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# Predicting Bond Betas using Macro-Finance Variables*

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# Predicting Bond Betas using Macro-Finance Variables

**Abstract:** We predict bond betas conditioning on various macro-finance variables. We explore differences across long-term government bonds, investment grade corporate bonds, and high yield corporate bonds. We conduct out-of-sample forecasting using the new approach of combining explanatory variables through complete subset regressions (CSR). We consider the robustness of CSR forecasts across the 1-month, 3-month, and 12-month forecasting horizon. The CSR method performs well in predicting bond betas.

**Keywords:** bond betas; complete subset regressions; corporate bonds; government bonds; macro-finance variables; model confidence set.

**JEL Classifications:** C22; C53; C55; G12.

# 1 Introduction

This paper examines the out-of-sample predictability of bond risk by means of macroeconomic and financial variables. We use a number of well-known predictors from the return predictability literature and explore differences across long-term government bonds, investment grade corporate bonds, and high yield corporate bonds. Our results provide evidence that combinations of forecasts from complete subset regressions (CSR) as suggested by Elliott, Gargano, and Timmermann (2013) improve out-of-sample predictability of the bond betas relative to using individual predictors. Furthermore, our results provide evidence that high yield corporate bonds are a different category of bonds given that, contrary to investment grade corporate bonds and government bonds, combinations of forecasts from complete subset regressions fitted to typical stock and bond predictors give the best performance, especially for longer horizons than one month.

The present paper draws on a recent approach in the financial literature that uses information from large data sets of macro-finance variables to predict asset related variables (Baele, Bekaert, and Inghelbrecht (2010), Ludvigson and Ng (2009), Ludvigson and Ng (2010), and Aslanidis and Christiansen (2014), among others). More specifically, we adopt forecast combinations from CSR that use financial variables from the literature on stock return predictability (the Goyal and Welch (2008) data set) and the VIX volatility index, in addition to macroeconomic predictors such as industrial production and the macroeconomic uncertainty index of Jurado, Ludvingson, and Ng (2015) along with an indicator of financial leverage and the liquidity factor of Pastor and Stambaugh (2003).

The choice of the predictors used in this paper is foremost motivated by the literature that relates business cycle proxies to aggregate comovements in bond and equity markets. Some authors (see Campbell and Ammer (1993), Fama and French (1993), Boudoukh, Richardson, and Whitelaw (1994), and more recently Campbell, Sunderam, and Viceira (2017)) explore fundamental factors such as macro drivers of interest rates (e.g. shocks to expected inflation and innovations to real interest rates), while others concentrate on non-fundamental determinants of the bond and stock return covariation. For example, Connolly, Stivers, and Sun (2007) show that the probability of negative bond-stock correlation increases with uncertainty (flight-to-safety). In a similar spirit, Baele, Bekaert, and Inghelbrecht (2010) show that macroeconomic fundamentals contribute little to explaining stock and bond return correlations while other factors, especially liquidity proxies, play a more important role. Further, Campbell, Pflueger, and Viceira (2015) make a New Keynesian general equilibrium model where changes in monetary policy contribute to shifts in bond risk.

We measure bond risk by its CAPM beta, i.e. its covariance with the stock market divided by the stock market variance. Beta is the normalized measure of the bond-stock covariance and it is readily available for interpretation as the CAPM risk. This measure of bond risk has been considered by previous studies such as Viceira (2012) and Campbell, Sunderam, and Viceira (2017). Viceira (2012) shows that the time variation in the government bond betas is related to the yield spread and the short rate. Unlike Viceira (2012), we consider variations across bond types and we use a large set of predictors.

The previous literature makes us expect that the behavior of bond betas differ across bond types. Recently, Choi, Richardson, and Whitelaw (2014) show that a firm's leverage is an important driver of the relation between its stock and bonds: the higher the leverage (measured by debt to asset ratio) is, the smaller is the degree of comovement. Moreover, other studies such as Bao, Hou, and Zhang (2015) and Bao and Hou (2017) stress the importance of firm capital structure in explaining comovements between bonds and stocks. Bao, Hou, and Zhang (2015) use structural form credit risk models to show both theoretically and empirically the importance of a systemic default risk measure as a common factor driving the prices of stocks and corporate bonds.

