Predicting Realized Bond Betas using Macro-Finance Variables*

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Abstract: In this paper we assess the out-of-sample forecasting performance of a number of macro-finance variables in predicting US bond risk measured by its beta with the stock market. We explore three different categories of bonds; long term government, investment grade and speculative grade bonds. The forecast evaluation period includes the financial turmoil (January 2007-December 2014). In terms of the Model Confidence Set approach, our results suggest that combining forecasts through Complete Subset Regressions outperforms a benchmark AR specification. Further, forecasts obtained from single predictors such as the book-to-market ratio and the treasury bill rate are best in terms of RMSEs.

Keywords: Bond Risk, Bond Beta, Complete Subset Regressions, Macro-Finance Variables, Wavelets.

JEL Classifications: C30, C53, G12.

1 Introduction

This paper examines the out-of-sample predictability of the bond risk by means of macroeconomic and financial variables. Our results show that the Complete Subset Regressions (CSR) method of Elliott, Gargano, and Timmermann (2013) along with smoothed predictors by wavelets improves predictability of the bond risk relative to a benchmark AR model. Furthermore, we find large differences in forecast behavior across bond types, ranging from government bonds over investment grade corporate bonds to high yield corporate bonds.

The paper draws on the recent approach in the financial literature that summarizes information in large data sets of macroeconomic and financial (macro-finance) variables to predict asset related variables (Baele, Bekaert, and Inghelbrecht (2010), Ludvigson and Ng (2009), Ludvigson and Ng (2010), Viceira (2012), and Aslanidis and Christiansen (2014), among others). More specifically, we consider financial variables from the literature on stock return predictability (the Goyal and Welch (2008) data-set), in addition to macroeconomic predictors such industrial production growth, and the macroeconomic uncertainty index of Jurado, Ludvingson, and Ng (forthcoming) along with an indicator of financial leverage and the liquidity factor of Pastor and Stambaugh (2003).

We measure the bond risk by its beta, i.e. its covariance with the stock market divided by the stock variance. It is the normalized measure of the stock-bond covariance and it is readily available for interpretation as the CAPM risk. This measure of bond risk has been considered by the previous literature. For instance, Viceira (2012) studies the time variation in the bond beta and shows it is related to the yield spread and the short rate. Campbell, Sunderam, and Viceira (2013) also investigate the bond risk by means of the bond beta.

Standard approaches in the literature relate business cycles proxies to aggregate comovements in bond and equity markets. Some authors (see Campbell and Ammer (1993), Fama and French (1993), and Boudoukh, Richardson, and Whitelaw (1994), among others) explore fundamental factors such as macro-drivers of interest rates (e.g., shocks to expected inflation and innovations to the real interest rates), while others concentrate more on non-fundamental determinants of the stock and bond return covariation (see Shiller and Baltratti (1992), Connolly, Stivers, and Sun (2007), Baele, Bekaert, and Inghelbrecht (2010), and Baker and Wurgler (2012)).

Campbell, Pflueger, and Viceira (2015) investigate the contribution of changes in monetary policy or changes in macroeconomic shocks to shifts in bonds' risk within a New Keynesian general equilibrium model. Nominal bond prices fall with rising inflation expectations and therefore cost push (supply side) shocks give rise to positive nominal bond betas. In contrast, monetary policy shocks such as innovations to the perceived central bank long-term inflation target reduce the beta of nominal bonds. A downward drift in the perceived inflation target induces firms with nominal rigidities to reduce output. Consequently, a negative inflation target shock raises the value of nominal bonds just as equity prices fall, decreasing the stock-market beta of nominal bonds. Moreover, the dynamic responses of risk premia in the model proposed by Campbell, Pflueger, and Viceira (2015) amplify sign changes in betas that originate from changes in monetary policy. In particular, assets with positive betas have risk premia that increase in recessions, driving down their prices and further increasing their betas. Assets with negative betas, on the other hand, become even more desirable hedging instruments during recessions; this increases their prices and makes their betas even more negative.

