HAKASE CAPITAL

The Corporate Bond Factor Zoo

Dickerson et al 2023

Finance Hub – May 2023

```r
rm(list = ls(all = T))    # Removes previous objects
graphics.off()            # Removes graphs
cat("\014")               # Clear console

# Load the Fama-French data
factors_3   <- c("Mkt.RF","SMB","HML")
tempf       <- tempfile(fileext = ".RData")
inputlist   <- c("Research_Data_Factors","Momentum_Factor",
                 "ST_Reversal_Factor","LT_Reversal_Factor" )
FFdownload::FFdownload(output_file = tempf,
                       inputlist=inputlist,
                       exclude_daily = TRUE,
                       download = TRUE,
                       download_only=FALSE)

load(tempf)
init   <- "1960-01-01/"

ff.3   <- cumsum(FFdata$`x_F-F_Research_Data_Factors`$monthl
ff.m   <- cumsum(FFdata$`x_F-F_Momentum_Factor`$monthly$Temp
ff.st  <- cumsum(FFdata$`x_F-F_ST_Reversal_Factor`$monthly$T
ff.lt  <- cumsum(FFdata$`x_F-F_LT_Reversal_Factor`$monthly$T

ff.data <- cbind(ff.3, ff.m, ff.st, ff.lt) |> exp() # Merge

ff.data <- sapply(ff.data, function(x) as.numeric(as.charact

x <- as.matrix(ff.data[, 1:5]) # Create the design matrix
y <- ff.data$SMB + ff.data$Mom # Create the response vector

lasso_fit <- glmnet::glmnet(x, y, alpha = 1) # Run the Lasso

# Identify the optimal lambda value using cross-validation
cv_fit     <- glmnet::cv.glmnet(x, y, alpha = 1)
lambda_min <- cv_fit$lambda.min

# Extract the coefficients at the optimal lambda value
lasso_coefs <- coef(lasso_fit, s = lambda_min)
lasso_coefs <- as.matrix(lasso_coefs[-1,])
```

Summary

- Extends the factor zoo analysis to the US bond market – USD 40 tri market capitalization
- Dataset: 64 bonds portfolios and 49 risk factors (bonds, equity and nontraded) from 1986:01 to 2021:09 (monthly)
- Econometric method: spike-and-slab prior to shrink and select risk factors
- Findings:

1. The SDF is dense
2. The majority of bond risk factors are disposable
3. Equity and nontraded are not disposable
4. Bayesian model averaging (BMA-SDF) explain excess bonds returns better than any other individual model

Data

Data

- Total return and duration-adjusted returns (openbondassetpricing.com)
  - LHM: 1986:01 to 1996:12
  - ICE: 1997:01 to 2021:09
  - FISD: bonds characteristics
  - Prices are sample exactly at the end of each month (TRACE/WRDS as alternative dataset)
  - 1986:01 to 2021:09 ($t = 429$ months) and 30k unique bonds
- 64 bonds portfolio:
  - 25 (credit spread vs size)
  - 25 (ratings vs time to maturity)
  - 14 bonds risk factors
- Factor zoo:
  - 14 bonds risk factors
  - 11 nontrade risk factors
  - 14 equity risk factors

Econometric Method

Econometric method

Given:

- $\boldsymbol{r}_t = \left(r_{1,t}, \dots, r_{N,t}\right)^T$ and $\boldsymbol{f}_t = \left(f_{1,t}, \dots, f_{k,t}\right)^T$

From the SDF model:

$$\boldsymbol{\mu}_r = \lambda_c \mathbf{1}_N + \boldsymbol{C}_f \boldsymbol{\lambda}_f + \boldsymbol{\alpha}$$

$$\boldsymbol{\mu}_r = \boldsymbol{C}\boldsymbol{\lambda} + \boldsymbol{\alpha}$$

Assuming $\pi(\boldsymbol{\alpha}) \sim MN(\mathbf{0}_N, \sigma^2 \boldsymbol{\Sigma}_r)$, the cross-sectional likelihood is given by:

$$\pi(data|\boldsymbol{\lambda}, \sigma^2) = (2\pi\sigma^2)^{-\frac{N}{2}} |\boldsymbol{\Sigma}_r|^{-\frac{1}{2}} exp\left\{-\frac{1}{2\sigma^2}(\boldsymbol{\mu}_r - \boldsymbol{C}\boldsymbol{\lambda})^T \boldsymbol{\Sigma}_r^{-1} (\boldsymbol{\mu}_r - \boldsymbol{C}\boldsymbol{\lambda})\right\}$$

