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Predicting Bond Betas using Macro-Finance Variables*

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Predicting Bond Betas using Macro-Finance Variables

Abstract: We conduct in-sample and out-of-sample forecasting using the new approach of combining explanatory variables through complete subset regressions (CSR). We predict bond CAPM betas and bond returns conditioning on various macro-finance variables. We explore differences across long-term government bonds, investment grade corporate bonds, and high-yield corporate bonds. The CSR method performs well in predicting bond betas, especially in-sample, and, mainly high-yield bond betas when the focus is out-of-sample. Bond returns are less predictable than bond betas.
Keywords: bond betas; complete subset regressions; corporate bonds; macro-finance variables; model confidence set; risk-return trade-off.
JEL Classifications: C30; C53; G12.

1 Introduction

Comovements between bond and equity markets are important for asset allocation, risk analysis, and hedging. This paper examines the in-sample and 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 the combination of forecasts from complete subset regressions (CSR) as suggested by Elliott, Gargano, and Timmermann (2013) improves predictability of the bond betas relative to a benchmark model. Furthermore, we find large differences in forecast behavior across bond types, ranging from long-term government bonds over investment grade corporate bonds to high-yield corporate bonds. Furthermore, we investigate differences in predictability of bond betas and bond returns.

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 uses financial variables from the literature on stock return predictability (the Goyal and Welch (2008) data set), 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).

We measure bond risk by its CAPM beta, i.e. its covariance with the stock market divided by the stock 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 Campbell, Sunderam, and Viceira (2013). Viceira (2012) studies the time variation in the government bond beta and shows that it is related to the yield spread and the short rate. Our contribution to Viceira (2012) is mainly to investigate if the term structure dependence of bond betas varies across bond type. Moreover, unlike Viceira (2012) we consider a large set of predictors.

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 (2013)) 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 having a 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.

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 (2016) stress the importance of firm capital structure to explain comovements between bond and equity. 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. Bond betas are predictable by the term structure of interest rates. Government and investment grade corporate bond betas depend positively on the term structure, whereas for high-yield corporate bond betas the dependence is negative. Based on the RMSEs, combining macro-finance variables via complete subset regressions is particularly advantageous for predicting bond betas in-sample whereas using single macro-finance variables is a competitive alternative for out-of-sample bond beta predictions. Based upon RMSEs the bond returns are more difficult to predict than bond betas. The predictability is similar across bond types. When using the model confidence set of Hansen, Lunde, and Nason (2011) as a goodness-of-fit measure, our results suggest that the complete subset regressions provide good bond beta predictions out-of-sample. Still, the bond returns are difficult to predict also when judged by the model confidence approach. The qualitative results are similar for 3-month and 12-month forecast horizons. The CSR results are also similar for stock industry portfolios and for corporate bond indices.

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. Various robustness results are delegated to the Appendix.

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 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 sample statistics for the monthly bond betas and bond returns for the full sample period. The average bond betas are decreasing with bond quality, i.e. for the government bond beta the mean is -0.127, for the investment grade bond beta -0.062 and for the high-yield bond beta 0.054. 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 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. As for the bond returns, the Sharpe ratio of investment grade bonds is 0.36, for government bonds it is lower at 0.26 and for high-yield bonds it is even lower at 0.22. The bonds returns are left skewed and all returns have fat tails. To examine the persistency in the data, Table 1 also reports the autocorrelation (at lag one) of the realized bond betas and bond returns. There is strong autocorrelation for bond betas and high-yield bond returns.

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 great recession.

[Insert Table 1 here]

[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 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 (*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), 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). 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.

For the out-of-sample analysis, 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. In the main analysis, we consider the 1-month horizon. In the Appendix 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. We use a 75% confidence level.

4 Empirical Results

This section contains the empirical analysis. As preliminary analysis, we conduct similar analysis as Viceira (2012). Second, we investigate bond beta predictability, followed by bond return predictability. At last, we investigate differences between bond and stock betas.

4.1 Effects of Term Structure of Interest Rates

Similarly to Viceira (2012), we investigate if bond betas are predictable from the term structure of interest rates. For this reason, we regress the bond beta on the one-period lagged treasury bill rate (TBL) and the one-period lagged term spread (TMS). We include the one-period lagged bond beta to account for any autocorrelation. We also contribute to the literature by investigating how the term structure dependence of bond betas varies across bond types.

[Insert Table 2]

Table 2 shows the results from these regressions. Although the sample period in Viceira (2012) is different (1962 to 2007), our results for the government bond beta is very similar. The government bond beta depends positively and significantly on the treasury bill rate and positively but insignificantly on the term spread. The explanatory power is large with an adjusted R-squared of 0.25. The explanatory power is not caused by including the lagged bond beta. When excluding the lagged bond beta, the adjusted R-squared is still as high as 0.17.

