# Cover sheet

**This is the accepted manuscript (post-print version) of the article.**
The content in the accepted manuscript version is identical to the final published version, although typography and layout may differ.

**How to cite this publication**
Please cite the final published version:

*Aslanidis, N., Christiansen, C., & Cipollini, A. (2019). Predicting bond betas using macro-finance variables. Finance Research Letters, 29, 193-199.* [*https://doi.org/10.1016/j.frl.2018.07.007*](https://doi.org/10.1016/j.frl.2018.07.007)

## Publication metadata

| | |
|---|---|
| **Title:** | Predicting bond betas using macro-finance variables |
| **Author(s):** | Aslanidis, Nektarios ; Christiansen, Charlotte ; Cipollini, Andrea. |
| **Journal:** | Finance Research Letters |
| **DOI/Link:** | 10.1016/j.frl.2018.07.007 |
| **Document version:** | Accepted manuscript (post-print) |

# Predicting Bond Betas using Macro-Finance Variables*

Nektarios Aslanidis†
Universitat Rovira i Virgili, CREIP

Charlotte Christiansen‡
CREATES, Aarhus University

Andrea Cipollini§
University of Palermo

July 11, 2018

*Aslanidis acknowledges support from the Spanish Ministry of Science and Innovation project grant (Reference N $^o$ ECO2013-42884-P). Christiansen acknowledges support from CREATES funded by the Danish National Research Foundation (DNRF78) and from the Danish Council for Independent Research, Social Sciences (DFF – 4003-00022).

†Universitat Rovira i Virgili, Department d´Economia, CREIP, Avinguda Universitat 1, 43204 Reus, Spain. Email: nektarios.aslanidis@urv.cat.

‡CREATES, Department of Economics and Business Economics, School of Business and Social Sciences, Aarhus University, Fuglesangs Allé 4, 8210 Aarhus V, Denmark and Lund University. Email: CChristiansen@econ.au.dk.

§Department of Economics, Management and Statistics, University of Palermo, Viale delle Scienze, Palermo, Italy. Email: andrea.cipollini@unipa.it.

Predicting Bond Betas using Macro-Finance Variables

**Abstract:** We predict bond betas conditioning on a number of 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 predictor variables through Complete Subset Regressions (CSR). We consider the robustness of CSR forecasts across the 1-month, 3-month, and 12-month forecasting horizons. 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 analyze bond betas as they are readily interpreted as the risk metric in the CAPM framework, where the bond beta measures how the returns comove with the overall stock market returns. Bond risk is an important input into investors' portfolio decisions. 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, we document that for high yield corporate bonds the CSR performs best especially for longer horizons (longer than 1 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 using well-known financial predictors from the literature on stock return predictability (the Goyal and Welch (2008) data set), the VIX volatility index, macroeconomic predictors, 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).

Moreover, 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 stock-bond return covariation. For example, Connolly, Stivers, and Sun (2007) show that the probability of negative bond-stock correlation increases with "flight-to-safety". In a similar spirit, Baele, Bekaert, and Inghelbrecht (2010) show that macroeconomic fundamentals contribute little to explaining stock-bond return correlations while other factors, especially liquidity proxies, play a more prominent role. Further, Campbell, Pflueger, and Viceira (2015) propose a general equilibrium model where changes in monetary policy contribute to shifts in bond risk.

We measure bond risk by its CAPM beta, where beta is the covariance between the bond return and the overall stock market return normalized by the stock market variance. As pointed out by Viceira, Campbell, and Sunderam (2010), inflation makes bonds risky at certain times, while giving them insurance or hedge value at others. For instance, if during a period of economic downturn inflation raises, then the real value of bond payments falls. In this case, bonds become risky assets and investors demand a risk premium for holding them. In contrast, if inflation falls during a period of economic downturn, bonds are like insurance, since the real value of bond payments is hardly affected. In this case, the risk premium should actually be negative. Moreover, in line with Viceira, Campbell, and Sunderam (2010), Viceira (2012), and Campbell, Sunderam, and Viceira (2017) we use bond beta as it is the Capital Asset Pricing Model (CAPM) measure of risk. The CAPM beta is a simple metric for the riskiness of an asset: how its returns comove with the overall stock market return (which in turn comoves positively with real economic growth). Viceira (2012) shows that the time variation in the government bond betas is related to the yield spread and the short rate. However, unlike Viceira (2012), we consider variations across bond types and we use a large set of predictor variables.