Recently, a number of studies appeal to structural models of capital structure valuation. According to Choi, Richardson, and Whitelaw (2014), the way interest rates affect the comovement between stocks and bonds would depend on the firm capital structure priority. The firm asset value sensitivity to interest rates would depend on the share of senior (and high credit quality) debt to total firm asset value. The firm value would be less dependent on senior debt, the higher the leverage is (e.g. the firm value ratio to its debt obligation). Therefore, according to the capital structure of a firm, leverage is an important driver of the relation between stock and bonds: the higher the leverage ratio, the higher is the degree of comovement between stock and bonds. Moreover, Choi, Richardson, and Whitelaw (2014) show the importance of capital structure priority for the beta of corporate bonds. Bao and Hou (2016) show that a bond's place in its issuer's maturity structure has influence on credit risk. They find robust evidence that bonds that are due later in their issuer's maturity structure are perceived to bear an higher degree of credit risk and, consequently, they have larger yield spreads and greater comovement with equity. This is motivated by acknowledging that a firm in financial trouble may remain solvent long enough to repay bonds that are due early in its maturity structure, but not bonds that are due later. The authors observe that a bond that matures after most of the other bonds issued by the same firm is potentially de fact junior even if all of the firm's bonds have the same explicit seniority.

Bao, Hou, and Zhang (2015) show both theoretically and empirically the importance of a systemic default risk measure (measured as the joint probability of default of x% of firms) as a common factor driving the prices of stocks and corporate bonds. In particular, the authors carry out an extensive out-of-sample forecasting exercise and they find the systemic default indicator a good robust predictor of future equity and BAA corporate bond returns, particularly for a one-year horizon. This predictability is robust to a series of control variables, including the control variables used by Goyal and Welch (2008) and the tail risk measure of Kelly and Jiang (forthcoming). As for the AAA corporate bonds there is only evidence of good in sample forecasting performance.

Our results are summarized as follows. In terms of the Model Confidence Set (Hansen, Lunde, and Nason (2011)), our results suggest that combining forecasts through Complete Subset Regressions outperforms a benchmark AR model. Further, forecasts obtained from single predictors such as the book-to-market ratio and treasury bill rate are best in terms of RMSEs compared to forecast combinations and the AR specification.

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 1998m8 to 2014m12. The start of the sample period is determined by the availability of the corporate bond data.

2.1 Realized 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). 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 from DataStream.

2.2 Explanatory Variables

As explanatory variables we use macro-finance variables from Goyal and Welch (2008) combined with some newer and popular explanatory 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 of Jurado, Ludvingson, and Ng (forthcoming) (available from Jurado's web page), the VIX volatility index (VIX) (available from the web page of the Chicago Board of Options Exchange), along with a measure of financial leverage called 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).

3 Econometric Methodology

The Complete Subset Regression (CSR) methodology comes from Elliott, Gargano, and Timmermann (2013). It 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 (macro-finance variables in our setting). The final forecast is the equally weighted average computed from all regressions. The forecasts are compared for all values of k; i.e. $k = 0, 1, \ldots, K$.

In the empirical analysis we make use of the 12 explanatory variables from Section 2.2. Thus, there are in total $2^{12} = 4,096$ different models. In addition, in all regressions we include a constant and an AR term (i.e. the lagged dependent variable) in order to account for any autocorrelation.

We also make use of the CSR methodology for the situation where we remove noise from each predictor by using the Maximal Overlapping Discrete Wavelet Transform, (see Percival and Walden (2000); Whitcher, Guttorp, and Percival (2000)) which decomposes a time series y_t into time scale orthogonal components:

$$y_t = D_{1t} + ...D_{Jt} + S_t \tag{1}$$

The details D_{jt} (for $j = 1, \dots, J$) reproduce the evolution over time of the original series for a particular level j of the decomposition, associated to a given frequency range. The smooth component S_t captures the long-run trending behavior (for frequency bands lower than those associated with level J) of the series y_t. In particular, at level j and scale $\lambda_j = 2^{j-1}$, the time series of wavelet coefficients, w_t, are able to capture frequencies spanning cycles with periodicity between 2^j and 2^{j+1}. Therefore, the lowest scale is associated to the highest frequency range and the highest scale (up to a maximum level of decomposition J) is associated to the lowest frequency range. We only consider $J = 1$, hence the noise-free components that we use as explanatory variables in the CSR setting are given by $(y_t - D_{1t})$.

We use the first nine years of our data $(1998m8 - 2006m12)$ as a warm-up sample to obtain initial estimates and the subsequent period $(2007m1 - 2014m12)$ for out-of-sample forecast evaluation. All forecasts are generated recursively by OLS and using an expanding estimation window. We consider 1-month, 3-month, and 12-month forecast horizons ($h = 1, 3, 12$) to compute the Root Mean Square Error (RMSE) for each of the forecasting models. We follow Hansen, Lunde, and Nason (2011) and compute the model confidence set (MCS) using the RMSE as the loss function. The MCS test is a procedure that allows us to identify a subset of superior (prediction) models containing the best one(s) at a given level of confidence. We use a 90% confidence level.