The investment grade bond beta is also predictable by the term structure and there is also a positive dependence. The relation is weaker with an adjusted R-squared of 0.19 (dropping only to 0.12 when excluding the lagged bond beta).

The high-yield bond beta has negative and significant coefficients for the treasury bill rate and the term spread. So, the dependence for high-yield bonds has opposite sign from government and investment grade bonds.

Table 2 also shows that the bond returns are not strongly predictable by the term structure of interest rates (low R-squared values). The weaker predictability of first moments than second moments is in accordance with the stock market results in Ludvigson and Ng (2009) and Aslanidis, Christiansen, and Savva (2016).

So far, our findings indicate that investment grade bond behave similar to government bonds whereas high-yield bonds stand out.

4.2 Predicting Bond Betas

Table 3 shows the in-sample (left columns) and out-of-sample (right columns) RMSEs for each of the realized bond betas for 1-month ahead forecasting models. At the top, we show the RMSEs from the benchmark model (the 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 3]

In-sample, the results are qualitatively identical across bond quality. According to the RMSE, the CSR delivers more accurate predictions the larger the k (the more variables are included in CSR). The CSR combinations are preferred to the benchmark AR (the RMSEs are reduced by about 15-20%). Importantly, all the CSR combinations have lower RMSEs than the single-variable regressions.

For the out-of-sample predictions, although most of the CSR combinations are better than the AR, the results vary qualitatively across bond quality. For example, for government and investment grade bond betas, single-predictor regressions now 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). This result supports Viceira (2012) and our results in Table 2. For the high-yield bond betas, there is not much difference across models with the most accurate predictability being achieved using individual predictors such as the treasury bill rate (TBL) and the book-to-market ratio (B/M), as well as CSR with $k = 6, 7, 8$. Overall and regardless of the bond type, the CSR combinations delivering the lowest RMSE are associated with fewer variables than for in-sample predictions. Therefore, out-of-sample, many predictors appear to result in over-fitting.

Table 4 reports the selected variables based upon the model confidence set (MCS) approach for predicting bond betas both in-sample and out-of-sample. In-sample, none of the individual predictors are included in the MCS, which confirms the superior in-sample forecasting performance of CSR combinations relative to individual predictors regardless of the bond type.

Out-of-sample the picture is, however, different. For government and investment grade bond betas, the MCS includes only individuals predictors (e.g. the treasury bill rate (TBL) and the book-to-market ratio (B/M)). This finding is in line with the results in Table 3 confirming the good out-of-sample performance of those individual predictors relative to CSR. 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 4].

4.3 Predicting Bond Returns

Table 5 shows the RMSEs for predicting bond returns in a manner similar to Table 3 for bond betas.

In-sample, the results are qualitatively similar to those for predicting bond betas. The CSR method delivers more accurate predictions the more variables are included (with the lowest RMSEs obtained when all 13 predictors are included).

Out-of-sample, single-variable predictions, as with bond betas, result in the lowest RMSEs. For example, for government and investment grade bonds the industrial production is the preferred macro-finance predictor. But for the high-yield bond, the benchmark AR delivers the lowest RMSE.

[Insert Table 5]

Table 6 shows the MCS results for predicting bond returns. In terms of the MCS approach, both in-sample and out-of-sample it is hard to distinguish between models as almost all specifications are included in the best model. Actually, the MCS confirms that the bond returns are difficult to predict. This finding is in line with the Viceira (2012) regressions in Table 2 above.

[Insert Table 6]

4.4 Variations across Horizon

The Appendix contains the RMSEs of the models for the 3-month and 12-month horizon predictions. Qualitatively, the results tend to be similar to the 1-month horizon results.

Table $A1$ shows the RMSEs for realized bond betas. As with the 1-month horizon results, the CSR delivers more accurate predictions the more variables are included in CSR combinations. Across horizons and bond types, almost all CSR combinations have lower RMSEs than the single-variable regressions.

However, out-of-sample, 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.

Table $A2$ shows the RMSEs for bond returns. While, in-sample, CSR predictions outperform individual predictors and the benchmark at the 3-month and 12-month horizons, the reverse occurs when the focus is on out-of-sample analysis.

4.5 Stock Industry Portfolios

To investigate if our empirical results are specific to corporate bond betas, we analyze stock industry betas. We apply the Fama-French five industry portfolios available from Kenneth French's online data library; consumer, manufacturing, high tech, health care, and other. Tables *A*3-*A*6 in the Appendix show the 1-month horizon results.

The means and standard deviations for stock industry betas are much larger than for bond betas. The Viceira (2012) regressions show that the stock industry betas depend negatively on the term structure (except for health care). This is similar to the high-yield bond betas. So, the high-yield bond betas behavior is closer to stock industry portfolios than to government bonds.