Building on previous literature, we expect that the behavior of bond betas is different across bond types. For instance, 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 stock-bond comovements. In particular, Bao, Hou, and Zhang (2015) use structural form credit risk models to show 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 Root Mean Squared Errors (RMSEs) and the Model Confidence Set (MCS) approach of Hansen, Lunde, and Nason (2011), we report that combining macro-finance variables via CSR can improve out-of-sample forecasts of bond betas. Instead, using individual predictors has the drawback that the best predictor vary across forecast horizons as well as across bond types. Another conclusion that we draw is that high yield corporate bonds behave differently from government and investment grade corporate 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 $2000M05$ to $2014M12$. 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. The monthly realized stock market variance is the sum of the daily squared returns during that month while the monthly realized covariance is the sum of the daily product of the bond and stock returns during that month.

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. Thus, the gains from portfolio diversification have increased recently for those investors holding government and investment grade corporate bonds.

[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 equally weighted combinations of forecasts based on all possible constituent models that include a particular subset of the predictor variables. Each subset is defined by the set of regression models that includes a fixed (given) number of predictors, $k \leq K$, where $k$ is the (fixed) number of predictors used in the subset regression and $K$ is the total number of possible predictors. With $K$ variables in the full model, there are $K!/((K-1)!k!)$ subset regressions to average over. A special case of subset regression is the univariate case ($k = 1$) with $K$ individual models as in Rapach, Strauss, and Zhou (2010). By diversifying across multiple models, CSR can deliver more stable forecasts than those obtained from the constituent models. Another advantage of the CSR is that it does not require any ranking of the constituent 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).

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. Firstly, we consider the 1-month horizon and then we show the corresponding results for the 3-month and 12-month horizons.

We first compare the 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 settle with the 75% confidence level as it includes fewer models in the superior set. We have a shorter forecasting evaluation period than Hansen, Lunde, and Nason (2011) and we therefore use the lower confidence level as the uncertainty becomes 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 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]

Generally, single-predictor regressions provide more accurate out-of-sample forecasts compared to CSR. Interestingly, the best predictor for government and investment grade bond betas is the treasury bill rate ($TBL$) in line with Viceira (2012). For the high yield bond betas, however, the treasury bill rate ($TBL$) and the book-to-market ratio ($B/M$) together with CSR (for $k = 6, 7, 8$) deliver the most accurate forecasts. 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 predictor 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 individual predictors (e.g. the treasury bill rate ($TBL$), book-to-market ratio ($B/M$)), and the the dividend-price ratio ($D/P$). As for the high yield bond beta and in terms of MCS, the CSR combinations with $k = 5, ..., 11$ perform about equally well as the $TBL$, $B/M$, and $D/P$ predictors, which corroborates with the RMSE results in Table 2.

[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 typically achieved by 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 choosing 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. Instead, for high yield bond betas, the selected models are mainly the CSR 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 corporate bonds on the one side and high yield corporate 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 predictors to apply. Hereby the CSR method 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.

Our findings have important implications for investors' portfolio decisions. Bond betas measure bonds' risk relative to the market portfolio and risk is one of the most important inputs to investors' asset allocation decision. For an investor to decide the composition of his or her optimal portfolio, it is important to be able to forecast the bond risk as precisely as possible. Moreover, bond betas have important implications for policy makers trying to measure inflation expectations, cf. Viceira, Campbell, and Sunderam (2010).

# References

Aslanidis, N., and C. Christiansen (2014): "Quantiles of the Realized Stock-Bond Correlation," *Journal of Empirical Finance*, 28, 321–331.

Baele, L., G. Bekaert, and K. Inghelbrecht (2010): "The Determinants of Stock and Bond Return Comovements," *Review of Financial Studies*, 23(6).

Bao, J., and K. Hou (2017): "De Facto Seniority, Credit Risk, and Corporate Bond Prices," *The Review of Financial Studies*, 30(11), 4038–4080.

Bao, J., K. Hou, and S. Zhang (2015): “Systemic Default and Return Predictability in the Stock and Bond Markets,” Working Paper.

Boudoukh, J., M. Richardson, and R. F. Whitelaw (1994): “Industry Returns and the Fisher Effect,” *Journal of Finance*, 49, 1595–1615.

Caggiano, G., E. Castelnuovo, and N. Groshenny (2014): “’Uncertainty Shocks and Unemployment Dynamics in U.S. Recessions,” *Journal of Monetary Economics*, 67, 78–92.

Campbell, J. Y., and J. Ammer (1993): “What Moves the Stock and Bond markets? A Variance Decomposition for Long-Term Asset Returns,” *Journal of Finance*, 48, 3–37.

Campbell, J. Y., C. Pflueger, and L. M. Viceira (2015): “Monetary Policy Drivers of Bond and Equity Risks,” Working Paper.