Our empirical results are summarized as follows. Based on the RMSEs and the model confidence set of Hansen, Lunde, and Nason (2011), combining macro-finance variables via CSR is advantageous for predicting bond betas out-of-sample. Using individual predictors has the drawback that the best predictor vary across forecast horizons as well as across bond types. The high yield corporate bonds behave differently from government and investment grade bonds.

The remaining part of the paper is structured as follows. First, we introduce the data and then, we provide the econometric methodology. Subsequently, we discuss the empirical findings before we conclude.

## 2 Data

We use monthly observations during the period 2000$M$05 to 2014$M$12. The start of the sample period is determined by the availability of the corporate bond data.

### 2.1 Realized CAPM Betas

In order to calculate the monthly realized bond betas, we use daily observations of bond and stock returns. This is done the same way as Viceira (2012), namely as the realized stock-bond covariance divided by the realized stock market variance.

For government bonds we apply the US benchmark 10-year DataStream government index, for investment grade corporate bonds we apply the Barclays US Corporate Investment Grade index, and for high yield corporate bonds we apply the Barclays US Corporate High Yield index. For the stock market we use the S&P 500 Composite Price Index. All bond and stock data are total return indices from DataStream.

Table 1 shows descriptive statistics for the monthly bond betas for the full sample period. The average bond betas are decreasing with bond quality, i.e. for the government bond beta the mean is $-0.13$, for the investment grade bond beta $-0.06$ and for the high yield bond beta 0.05. Government and investment grade bonds appear to be on average safe investments that exhibit a negative correlation with aggregate wealth as proxied by the stock market, while the riskier high yield bonds exhibit a positive correlation. The standard deviation of the bond betas is increasing with bond quality, so the government bond beta is the most variable. The bond betas are slightly right skewed and the high yield bond beta has a fat tail whereas the other bond betas are close to being mesokurtic. To examine the persistency, Table 1 reports the autocorrelation (at lag one) of the realized bond betas. There is semi-strong autocorrelation for the bond betas.

[Insert Table 1 here]

Figure 1 plots the realized bond betas (shaded areas are NBER recessions). In most of the sample, the high yield bond beta is small and positive and shows little variation. Interestingly, the government and to a lesser extend the investment grade bond betas turn negative in 2008. This might be driven by "flight-to-quality" episodes during the recent financial crisis and subsequent recession.

[Insert Figure 1 here]

### 2.2 Explanatory Variables

As explanatory variables we use macro-finance variables from Goyal and Welch (2008) combined with some newer and popular macro-finance variables. The Goyal and Welch (2008) variables (available from Goyal's web page) include the dividend-price ratio ($D/P$), the earnings-price ratio ($E/P$), the book-to-market ratio ($B/M$), the treasury bill rate ($TBL$), the term spread ($TMS$), the default return spread ($DFR$), and inflation ($INFL$). Moreover, we use growth in industrial production ($IP$) (available from DataStream), the macroeconomic uncertainty index (*uncertainty*) of Jurado, Ludvingson, and Ng (2015) (available from Jurado's web page), the VIX volatility index ($VIX$) (available from the web page of the Chicago Board of Options Exchange), the Chicago Fed National Financial Conditions Leverage Subindex (*leverage*) (available from the Federal Reserve Bank of St. Louis), and the liquidity factor (*liquidity*) of Pastor and Stambaugh (2003) (available from Pastor's web page).