The results for CSR are similar when applied to industry portfolio betas rather than bond betas. Although CSR outperforms in-sample individual variables and the benchmark, they perform poorly out-of-sample, since their predictions are not statistically different from the benchmark. Moreover, there is no difference between CSR, individuals and benchmark when the focus is on out-of-sample prediction of industry stock returns. Still, it could be the case that the CSR methodology would provide better results if it were used to individual asset betas.

5 Conclusion

In this paper we explore the role played by macro-finance variables for predicting bond betas and bond returns. We investigate three different categories of bonds, namely long-term government bonds, investment grade corporate bonds, and speculative grade corporate bonds. We make use of a new method for combining predictions from various explanatory variables, namely the complete subset regressions method. We find that the complete subset regression method performs well at predicting bond betas. Bond returns are less predictable. The differences across bond types are not so pronounced. The complete subset regression method appears to perform better for in-sample than out-of-sample predictions.

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A Appendix: Longer Forecasting Horizons

Here we show the results from analyzing corporate bonds at the 3-month and 12-month horizon.

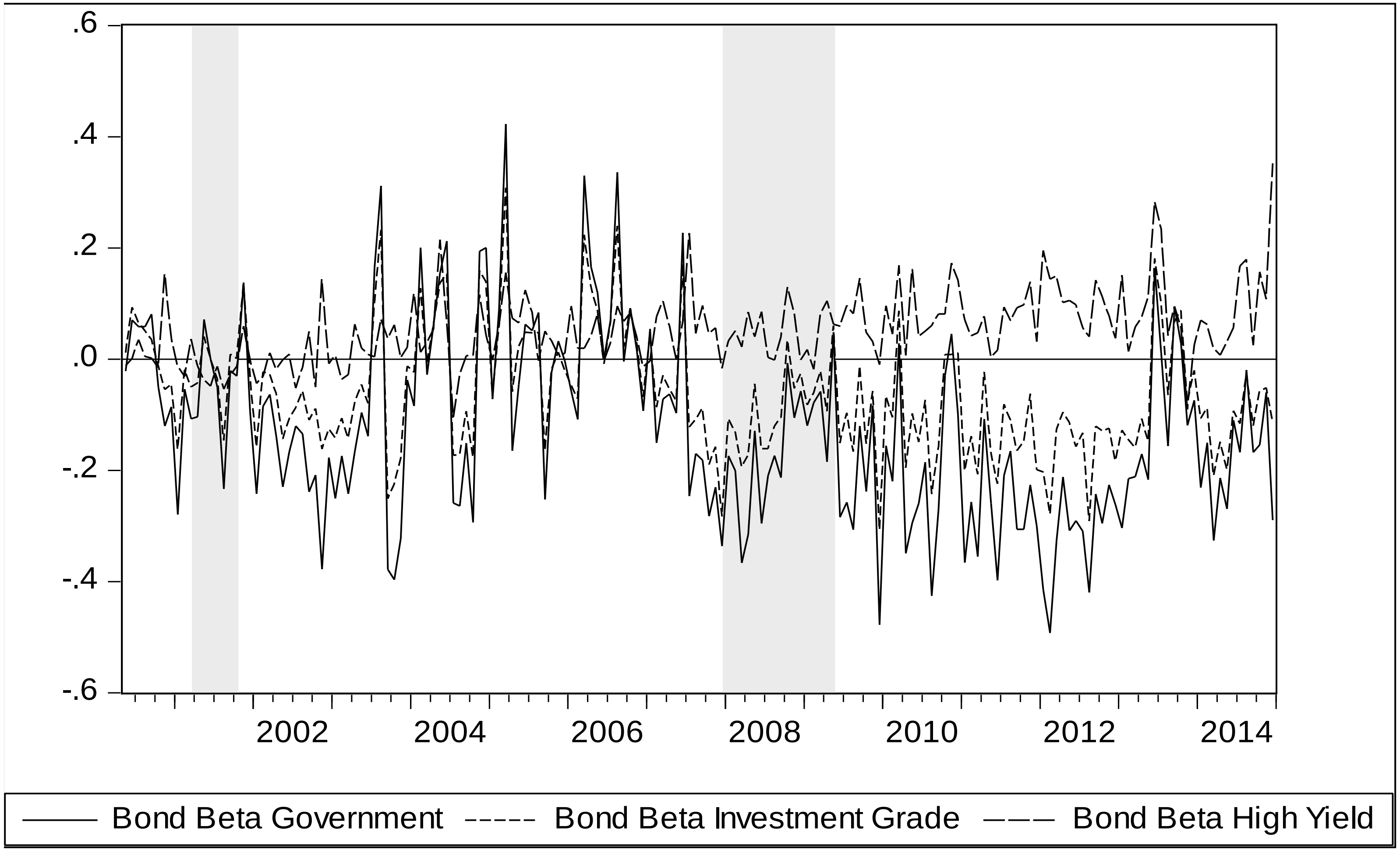
[Insert Tables A1 and A2]

B Appendix: Industry Portfolios

Here we show the results from analyzing the 5-industry stock portfolios.