4 Results

Figures 1-3 show the RMSE for each of the realized bond beta forecasting models. Figure 1 concerns government bonds, Figure 2 investment grade corporate bonds, and Figure 3 high yield corporate bonds. In each figure we show three separate sub-figures corresponding to the three forecasting horizons ($h = 1, 3, 12$). Figure 1a, say, is concerned with the 1-month forecast horizon. Here we show the RMSE based on the CSR method for each possible k (number of explanatory variables) both using the raw and wavelet smoothed explanatory variables. In the same figure, we show the RMSEs for the single variable regressions, again using raw and smoothed explanatory variables.

In general, the results are qualitatively identical at the 1-month and 3-month horizons, so the choice of forecast horizon at the short end is not too important. Note that at the 12-step ahead horizon the performance of the models tends to be similar.

According to the RMSE criterion, the CSR combinations outperform the benchmark AR ($k = 0$) specification. We see this as the RMSE is smallest for $k \neq 0$. The CSR combinations are also preferred to the AR specification for the case of single predictors, where the book-to-market ratio and the treasury bill rate delivers the most accurate forecasts.

Adopting the CSR for the wavelet smoothed predictors generally improves predictability whereas smoothing hardly has any effect when using single-variables.

The government bonds and the investment grade corporate bonds behave very similarly. This is not surprising as these are both bonds with high credit quality issuers. For those two types of bonds, the advantage of using smoothed predictor variables is big, whereas the RMSE is actually worsened a lot by using smoothed variables for the case of the high yield corporate bonds issued by low credit quality issuers.

Tables 1-3 report the Model Confidence Set tests for each of the three forecasting horizons. All tables shows the selected variables from the MCS tests for the three types of bonds using both raw and wavelet smoothed explanatory variables.

In terms of the Model Confidence Set approach, our results suggest that at the 1- and 3-step ahead horizons quite a few CSR models reside in the model confidence set. From the single predictor model, we can distinguish the dividend-price ratio, the book-to-market ratio, and the treasury bill rate as important variables. The benchmark AR model is generally excluded from the model confidence set. At the 12-step ahead horizon quite a few models are include in the MCS, which corroborates that at the long-term horizon the performance of the models is similar. It is not easy to find any pattern in the differences in behavior in the model confidence sets across bond types.

5 Conclusion

In this paper we explore the role played by macro-finance variables for prediction bond betas. We investigate three different categories of bonds, namely long term government bonds, investment grade corporate bonds, and speculative grade corporate bonds. The forecast evaluation period includes the recent period of financial turmoil (January 2007-December 2014). In terms of the Model Confidence Set approach, our results suggest that combining forecasts through Complete Subset Regressions outperforms the benchmark AR model. In contrast, forecasts obtained from single predictors such as the book-to-market ratio and treasury bill rate are best in terms of RMSEs.

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1-step ahead RMSE for realized government bond beta