## 3 Econometric Methodology

The complete subset regression (CSR) methodology comes from Elliott, Gargano, and Timmermann (2013). CSR is a simple approach to deal with estimation error, model uncertainty, and model instability. By diversifying across multiple models, CSR can deliver more stable forecasts than those obtained from individual models. The method consists of using $k$ out of $K$ variables ($k \leq K$) to fit linear regressions for all possible combinations of the $k$ variables. $K$ is the total number of predictors. The final forecast is the equally weighted average forecast computed from all regressions. Another advantage of the CSR is that it does not require any ranking of individual models. The forecasts are compared for all values of $k$. Each regression includes a constant and between 1 and $K$ regressors. In our setting there are 13 predictors (12 macro-finance variables plus the lagged dependent variable). There are in total $2^{13} = 8,191$ different models. An exhaustive forecast combination of all possible models is no longer feasible.

We use the first six years of the sample ($2000M05 - 2006M12$) as warm-up to obtain initial estimates and the subsequent period ($2007M01 - 2014M12$) for out-of-sample forecast evaluation. All forecasts are generated recursively by OLS using an expanding estimation window. First, we consider the 1-month horizon and second, we show the corresponding results for the 3-month and 12-month horizons.

We first compare model fit by computing the root mean square error (RMSE) for each of the forecasting models. Second, we follow Hansen, Lunde, and Nason (2011) and use the model confidence set (MCS) based on the RMSE as the loss function to compare model fit. The MCS test is a procedure that allows us to identify a subset of superior (prediction) models containing the best model(s) at a given level of confidence. Hansen, Lunde, and Nason (2011) consider both the 90% and 75% confidence level. We use the 75% confidence level because it includes fewer models in the superior set. In addition, we have a shorter forecast evaluation period than in Hansen, Lunde, and Nason (2011) and we use the lower confidence level as the uncertainty is larger in shorter forecasting periods. This is similar in spirit to Sims and Zha (1999) and Caggiano, Castelnuovo, and Groshenny (2014).

# 4 Empirical Results

This section contains the empirical analysis. First, we investigate the 1-month bond beta out-of-sample predictability, followed by an analysis of the longer forecasting horizons.

## 4.1 Predicting Bond Betas

Table 2 shows the out-of-sample RMSEs for each of the realized bond betas for 1-month ahead forecasting models. At the top, we show the RMSEs from the benchmark AR(1) specification, followed by the RMSEs based on the CSR combination method for each possible $k$ and at the bottom are the RMSEs for the single-variable regressions.

[Insert Table 2]

First notice, that there are only small differences in the RMSEs across models.

Single-predictor regressions provide more accurate out-of-sample predictions compared to CSR. Interestingly, the best predictor for government and investment grade bond betas is the treasury bill rate ($TBL$) which is in accordance Viceira (2012). For the high yield bond betas, the most accurate predictability is achieved using individual predictors such as the treasury bill rate ($TBL$) and the book-to-market ratio ($B/M$), as well as CSR with $k = 6, 7, 8$. The book-to-market variable is a stock market variable and its significance points to high yield bonds resembling stocks rather than bonds.

Overall and regardless of the bond type, the CSR combinations delivering the lowest RMSE are associated with medium number of variables. Therefore, many predictors appear to result in over-fitting.

Table 3 reports the selected models based upon the model confidence set (MCS) approach for predicting bond betas out-of-sample. For government and investment grade bond betas, the preferred models include only individuals predictors (e.g. the treasury bill rate ($TBL$) and the book-to-market ratio ($B/M$)). As for the high yield bond beta and in terms of MCS, the CSR combinations with $k = 5, ..., 11$ perform about as well as the $TBL$ and $B/M$ predictors.

[Insert Table 3]

### 4.2 Variations across Horizon

Table 4 contains the RMSEs of the models for the 3-month and 12-month horizon predictions.

[Insert Table 4]

Based on the RMSEs, the best forecasts of government and investment grade bond betas are those related to individual variables while for the high yield bonds the best forecasts are CSR combinations.

[Insert Table 5]

Table 5 show shows the selected models based on the MCS for the longer horizons. At the 3-month horizon, for the government and investment grade bond betas, most models are included, and the MCS approach does not help us chose the best model. At the 12-month horizon, the MCS points towards individual predictors for predicting government and investment grade bond betas out-of-sample.

