.113 ***
	0.3	-0.056 ***	-0.048 ***	-0.050 ***	-0.046 ***	-0.049 ***	-0.048 ***	-0.046 ***	-0.053 ***	-0.056 ***
	0.4	-0.019 *	-0.025 **	-0.018 *	-0.021 **	-0.018 *	-0.021 *	-0.023 **	-0.022 **	-0.028 ***
	0.5	0.013	0.011	0.015	0.017	0.014	0.022	0.013	0.015	0.006
	0.6	0.057 ***	0.060 ***	0.068 ***	0.069 ***	0.067 ***	0.063 ***	0.066 ***	0.069 ***	0.062 ***
	0.7	0.091 ***	0.094 ***	0.096 ***	0.100 ***	0.098 ***	0.097 ***	0.098 ***	0.100 ***	0.099 ***
	0.8	0.138 ***	0.138 ***	0.140 ***	0.137 ***	0.137 ***	0.132 ***	0.137 ***	0.136 ***	0.140 ***
	0.9	0.193 ***	0.198 ***	0.199 ***	0.193 ***	0.183 ***	0.192 ***	0.194 ***	0.190 ***	0.213 ***
C lagged	0.1	0.974 ***	0.866 ***	0.941 ***	1.007 ***	1.018 ***	0.967 ***	0.979 ***	0.992 ***	0.949 ***
	0.2	0.920 ***	0.914 ***	0.959 ***	0.972 ***	0.976 ***	0.957 ***	0.970 ***	0.971 ***	0.946 ***
	0.3	0.907 ***	0.892 ***	0.946 ***	0.944 ***	0.966 ***	0.944 ***	0.940 ***	0.948 ***	0.922 ***
	0.4	0.901 ***	0.914 ***	0.956 ***	0.944 ***	0.955 ***	0.954 ***	0.953 ***	0.950 ***	0.937 ***
	0.5	0.857 ***	0.876 ***	0.925 ***	0.927 ***	0.933 ***	0.904 ***	0.927 ***	0.929 ***	0.909 ***
	0.6	0.817 ***	0.838 ***	0.875 ***	0.842 ***	0.852 ***	0.875 ***	0.855 ***	0.850 ***	0.866 ***
	0.7	0.822 ***	0.814 ***	0.853 ***	0.831 ***	0.835 ***	0.842 ***	0.825 ***	0.828 ***	0.820 ***
	0.8	0.821 ***	0.829 ***	0.832 ***	0.843 ***	0.844 ***	0.856 ***	0.850 ***	0.850 ***	0.849 ***
	0.9	0.803 ***	0.781 ***	0.808 ***	0.835 ***	0.831 ***	0.847 ***	0.815 ***	0.847 ***	0.864 ***
X lagged	0.1	0.007	0.066 **	-0.076 *	0.028	0.029	0.071 **	-0.021	0.037 *	-0.014
	0.2	0.041 ***	0.043 ***	-0.039 ***	0.007	0.022	0.052 **	-0.012	0.012	-0.016
	0.3	0.035	0.032 ***	-0.024 *	-0.003	0.029 *	0.029	0.003	0.010	-0.015
	0.4	0.027 **	0.025 ***	-0.019 *	-0.004	0.016 *	0.018	-0.002	-0.001	-0.007
	0.5	0.036 ***	0.028 ***	-0.024 **	-0.004	0.016	0.033	0.000	0.004	-0.004
	0.6	0.026 **	0.017	-0.027 **	-0.006	0.000	0.031	0.002	-0.002	0.005
	0.7	0.014	0.013	-0.020 *	0.001	-0.012	0.027	0.005	0.002	-0.008
	0.8	0.013	0.009	-0.030 ***	-0.008	-0.020	0.033	-0.003	-0.005	0.004
	0.9	0.019	0.038	-0.050 ***	-0.008	-0.022	0.029	0.018	-0.011	0.024
Pseudo	0.1	0.54	0.55	0.55	0.55	0.54	0.55	0.54	0.55	0.51
R-squared	0.2	0.60	0.60	0.60	0.60	0.60	0.61	0.60	0.60	0.57
	0.3	0.62	0.62	0.62	0.61	0.61	0.62	0.61	0.61	0.60
	0.4	0.62	0.62	0.61	0.61	0.61	0.61	0.61	0.61	0.61
	0.5	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59
	0.6	0.57	0.56	0.57	0.56	0.56	0.56	0.56	0.56	0.57
	0.7	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
	0.8	0.50	0.50	0.52	0.50	0.51	0.51	0.50	0.50	0.51
	0.9	0.46	0.46	0.48	0.46	0.46	0.46	0.46	0.46	0.46
Slope equality test		5.1	9.1 *	12.2 **	11.3 **	11.8 **	4.8	11.0 **	11.2 **	4.0

The table shows the results from estimating quantile regressions for each of the explanatory variables (X). With the exception of the VIX model (1986M08-2006M12), the estimation period is 1983M03-2006M12. The slope equality test statistic compares the 0.1, 0.5, and 0.9 quantiles. ***/**/* indicates that the variable is significant at the 1%/5%/10% level (based on bootstrapped standard errors).

Table A4: In-Sample Quantile Regressions for Factor Models, Sub-Sample 1983-2006

Q	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	OLS
cons	-0.176 ***	-0.106 ***	-0.071 ***	-0.035 **	-0.006	0.042 **	0.076 ***	0.129 ***	0.177 ***	0.004
C lagged	0.735 ***	0.814 ***	0.843 ***	0.867 ***	0.848 ***	0.809 ***	0.833 ***	0.787 ***	0.792 ***	0.790 ***
PC1(-1)	0.060 ***	0.039 ***	0.033 ***	0.026 ***	0.024 ***	0.020 ***	0.018 **	0.015	0.015	0.032 ***
PC2(-1)	-0.094 ***	-0.061 ***	-0.048 ***	-0.038 **	-0.035 ***	-0.043 ***	-0.047 ***	-0.046 ***	-0.044 **	-0.056 ***
PC3(-1)	-0.180 ***	-0.103 **	-0.082 ***	-0.060 **	-0.063 ***	-0.060 **	-0.064 *	-0.060 *	-0.050	-0.066 ***
Pseudo R-squared	0.62	0.65	0.65	0.64	0.61	0.58	0.55	0.52	0.48	0.83
Slope equility test					17.2 **					

The table shows the results from estimating quantile and OLS regressions for the PCA models for the sample period is 1983M03-2006M12. The slope equality test statistic compares the 0.1, 0.5, and 0.9 quantiles. ***/**/* indicates that the variable is significant at the 1%/5%/10% level (based on bootstrapped standard errors).

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