[Insert Tables A3-A6]

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

		Mean	St.Dev.	Skew.	Kurt.	Autocor(1)
Betas	GOV	-0.1265	0.169	0.54	3.20	0.45
	IG	-0.0623	0.110	0.60	3.43	0.38
	HY	0.0536	0.067	0.99	5.22	0.32
Returns	GOV	0.0056	0.022	-0.22	4.26	0.04
	IG	0.0060	0.017	-1.17	8.66	0.22
	HY	0.0065	0.030	-1.19	10.77	0.33

Table 2: Viceira Regressions for Bonds

		GOV		IG		HY	
Betas	Constant	-0.20	***	-0.12	***	0.16	***
	Lagged	0.33	***	0.28	***	0.19	**
	TBL	3.56	***	2.21	***	-2.51	***
	TMS	1.97		1.33		-2.78	***
	Adj. R-squared	0.25		0.19		0.22	
Returns	Constant	-0.01	*	-0.01		0.01	*
	Lagged	0.06		0.23	***	0.32	***
	TBL	0.39	***	0.19	*	-0.26	
	TMS	0.48	**	0.29	**	-0.20	
	Adj. R-squared	0.02		0.05		0.10	

Table 3: RMSEs for Bond Betas

	>>> In-Sample <<<			>>> Out-of-Sample <<<		
	GOV	IG	HY	GOV	IG	HY
AR	0.158	0.107	0.073	0.143	0.099	0.070
CSR, k=1	0.145	0.097	0.069	0.161	0.106	0.073
CSR, k=2	0.140	0.095	0.067	0.157	0.104	0.072
CSR, k=3	0.137	0.094	0.066	0.155	0.104	0.070
CSR, k=4	0.135	0.093	0.065	0.154	0.103	0.069
CSR, k=5	0.133	0.092	0.065	0.153	0.104	0.069
CSR, k=6	0.132	0.091	0.064	0.153	0.104	0.068
CSR, k=7	0.131	0.091	0.064	0.154	0.104	0.068
CSR, k=8	0.130	0.090	0.064	0.154	0.105	0.068
CSR, k=9	0.129	0.090	0.064	0.155	0.105	0.069
CSR, k=10	0.128	0.089	0.064	0.156	0.106	0.069
CSR, k=11	0.127	0.089	**0.063**	0.158	0.107	0.069
CSR, k=12	0.126	0.088	**0.063**	0.160	0.109	0.070
CSR, k=13	**0.126**	**0.088**	**0.063**	0.163	0.110	0.070
D/P	0.154	0.105	0.071	0.140	0.097	0.069
E/P	0.158	0.107	0.073	0.149	0.102	0.072
B/M	0.154	0.104	0.071	0.140	0.097	**0.068**
TBL	0.159	0.107	0.071	**0.136**	**0.095**	0.068
TMS	0.158	0.107	0.072	0.143	0.099	0.070
DFR	0.158	0.107	0.073	0.146	0.101	0.071
INFL	0.158	0.107	0.073	0.143	0.099	0.070
IP	0.158	0.107	0.073	0.147	0.101	0.071
VIX	0.159	0.107	0.073	0.144	0.100	0.071
leverage	0.158	0.107	0.073	0.144	0.099	0.070
uncertainty	0.158	0.106	0.073	0.149	0.101	0.071
liquidity	0.157	0.106	0.072	0.145	0.100	0.072

Table 4: MCS Results for Bond Betas (at 75% level)

	>>> In-Sample <<<			>>> Out-of-Sample <<<		
	GOV	IG	HY	GOV	IG	HY
AR						
CSR, k=1						
CSR, k=2						
CSR, k=3	Yes					
CSR, k=4	Yes					
CSR, k=5	Yes					Yes
CSR, k=6	Yes					Yes
CSR, k=7	Yes		Yes			Yes
CSR, k=8	Yes		Yes			Yes
CSR, k=9	Yes		Yes			Yes
CSR, k=10	Yes		Yes			Yes
CSR, k=11	Yes		Yes			Yes
CSR, k=12	Yes		Yes			
CSR, k=13	Yes	Yes	Yes			
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 5: RMSEs for Bond Returns