For high yield bond betas, the selected models are mainly the complete subset regressions with a medium range of included predictors. This is the case for both the 3-month and 12-month horizons.

The findings for longer horizons underscore the differences between government and investment grade bonds on the one side and high yield bonds on the other side.

The fact that the best individual predictors vary across horizon and across bond type points to an additional advantage of using CSR combinations, because here we do not need to make any ex ante decisions on which specific predictor to apply. So, the CSR methods points to stable predictive models.

## 5 Conclusion

In this paper we explore the role played by macro-finance variables for predicting bond betas. We investigate three different categories of bonds, namely long-term government bonds, investment grade corporate bonds, and high yield corporate bonds. We make use of a new method for combining predictions from various explanatory variables, namely the complete subset regressions (CSR) method. We find that high yield bonds behave like stocks and differently from government and investment grade bonds.

The CSR method has the added benefit that we do not need to decide which particular predictor to use. This is important because the best individual predictor vary across bond types and forecasting horizon.

The CSR superior out-of-sample forecasting performance suggest that not only traditional predictors employed to predict government bond returns but also predictors used to predict stock returns are important drivers of the high yield bond risk.

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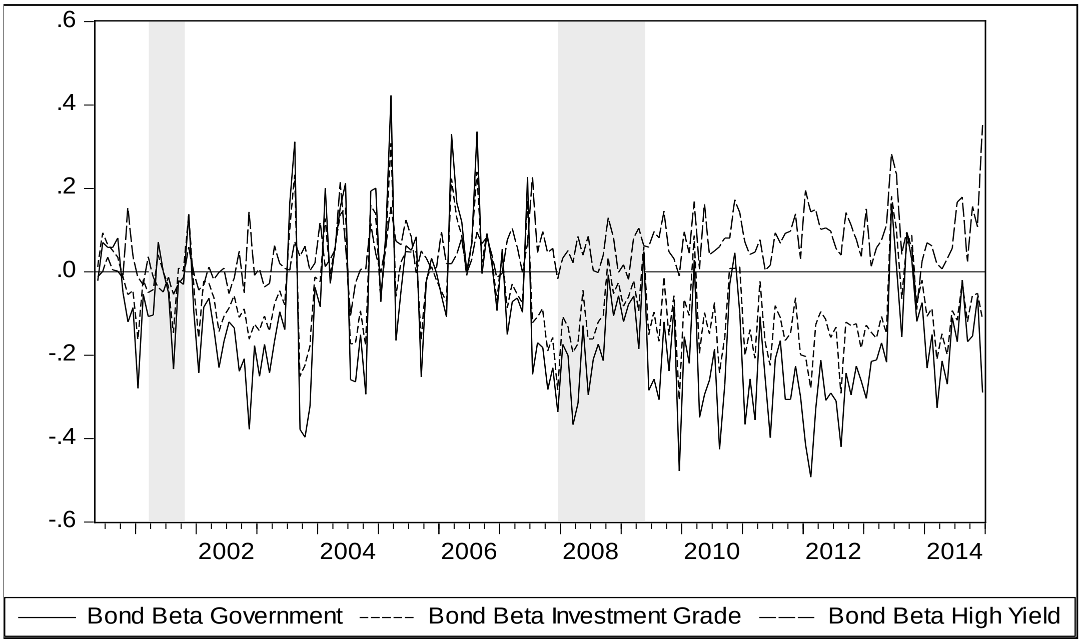
**Figure 1** Realized Bond Betas




The figure shows the time series of the bond betas. The grey-shaded areas are the NBER recession periods.