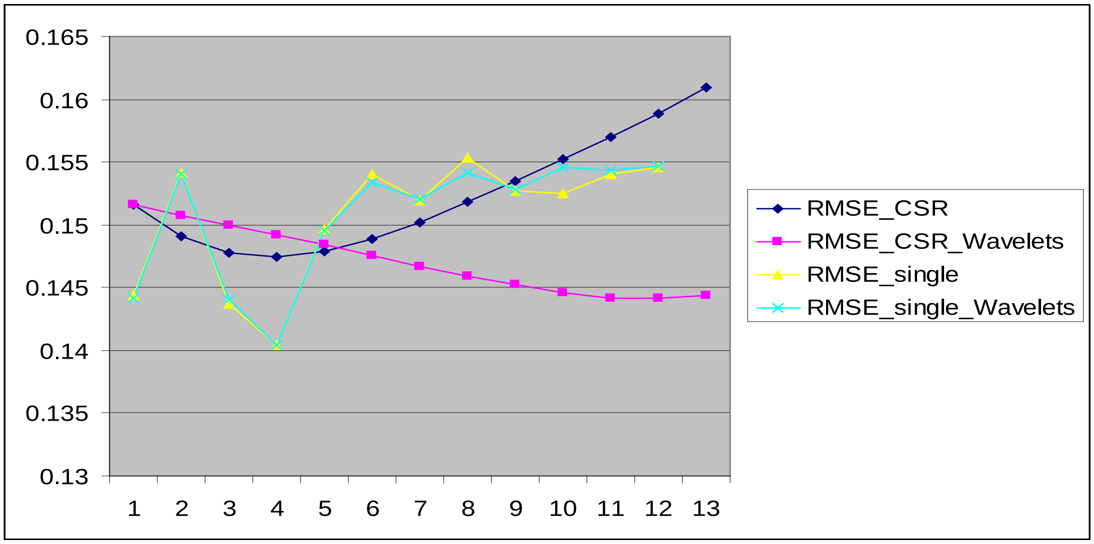

Figure 1a: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12), and AR (*k*=0) and single predictor models.

3-step ahead RMSE for realized government bond beta

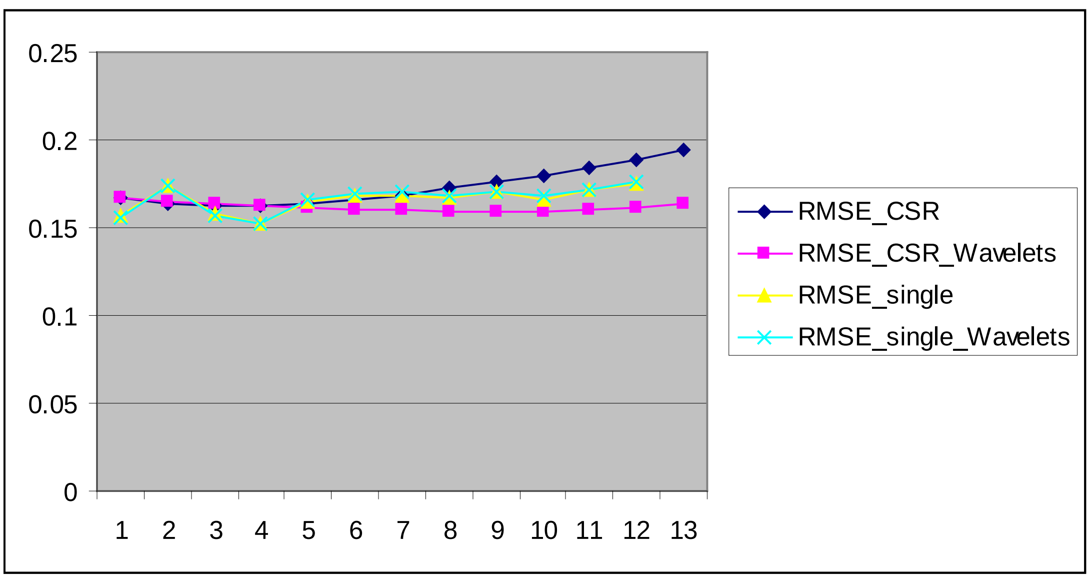

Figure 1b: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12), and AR (*k*=0) and single predictor models.