	>>> In-Sample <<<			>>> Out-of-Sample <<<		
	GOV	IG	HY	GOV	IG	HY
AR	2.207	1.890	3.507	2.235	1.848	**3.214**
CSR, k=1	2.190	1.803	3.266	2.239	1.850	3.367
CSR, k=2	2.162	1.762	3.182	2.251	1.849	3.374
CSR, k=3	2.130	1.724	3.102	2.258	1.852	3.387
CSR, k=4	2.095	1.688	3.026	2.259	1.856	3.401
CSR, k=5	2.058	1.656	2.955	2.254	1.861	3.412
CSR, k=6	2.022	1.626	2.889	2.244	1.867	3.422
CSR, k=7	1.988	1.600	2.830	2.233	1.876	3.431
CSR, k=8	1.959	1.577	2.779	2.227	1.889	3.444
CSR, k=9	1.936	1.558	2.735	2.231	1.908	3.461
CSR, k=10	1.918	1.542	2.698	2.248	1.934	3.485
CSR, k=11	1.905	1.529	2.669	2.285	1.971	3.519
CSR, k=12	1.897	1.520	2.646	2.345	2.018	3.561
CSR, k=13	**1.892**	**1.514**	**2.629**	2.432	2.077	3.615
D/P	2.209	1.886	3.462	2.282	1.897	3.261
E/P	2.229	1.869	3.499	2.264	1.834	3.231
B/M	2.207	1.889	3.513	2.252	1.859	3.233
TBL	2.202	1.890	3.469	2.248	1.865	3.229
TMS	2.208	1.872	3.480	2.242	1.846	3.220
DFR	2.203	1.908	3.507	2.273	1.865	3.442
INFL	2.216	1.901	3.496	2.267	1.878	3.257
IP	2.235	1.956	3.588	**2.167**	**1.828**	3.337
VIX	2.206	1.876	3.500	2.330	1.971	3.394
leverage	2.205	1.893	3.535	2.255	1.866	3.243
uncertainty	2.226	1.882	3.460	2.284	1.863	3.227
liquidity	2.212	1.894	3.505	2.289	1.896	3.311

Table 6: MCS Results for Bond Returns (at 75% level)

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

Table A1: RMSEs for Bond Betas for Longer Horizons

	>>> Horizon 3-Month <<<					
	>>> In-Sample <<<			>>> Out-of-Sample <<<		
	GOV	IG	HY	GOV	IG	HY
AR	0.151	0.101	0.070	0.154	0.104	0.075
CSR, k=1	0.144	0.097	0.069	0.164	0.107	0.074
CSR, k=2	0.141	0.095	0.067	0.162	0.107	0.073
CSR, k=3	0.138	0.094	0.066	0.162	0.107	0.072
CSR, k=4	0.136	0.094	0.065	0.163	0.108	0.071
CSR, k=5	0.134	0.093	0.065	0.164	0.109	0.070
CSR, k=6	0.133	0.092	0.064	0.166	0.111	0.070
CSR, k=7	0.131	0.091	0.063	0.169	0.113	**0.069**
CSR, k=8	0.130	0.090	0.063	0.171	0.114	**0.069**
CSR, k=9	0.129	0.090	0.063	0.174	0.117	0.070
CSR, k=10	0.128	0.089	0.062	0.178	0.119	0.070
CSR, k=11	0.127	0.089	**0.062**	0.183	0.123	0.071
CSR, k=12	**0.127**	**0.088**	**0.062**	0.189	0.127	0.073
CSR, k=13	0.127	0.088	**0.062**	0.197	0.131	0.075
D/P	0.147	0.099	0.070	0.152	0.104	0.072
E/P	0.151	0.101	0.071	0.169	0.113	0.079
B/M	0.147	0.098	0.069	0.155	0.105	0.069
TBL	0.151	0.101	0.068	**0.147**	**0.101**	0.072
TMS	0.150	0.101	0.070	0.156	0.106	0.075
DFR	0.150	0.101	0.070	0.155	0.106	0.076
INFL	0.151	0.101	0.071	0.155	0.105	0.075
IP	0.151	0.101	0.071	0.154	0.104	0.076
VIX	0.151	0.101	0.070	0.157	0.106	0.077
leverage	0.151	0.101	0.070	0.154	0.105	0.075
uncertainty	0.151	0.101	0.071	0.166	0.110	0.077
liquidity	0.150	0.100	0.070	0.161	0.108	0.078