**Table 1:** Descriptive Statistics for Bond Betas

| | GOV | IG | HY |
|---|---|---|---|
| Mean | -0.13 | -0.06 | 0.05 |
| St.Dev. | 0.17 | 0.11 | 0.07 |
| Skew. | 0.54 | 0.60 | 0.99 |
| Kurt. | 3.20 | 3.43 | 5.22 |
| Autocor(1) | 0.45 | 0.38 | 0.32 |

**Table 2:** Out-of-Sample RMSEs for Bond Betas (Horizon 1-Month)

| | GOV | IG | HY |
|---|---|---|---|
| AR | 0.143 | 0.099 | 0.070 |
| CSR, k=1 | 0.161 | 0.106 | 0.073 |
| CSR, k=2 | 0.157 | 0.104 | 0.072 |
| CSR, k=3 | 0.155 | 0.104 | 0.070 |
| CSR, k=4 | 0.154 | 0.103 | 0.069 |
| CSR, k=5 | 0.153 | 0.104 | 0.069 |
| CSR, k=6 | 0.153 | 0.104 | 0.068 |
| CSR, k=7 | 0.154 | 0.104 | 0.068 |
| CSR, k=8 | 0.154 | 0.105 | 0.068 |
| CSR, k=9 | 0.155 | 0.105 | 0.069 |
| CSR, k=10 | 0.156 | 0.106 | 0.069 |
| CSR, k=11 | 0.158 | 0.107 | 0.069 |
| CSR, k=12 | 0.160 | 0.109 | 0.070 |
| CSR, k=13 | 0.163 | 0.110 | 0.070 |
| D/P | 0.140 | 0.097 | 0.069 |
| E/P | 0.149 | 0.102 | 0.072 |
| B/M | 0.140 | 0.097 | **0.068** |
| TBL | **0.136** | **0.095** | 0.068 |
| TMS | 0.143 | 0.099 | 0.070 |
| DFR | 0.146 | 0.101 | 0.071 |
| INFL | 0.143 | 0.099 | 0.070 |
| IP | 0.147 | 0.101 | 0.071 |
| VIX | 0.144 | 0.100 | 0.071 |
| leverage | 0.144 | 0.099 | 0.070 |
| uncertainty | 0.149 | 0.101 | 0.071 |
| liquidity | 0.145 | 0.100 | 0.072 |

**Table 3:** Out-of-Sample MCS Results for Bond Betas (Horizon 1-Month)

| | GOV | IG | HY |
|---|---|---|---|
| AR | | | |
| CSR, k=1 | | | |
| CSR, k=2 | | | |
| CSR, k=3 | | | |
| CSR, k=4 | | | |
| CSR, k=5 | | | Yes |
| CSR, k=6 | | | Yes |
| CSR, k=7 | | | Yes |
| CSR, k=8 | | | Yes |
| CSR, k=9 | | | Yes |
| CSR, k=10 | | | Yes |
| CSR, k=11 | | | Yes |
| CSR, k=12 | | | |
| CSR, k=13 | | | |
| D/P | Yes | Yes | Yes |
| E/P | | | |
| B/M | Yes | Yes | Yes |
| TBL | Yes | Yes | Yes |
| TMS | Yes | Yes | |
| DFR | | | |
| INFL | | | |
| IP | | | |
| VIX | | | |
| leverage | | | |
| uncertainty | | | |
| liquidity | | | |