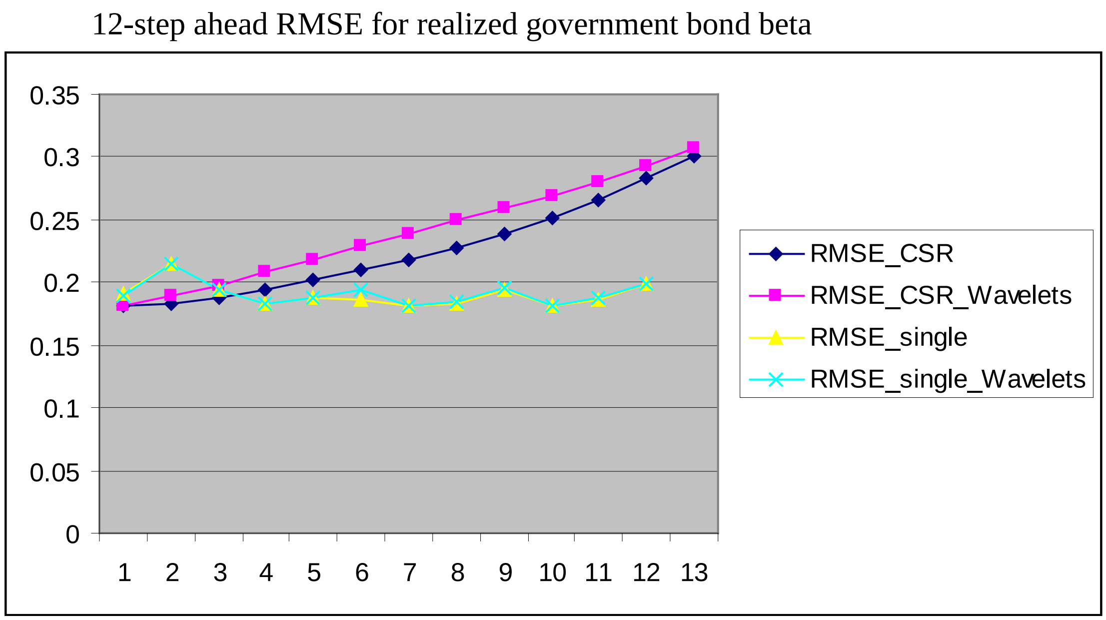

Figure 1c: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12), and AR (*k*=0) and single predictor models.

1-step ahead RMSE for realized investment-grade corporate bond beta

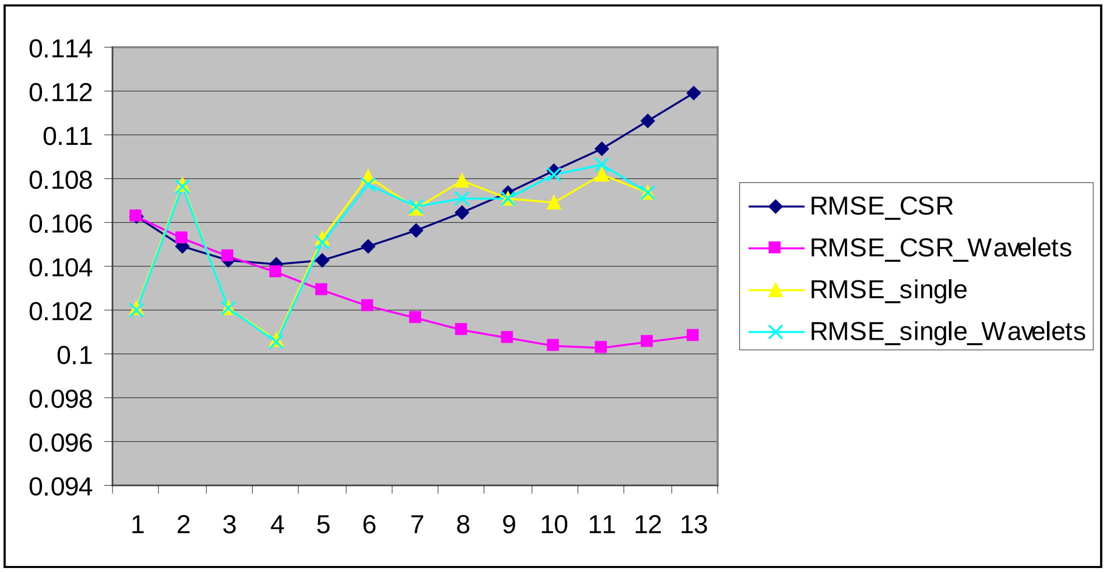

Figure 2a: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12, and AR (*k*=0) and single predictor models.

