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Quantiles of the realized stock–bond correlation and links to the macroeconomy☆

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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 factors constructed from a large number of macro-finance predictors well-known from the return predictability literature. Strong in-sample predictability is obtained from the factor quantile model. Out-of-sample the quantile factor model outperforms benchmark models.

1. Introduction

Understanding the relation between stock and bond returns has a key relevance for asset allocation, risk analysis, and hedging. There is substantial time variation in this comovement; until the mid-1990s the US stock–bond correlation is strongly positive, only to drop to extremely large negative levels by the early 2000s. 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 Value-at-Risk (VaR) of a combined stock–bond portfolio is largest when the stock–bond correlation is large positive. A large positive correlation typically implies a higher allocation to stocks, because bonds generally have lower expected returns.

The main contributions and findings of our paper are as follows. We adopt quantile regressions and provide the first analysis of the influence of macro-finance variables upon the tails of the realized stock–bond correlation. The quantile regression approach

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provides a more complete picture of the correlation distribution compared to conditional mean and variance models. The extreme quantiles of the correlation correspond to strongly negative and strongly positive correlation, respectively. We provide comprehensive analysis of the predictability of the extreme quantiles by considering a large number of potential macro-finance predictors well known from the return predictability literature. Further, we explore a principal components factor approach to extract five factors from the macro-finance state variables. Our in-sample analysis shows that macro-finance factors are significant at explaining the quantiles of the realized correlation, in particular the low quantiles. Importantly, out-of-sample, we find that the factor model delivers more accurate forecasts than benchmark models.

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 instance, (Harvey and Siddique, 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.

(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. By using regime switching models, Aslanidis and Christiansen (2012) also argue for the role of macro-finance variables in determining correlation regimes. The current analysis is more general in that we examine predictability of the entire stock–bond correlation distribution and that we consider a much larger set of predictive variables.

Ilmanen (2003) finds that during periods of high inflation, changes in the discount rates dominate in cash flow expectations, thereby inducing a positive stock–bond correlation. Further, Connolly et al. (2005) ascribe the sustained negative stock–bond correlation observed since the late 1990s to a "flight-to-safety" phenomenon, where increased stock market uncertainty induces investors to flee stocks in favor of bonds. From a term structure modeling perspective, Campbell et al. (2009) adopt a stochastic discount factor analysis 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.

Our work is also related to Pedersen (2010) who applies bivariate quantile regressions to model the joint stock–bond return distribution whereby the stock–bond correlation is a latent variable. Instead, we apply the realized correlation as the dependent variable, which is in line with the recent studies on realized volatility e.g. Andersen et al. (2004), Andersen et al. (2003), and Barndorff-Nielsen and Sheppard (2004). An attractive feature of using the realized correlation is that this facilitates exploring the impact of macro-finance variables on its time series properties.

The present paper also draws on the recent approach in the financial literature that uses information in large sets of macro-finance variables to predict asset returns. Goyal and Welch (2008) show 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. Using dynamic factor analysis, Ludvigson and Ng (2007) and Ludvigson and Ng (2009) study the ability of a large set of macroeconomic variables to explain equity and bond risk premia, respectively. Stock and Watson (2002) show that a large amount of economic information is summarized by few estimated factors. In line with this research and similar to Ando and Tsay (2011), we adopt a quantile regression with factor-augmented predictors. In the financial economics literature, the quantile regression is mainly applied to value-at-risk calculations starting with Engle and Manganelli (2004).

The balance of the paper is structured as follows. First, we lay out the quantile model. Second, we introduce the data. Third, we discuss our empirical results. Finally, we conclude.

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 medium of the distribution.

In the quantile regression for the stock–bond correlation, the two extreme quantiles 0.1 and 0.9 correspond to large negative and large positive correlations. 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 median we have to be until the behavior of the stock–bond correlation is different.

The quantile regression takes the following form

$$C_{t+1} = X_t{}'\beta^\tau + \varepsilon_{t+1}^\tau \tag{1}$$

where C_{t+1} is the realized stock–bond correlation and X_t the vector of predictor variables. The parameter vector β^τ is associated with the τ-quantile while ε_{t+1}^τ is the error term, allowed to have a different distribution across quantiles. Note that the local effect of X_t on the τ-quantile is assumed to be linear. However, since the slope coefficient vector β^τ differs across quantiles, the