Campbell, J. Y., A. Sunderam, and L. M. Viceira (2017): “Inflation Bets or Deflation Hedges? The Changing Risks of Nominal Bonds,” *Critical Finance Review*, 6, 263âĂŞ301.

Choi, J., M. P. Richardson, and R. Whitelaw (2014): “On the Fundamental Relation between Equity Returns and Interest Rates,” Working Paper, SSRN.

Connolly, R. A., C. Stivers, and L. Sun (2007): “Commonality in the Time-Variation of Stock-Stock and Stock-Bond Return Comovements,” *Journal of Financial Markets*, 10(2), 192–218.

Elliott, G., A. Gargano, and A. Timmermann (2013): “Complete Subset Regressions,” *Journal of Econometrics*, 177, 357–373.

Fama, and French (1993): “Common Risk Factors in the Returns on Stocks and Bonds,” *Journal of Financial Economics*, 33, 3–56.

Goyal, A., and I. Welch (2008): “A Comprehensive Look at The Empirical Performance of Equity Premium Prediction,” *The Review of Financial Studies*, 21(4), 1455–1508.

Hansen, P., A. Lunde, and J. Nason (2011): “The Model Confidence Set,” *Econometrica*, 79, 453–497.

Jurado, K., S. Ludvingson, and S. Ng (2015): “Measuring Uncertainty,” *American Economic Review*, 105(3), 1177–1216.

Ludvigson, S., and S. Ng (2010): “A Factor Analysis of Bond Risk Premia,” in *Handbook of Empirical Economics and Finance*, ed. by A. Uhla, and D. E. A. Giles, pp. 313–372. Chapman and Hall, Boca Raton, FL.

Ludvigson, S. C., and S. Ng (2009): “Macro Factors in Bond Risk Premia,” *Review of Financial Studies*, 22(2), 5027–5067.

Pastor, L., and R. F. Stambaugh (2003): "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111(3), 642–685.

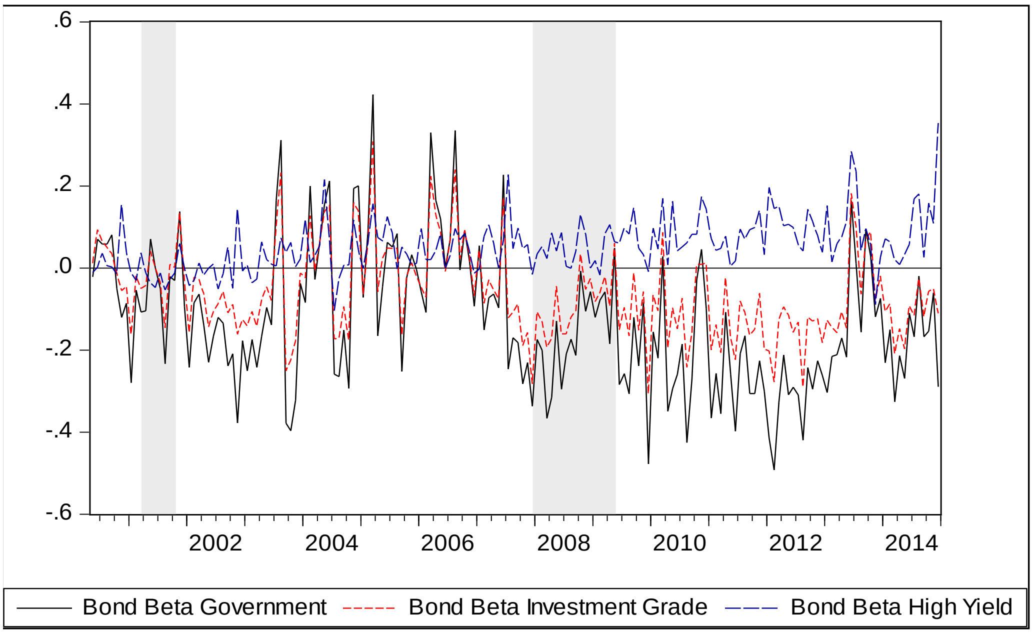
Rapach, D. E., J. K. Strauss, and G. Zhou (2010): "Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy," *Review of Financial Studies*, 23(2), 821–862.

Sims, C., and T. Zha (1999): "Error Bands for Impulse Responses," *Econometrica*, 67(5), 1113–1156.

Viceira, L., J. Campbell, and A. Sunderam (2010): "Is There a Bubble in the Bond Market?," VOX, CEPR Policy Portal.

Viceira, L. M. (2012): "Bond Risk, Bond Return Volatility, and the Term Structure of Interest Rates," *International Journal of Forecasting*, 28, 97–117.

**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 | | | | |