3-step ahead RMSE for realized investment-grade corporate bond beta

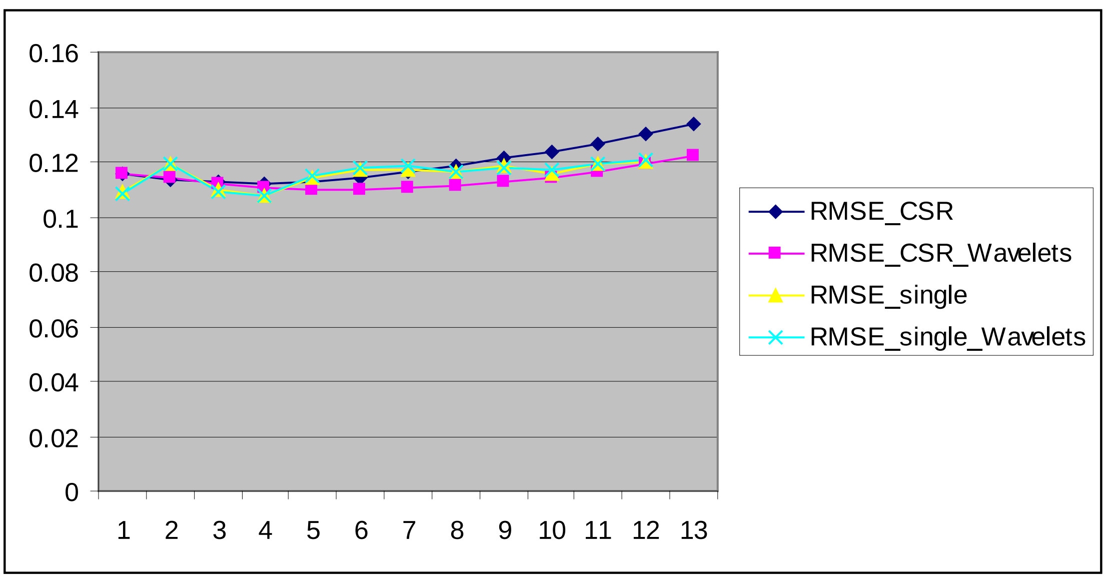

Figure 2b: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12, and AR (*k*=0) and single predictor models.

12-step ahead RMSE for realized investment-grade corporate bond beta

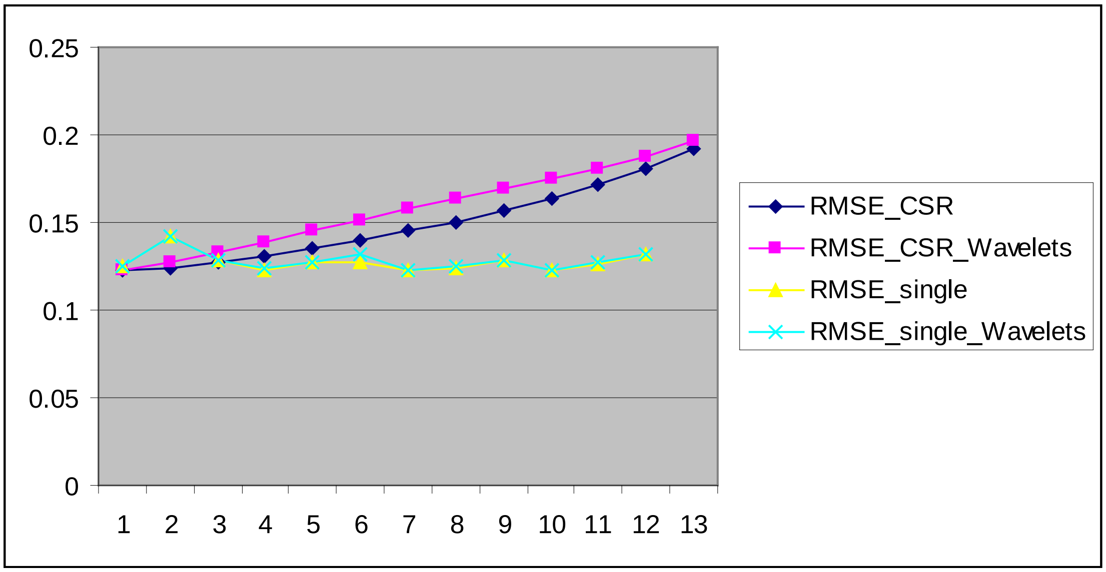

Figure 2c: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12, and AR (*k*=0) and single predictor models.