**Table 4:** Out-of-Sample RMSEs for Bond Betas for Longer Horizons

| | >>> Horizon 3-Month <<< | | | >>> Horizon 12-Month <<< | | |
|---|---|---|---|---|---|---|
| | GOV | IG | HY | GOV | IG | HY |
| AR | 0.154 | 0.104 | 0.075 | 0.169 | 0.111 | 0.074 |
| CSR, k=1 | 0.164 | 0.107 | 0.074 | 0.177 | 0.114 | 0.074 |
| CSR, k=2 | 0.162 | 0.107 | 0.073 | 0.183 | 0.118 | 0.072 |
| CSR, k=3 | 0.162 | 0.107 | 0.072 | 0.190 | 0.122 | 0.071 |
| CSR, k=4 | 0.163 | 0.108 | 0.071 | 0.196 | 0.127 | 0.070 |
| CSR, k=5 | 0.164 | 0.109 | 0.070 | 0.203 | 0.131 | 0.069 |
| CSR, k=6 | 0.166 | 0.111 | 0.070 | 0.210 | 0.134 | **0.069** |
| CSR, k=7 | 0.169 | 0.113 | **0.069** | 0.217 | 0.138 | 0.069 |
| CSR, k=8 | 0.171 | 0.114 | **0.069** | 0.225 | 0.143 | 0.070 |
| CSR, k=9 | 0.174 | 0.117 | 0.070 | 0.234 | 0.148 | 0.071 |
| CSR, k=10 | 0.178 | 0.119 | 0.070 | 0.245 | 0.155 | 0.073 |
| CSR, k=11 | 0.183 | 0.123 | 0.071 | 0.259 | 0.163 | 0.075 |
| CSR, k=12 | 0.189 | 0.127 | 0.073 | 0.276 | 0.174 | 0.078 |
| CSR, k=13 | 0.197 | 0.131 | 0.075 | 0.297 | 0.189 | 0.082 |
| D/P | 0.152 | 0.104 | 0.072 | 0.185 | 0.119 | 0.074 |
| E/P | 0.169 | 0.113 | 0.079 | 0.201 | 0.129 | 0.082 |
| B/M | 0.155 | 0.105 | 0.069 | 0.190 | 0.122 | 0.071 |
| TBL | **0.147** | **0.101** | 0.072 | 0.177 | 0.115 | 0.072 |
| TMS | 0.156 | 0.106 | 0.075 | 0.177 | 0.117 | 0.076 |
| DFR | 0.155 | 0.106 | 0.076 | 0.181 | 0.118 | 0.075 |
| INFL | 0.155 | 0.105 | 0.075 | **0.168** | **0.110** | 0.075 |
| IP | 0.154 | 0.104 | 0.076 | 0.173 | 0.112 | 0.076 |
| VIX | 0.157 | 0.106 | 0.077 | 0.179 | 0.115 | 0.086 |
| leverage | 0.154 | 0.105 | 0.075 | 0.171 | 0.111 | 0.075 |
| uncertainty | 0.166 | 0.110 | 0.077 | 0.174 | 0.114 | 0.077 |
| liquidity | 0.161 | 0.108 | 0.078 | 0.203 | 0.127 | 0.074 |

**Table 5 :** Out-of-Sample MCS Results for Bond Betas for Longer Horizons

| | >>> Horizon 3-Month <<< | | | >>> Horizon 12-Month <<< | | |
|---|---|---|---|---|---|---|
| | GOV | IG | HY | GOV | IG | HY |
| AR | Yes | Yes | | Yes | Yes | |
| CSR, k=1 | Yes | Yes | | | | |
| CSR, k=2 | Yes | Yes | | | | |
| CSR, k=3 | Yes | Yes | | | | |
| CSR, k=4 | | Yes | Yes | | | Yes |
| CSR, k=5 | | Yes | Yes | | | Yes |
| CSR, k=6 | | Yes | Yes | | | Yes |
| CSR, k=7 | Yes | Yes | Yes | | | Yes |
| CSR, k=8 | Yes | Yes | Yes | | | Yes |
| CSR, k=9 | | Yes | Yes | | | |
| CSR, k=10 | | Yes | Yes | | | |
| CSR, k=11 | | Yes | Yes | | | |
| CSR, k=12 | | Yes | | | | |
| CSR, k=13 | | Yes | | | | |
| D/P | Yes | Yes | Yes | | | |
| E/P | | Yes | | | | |
| B/M | Yes | Yes | Yes | | | Yes |
| TBL | Yes | Yes | | | | |
| TMS | Yes | Yes | | | | |
| DFR | Yes | Yes | | | | |
| INFL | Yes | Yes | | Yes | Yes | |
| IP | Yes | Yes | | | | |
| VIX | Yes | Yes | | | | |
| leverage | Yes | Yes | | Yes | Yes | |
| uncertainty | Yes | Yes | | Yes | Yes | |
| liquidity | Yes | Yes | | | | |