>>> Horizon 12-Month <<<						
	>>> In-Sample <<<			>>> Out-of-Sample <<<		
	GOV	IG	HY	GOV	IG	HY
AR	0.147	0.098	0.070	0.169	0.111	0.074
CSR, k=1	0.145	0.097	0.068	0.177	0.114	0.074
CSR, k=2	0.143	0.096	0.067	0.183	0.118	0.072
CSR, k=3	0.142	0.096	0.066	0.190	0.122	0.071
CSR, k=4	0.142	0.096	0.066	0.196	0.127	0.070
CSR, k=5	0.141	0.096	0.065	0.203	0.131	0.069
CSR, k=6	0.141	0.096	0.065	0.210	0.134	**0.069**
CSR, k=7	0.140	0.095	0.064	0.217	0.138	0.069
CSR, k=8	0.140	**0.095**	0.064	0.225	0.143	0.070
CSR, k=9	0.140	**0.095**	0.064	0.234	0.148	0.071
CSR, k=10	**0.140**	**0.095**	0.064	0.245	0.155	0.073
CSR, k=11	**0.140**	0.095	0.063	0.259	0.163	0.075
CSR, k=12	0.140	0.096	0.063	0.276	0.174	0.078
CSR, k=13	0.141	0.096	**0.063**	0.297	0.189	0.082
D/P	0.143	0.097	0.070	0.185	0.119	0.074
E/P	0.148	0.099	0.070	0.201	0.129	0.082
B/M	0.144	0.096	0.069	0.190	0.122	0.071
TBL	0.145	0.098	0.067	0.177	0.115	0.072
TMS	0.145	0.098	0.069	0.177	0.117	0.076
DFR	0.146	0.099	0.070	0.181	0.118	0.075
INFL	0.147	0.098	0.070	**0.168**	**0.110**	0.075
IP	0.147	0.098	0.069	0.173	0.112	0.076
VIX	0.147	0.099	0.070	0.179	0.115	0.086
leverage	0.147	0.098	0.070	0.171	0.111	0.075
uncertainty	0.147	0.098	0.070	0.174	0.114	0.077
liquidity	0.146	0.098	0.070	0.203	0.127	0.074

Table A2: RMSEs for Bond Returns for Longer Horizons

	>>> Horizon 3-Month <<<					
	>>> In-Sample <<<			>>> Out-of-Sample <<<		
	GOV	IG	HY	GOV	IG	HY
AR	2.205	1.844	3.363	2.210	1.898	3.440
CSR, k=1	2.195	1.822	3.272	2.225	**1.871**	3.382
CSR, k=2	2.178	1.805	3.211	2.236	1.898	3.404
CSR, k=3	2.161	1.790	3.162	2.254	1.933	3.446
CSR, k=4	2.144	1.777	3.118	2.278	1.976	3.503
CSR, k=5	2.127	1.763	3.074	2.308	2.025	3.571
CSR, k=6	2.110	1.749	3.031	2.345	2.076	3.647
CSR, k=7	2.093	1.735	2.989	2.388	2.128	3.729
CSR, k=8	2.076	1.722	2.949	2.436	2.181	3.816
CSR, k=9	2.061	1.710	2.912	2.490	2.235	3.906
CSR, k=10	2.046	1.699	2.880	2.551	2.289	3.997
CSR, k=11	2.033	1.690	2.852	2.619	2.345	4.088
CSR, k=12	2.021	1.683	2.829	2.698	2.401	4.178
CSR, k=13	**2.011**	**1.678**	**2.811**	2.789	2.457	4.267
D/P	2.219	1.836	3.322	**2.185**	2.007	3.546
E/P	2.209	1.821	3.345	2.240	**1.871**	3.518
B/M	2.215	1.844	3.401	2.204	1.914	3.418
TBL	2.199	1.842	3.313	2.214	1.922	3.446
TMS	2.205	1.826	3.301	2.216	1.903	3.430
DFR	2.206	1.844	3.361	2.245	1.967	3.461
INFL	2.182	1.846	3.356	2.215	1.974	3.400
IP	2.213	1.844	3.321	2.361	1.935	3.435
VIX	2.212	1.811	3.292	2.253	2.110	4.185
leverage	2.210	1.852	3.364	2.215	1.909	3.450
uncertainty	2.221	1.841	3.374	2.202	1.874	**3.199**
liquidity	2.203	1.845	3.338	2.230	1.959	3.671