1-step ahead RMSE for realized high-yield corporate bond beta

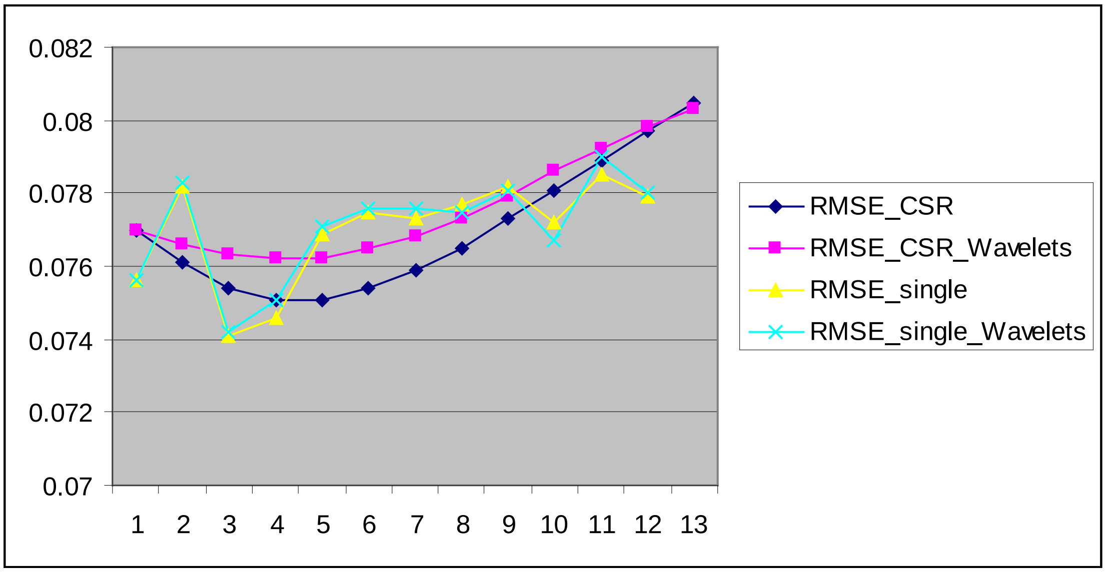

Figure 3a: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12), and AR (*k*=0) and single predictor models.

3-step ahead RMSE for realized high-yield corporate bond beta

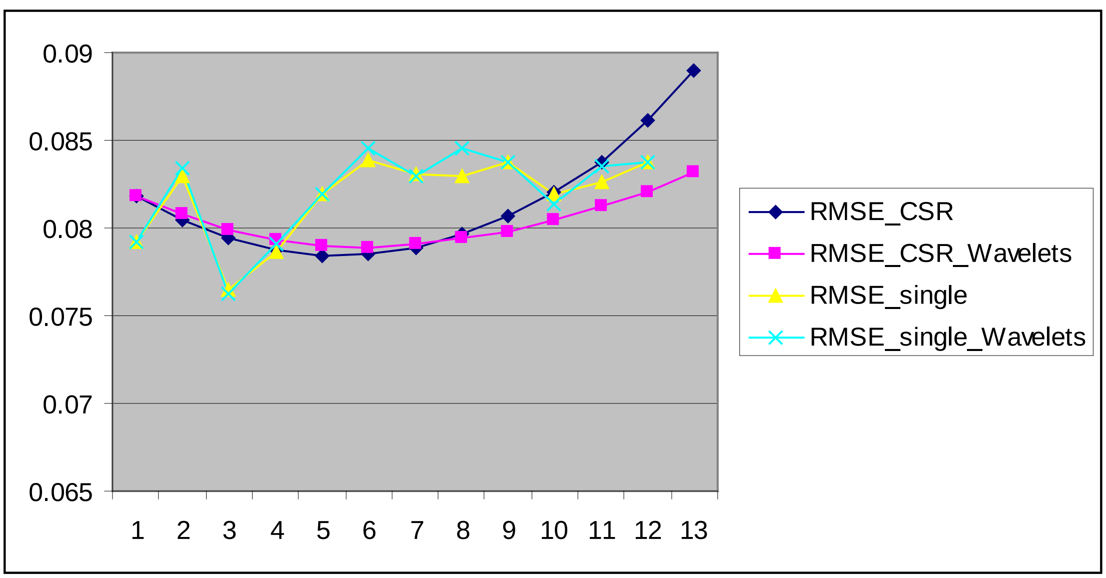

Figure 3b: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12), and AR (*k*=0) and single predictor models.