>>> Horizon 12-Month <<<						
	>>> In-Sample <<<			>>> Out-of-Sample <<<		
	GOV	IG	HY	GOV	IG	HY
AR	2.211	1.843	3.356	2.238	1.862	3.380
CSR, k=1	2.206	1.824	3.313	2.233	1.836	3.378
CSR, k=2	2.199	1.808	3.285	2.255	1.823	3.398
CSR, k=3	2.191	1.796	3.265	2.288	1.817	3.444
CSR, k=4	2.183	1.784	3.249	2.335	1.820	3.515
CSR, k=5	2.175	1.773	3.235	2.397	1.837	3.611
CSR, k=6	2.166	1.763	3.222	2.471	1.868	3.725
CSR, k=7	2.157	1.752	3.208	2.556	1.912	3.849
CSR, k=8	2.149	1.742	3.196	2.649	1.967	3.975
CSR, k=9	2.141	1.733	3.184	2.747	2.028	4.097
CSR, k=10	2.134	1.725	3.173	2.850	2.091	4.210
CSR, k=11	2.127	1.717	3.163	2.956	2.157	4.313
CSR, k=12	2.123	1.712	3.155	3.067	2.224	4.412
CSR, k=13	**2.120**	**1.710**	**3.148**	3.187	2.294	4.518
D/P	2.211	1.837	3.322	2.293	1.973	3.415
E/P	2.202	1.818	3.330	2.256	1.857	3.438
B/M	2.214	1.845	3.357	2.277	1.873	3.397
TBL	2.206	1.831	3.301	2.244	1.871	3.379
TMS	2.211	1.809	3.264	2.239	1.840	**3.322**
DFR	2.206	1.844	3.353	2.265	1.863	3.473
INFL	2.190	1.843	3.349	**2.235**	1.873	3.371
IP	2.206	1.839	3.325	2.263	1.867	3.553
VIX	2.211	1.793	3.270	2.507	**1.795**	3.570
leverage	2.209	1.842	3.351	2.243	1.862	3.384
uncertainty	2.209	1.834	3.319	2.243	1.849	3.345
liquidity	2.211	1.833	3.336	2.308	1.945	3.753

Table A3: Descriptive Statistics for Stocks

		Mean	St.Dev.	Skew.	Kurt.	Autocor.
Betas	CON	0.809	0.16	-1.01	5.68	0.65
	MAN	0.927	0.23	-0.97	4.46	0.71
	HT	1.173	0.30	1.34	4.12	0.83
	HEL	0.751	0.24	-0.88	6.06	0.55
	OTH	1.089	0.21	0.97	5.87	0.68
Returns	CON	0.881	3.74	-0.79	4.67	0.12
	MAN	1.051	4.63	-0.87	4.54	0.02
	HT	0.301	6.68	-0.69	4.27	0.06
	HE	0.734	3.95	-0.32	3.43	0.03
	OT	0.786	5.21	-0.47	5.25	0.16

Table A4: Viceira Regressions for Stocks

		CON		MAN		HT		HEL		OTH	
Betas	Constant	0.35	***	0.51	***	0.12	**	0.47	***	0.57	***
	Lagged	0.63	***	0.63	***	0.72	***	0.49	***	0.59	***
	TBL	-1.06		-3.98	***	4.80	***	-2.99	*	-3.24	***
	TMS	-0.93		-3.73	***	4.54	**	-1.17		-2.41	**
	Adj. R-squared	0.44		0.53		0.72		0.33		0.49	
Returns	Constant	4.05	***	3.45	**	6.96	***	5.90	***	4.50	***
	Lagged	0.10		0.01		0.02		-0.03		0.15	*
	TBL	-64.11	***	-42.30		-146.64	***	-101.56	***	-76.87	***
	TMS	-80.75	**	-63.65		-153.93	**	-128.81	***	-95.37	***
	Adj. R-squared	0.03		-0.01		0.04		0.05		0.03	

Table A5: RMSEs for Stock Betas

	CON	MAN	HT	HEL	OTH	CON	MAN	HT	HEL	OTH
AR	0.115	0.177	0.138	0.179	0.221	0.097	0.113	0.102	0.157	0.171
CSR, k=1	0.093	0.145	0.159	0.173	0.184	0.093	0.162	0.214	0.180	0.214
CSR, k=2	0.090	0.137	0.135	0.159	0.163	**0.092**	0.147	0.169	0.166	0.189
CSR, k=3	0.089	0.132	0.120	0.151	0.151	0.095	0.140	0.139	0.158	0.174
CSR, k=4	0.089	0.128	0.111	0.146	0.143	0.100	0.137	0.122	0.155	0.165
CSR, k=5	0.088	0.126	0.105	0.144	0.139	0.105	0.138	0.114	0.155	0.161
CSR, k=6	0.088	0.124	0.101	0.143	0.136	0.109	0.139	0.110	0.156	0.161
CSR, k=7	0.087	0.122	0.098	0.142	0.134	0.111	0.140	0.109	0.159	0.162
CSR, k=8	0.086	0.120	0.095	0.141	0.133	0.113	0.142	0.109	0.162	0.165
CSR, k=9	0.085	0.118	0.093	0.140	0.132	0.114	0.144	0.109	0.166	0.168
CSR, k=10	0.085	0.117	0.092	0.139	0.131	0.115	0.147	0.111	0.171	0.172
CSR, k=11	0.084	0.116	0.091	0.138	0.130	0.116	0.150	0.113	0.178	0.177
CSR, k=12	0.083	0.115	0.091	**0.138**	0.130	0.117	0.155	0.116	0.187	0.182
CSR, k=13	**0.083**	**0.115**	**0.090**	**0.138**	**0.130**	0.119	0.161	0.121	0.199	0.187
D/P	0.113	0.163	0.140	0.177	0.228	0.116	0.132	0.115	0.177	**0.152**
E/P	0.118	0.178	0.136	0.186	0.225	0.098	0.123	0.115	0.151	0.172
B/M	0.112	0.162	0.140	0.169	0.225	0.103	0.121	0.118	0.165	0.171
TBL	0.114	0.171	0.146	0.165	0.230	0.098	**0.111**	**0.099**	0.165	0.171
TMS	0.115	0.175	0.141	0.176	0.225	0.097	0.113	0.101	0.161	0.172
DFR	0.116	0.176	0.137	0.184	0.221	0.100	0.116	0.102	0.163	0.179
INFL	0.117	0.177	0.138	0.179	0.222	0.096	0.113	0.103	0.159	0.175
IP	0.115	0.176	0.138	0.179	0.221	0.105	0.114	0.109	0.157	0.175
VIX	0.114	0.177	0.138	0.178	0.223	0.099	0.117	0.108	0.162	0.172
leverage	0.115	0.177	0.138	0.182	0.222	0.097	0.113	0.102	0.157	0.173
uncertainty	0.114	0.180	0.137	0.184	0.229	0.096	0.125	0.113	**0.151**	0.163
liquidity	0.115	0.173	0.135	0.177	0.212	0.099	0.115	0.107	0.156	0.157