12-step ahead RMSE for realized high-yield corporate bond beta

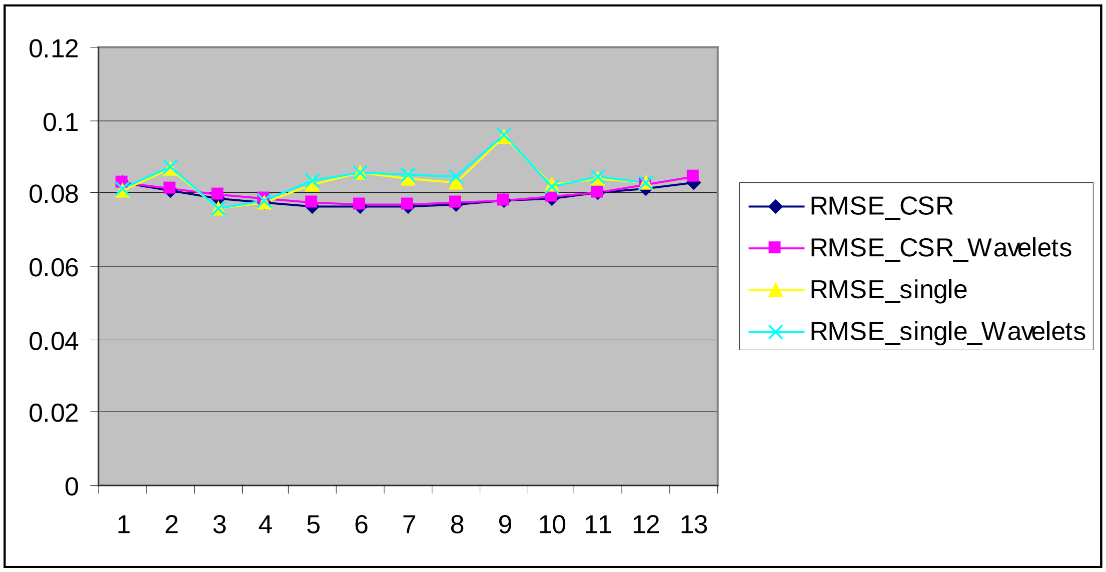

Figure 3c: Complete Subset Regression (CSR) combinations of the *k*-variate models (*k*=1,...,12, and AR (*k*=0) and single predictor models.

Table 1: Model Confidence Sets at 90% level
(1-step ahead forecast horizon)

	GOV raw	IG raw	HY raw	GOV wavelet	IG wavelet	HY wavelet
Selected Predictors	D/P, b/m, tbl, TMS, CSR_k=2, CSR_k=4, CSR_k=5, CSR_k=6	D/P, b/m, tbl, TMS, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8	AR, D/P, b/m, tbl, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8	D/P, b/m, tbl, TMS, CSR_k=6, CSR_k=7, CSR_k=8, CSR_k=9, CSR_k=10, CSR_k=11, CSR_k=12	D/P, b/m, tbl, TMS, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8 CSR_k=9, CSR_k=10, CSR_k=11, CSR_k=12	AR, D/P, E/P, b/m, tbl, TMS, DFR, infl, IP, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8

Notes: The MCS tests is computed using 1000 bootstrap replications and a block size of 12.

Table 2: Model Confidence Sets at 90% level
(3-step ahead forecast horizon)

	GOV raw	IG raw	HY raw	GOV wavelet	IG wavelet	HY wavelet
Selected Predictors	D/P, b/m, tbl, TMS, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6	D/P, b/m, tbl, TMS, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6,	b/m, CSR_k=5	D/P, b/m, tbl, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8, CSR_k=9, CSR_k=10, CSR_k=11, CSR_k=12	D/P, b/m, tbl, TMS, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8 CSR_k=9, CSR_k=10	b/m CSR_k=6

Notes: The MCS tests is computed using 1000 bootstrap replications and a block size of 12.

Table 3: Model Confidence Sets at 90% level
(12-step ahead forecast horizon)

	GOV raw	IG raw	HY raw	GOV wavelet	IG wavelet	HY wavelet
Selected Predictors	AR, D/P, b/m, tbl, TMS, DFR, infl, IP, VIX, Leverage, Jurado et al index, Pastor liquidity, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6	AR, D/P, E/P, b/m, tbl, TMS, DFR,infl, IP,VIX, Leverage, Jurado et al index, Pastor liquidity, CSR_k=1, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6,	b/m, tbl, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8	AR, D/P, b/m, tbl, TMS, DFR, infl, IP, VIX, Leverage, Jurado et al index, Pastor liquidity, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8, CSR_k=9, CSR_k=10, CSR_k=11, CSR_k=12	AR, D/P, E/P, b/m, tbl, TMS, DFR,infl, IP,VIX, Leverage, Jurado et al index, Pastor liquidity, CSR_k=1,	b/m, tbl TMS, CSR_k=2, CSR_k=3, CSR_k=4, CSR_k=5, CSR_k=6, CSR_k=7, CSR_k=8 CSR_k=9, CSR_k=10 CSR_k=11

Notes: The MCS tests is computed using 1000 bootstrap replications and a block size of 12.