Table A6: RMSEs for Stock Returns

	CON	MAN	HT	HEL	OTH	CON	MAN	HT	HEL	OTH
AR	4.025	5.081	5.111	4.114	6.082	4.054	5.155	5.187	4.169	6.136
CSR, k=1	3.954	5.020	5.033	4.058	6.010	4.047	5.092	5.184	4.174	6.158
CSR, k=2	3.898	4.969	4.954	4.017	5.917	4.063	5.102	5.201	4.199	6.192
CSR, k=3	3.842	4.921	4.874	3.977	5.822	4.076	5.123	5.245	4.225	6.228
CSR, k=4	3.783	4.872	4.792	3.936	5.722	4.087	5.150	5.312	4.252	6.265
CSR, k=5	3.724	4.823	4.705	3.895	5.617	4.097	5.183	5.395	4.281	6.302
CSR, k=6	3.665	4.773	4.615	3.854	5.513	4.107	5.225	5.492	4.313	6.341
CSR, k=7	3.610	4.726	4.526	3.816	5.412	4.123	5.277	5.604	4.352	6.387
CSR, k=8	3.560	4.682	4.443	3.782	5.320	4.147	5.343	5.736	4.400	6.442
CSR, k=9	3.517	4.645	4.370	3.755	5.241	4.181	5.427	5.895	4.459	6.508
CSR, k=10	3.483	4.614	4.310	3.735	5.175	4.228	5.528	6.084	4.532	6.588
CSR, k=11	3.457	4.592	4.265	3.722	5.123	4.287	5.645	6.307	4.619	6.682
CSR, k=12	3.439	4.577	4.238	3.716	5.085	4.356	5.777	6.561	4.720	6.789
CSR, k=13	**3.428**	**4.569**	**4.232**	**3.714**	**5.058**	4.434	5.923	6.846	4.837	6.911
D/P	4.011	5.088	5.173	4.127	6.052	4.091	5.271	5.402	4.180	6.255
E/P	4.025	5.081	5.111	4.086	6.085	4.137	5.350	5.607	4.285	6.362
B/M	4.010	5.091	5.165	4.060	6.073	4.071	5.193	5.142	**4.137**	6.163
TBL	3.968	5.075	4.979	4.036	6.003	4.066	5.187	**5.114**	4.172	6.168
TMS	4.051	5.111	5.078	4.145	6.110	4.070	5.161	5.196	4.198	6.160
DFR	4.040	5.078	5.111	4.118	6.084	4.205	5.212	5.579	4.355	6.420
INFL	4.024	5.062	5.092	4.099	6.079	4.077	5.244	5.229	4.230	6.170
IP	4.096	5.173	5.207	4.149	6.279	**4.024**	**4.979**	5.158	4.153	**6.107**
VIX	4.058	5.160	5.176	4.120	6.162	4.229	5.261	5.304	4.237	6.330
leverage	4.057	5.052	5.139	4.141	6.098	4.072	5.208	5.182	4.148	6.223
uncertainty	4.012	5.074	5.116	4.113	6.066	4.102	5.282	5.225	4.220	6.255
liquidity	4.059	5.064	5.112	4.112	6.150	4.086	5.322	5.567	4.322	6.247

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