Shrink and select risk factors: spike-and-slab prior to $\boldsymbol{\lambda}$

Econometric method

Shrink and select risk factors: spike-and-slab prior to $\boldsymbol{\lambda}$:

$$\pi(\boldsymbol{\lambda}, \sigma^2, \boldsymbol{\gamma}, \boldsymbol{\omega}) = \pi(\boldsymbol{\lambda}|\sigma^2, \boldsymbol{\gamma})\pi(\sigma^2)\pi(\boldsymbol{\gamma}|\boldsymbol{\omega})\pi(\boldsymbol{\omega})$$

and:

- $\pi(\lambda_k|\sigma^2, \gamma_k) \sim N(0, r(\gamma_k)\psi_k\sigma^2)$ where:
  - Selection: $r(\gamma_k = 1) = 1 \Rightarrow f_k$ is selected and $r(\gamma_k = 0) = 0 \Rightarrow f_k$ is not selected
  - Shrinkage: $\psi_k = \psi \widehat{\boldsymbol{\rho}}_k^T \widehat{\boldsymbol{\rho}}_k$ and $\widehat{\boldsymbol{\rho}}_k = \boldsymbol{\rho}_k - \left(\frac{1}{N}\sum_{i=1}^{N} \boldsymbol{\rho}_{i,k}\right) \mathbf{1}_N$
  - ψ is hyper parameter link to the Sharpe ratio since $E(SR_k|\sigma^2) = \frac{1}{2}\psi\sigma^2 \sum_{i=1}^{K} \widehat{\boldsymbol{\rho}}_k^T \widehat{\boldsymbol{\rho}}_k$
  - Prior for $E(SR_k|\sigma^2) = (0.2, 0.4, 0.6, 0.8)$
- $\pi(\gamma_k = 1|\omega_k) = \omega_k$ and $\omega_k \sim Beta(a, b)$
  - Belief about the sparsity of the true model
  - $a = b = 1$ implies 50% change of f_k been selected pior

Econometric method

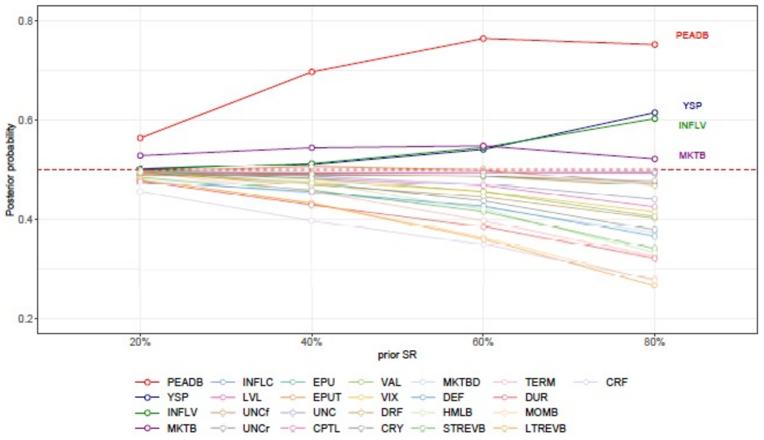
Bayesian model averaging (BMA-SDF) definition:

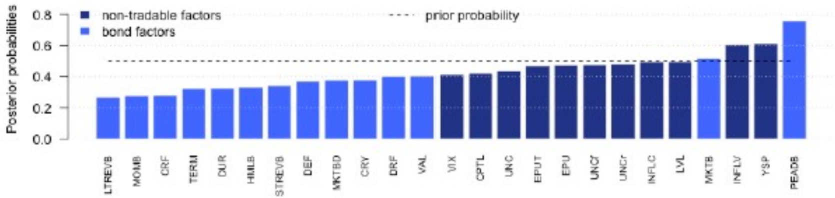
- Given model γ^m we have the SDF: $M_{t,\gamma^m} = 1 - \left(\boldsymbol{f}_{t,\gamma^m} - \boldsymbol{\mu}_{f,\gamma^m}\right)^T \boldsymbol{\lambda}_{\gamma^m}$
- $M_t^{BMA} = \sum_{m=1}^{M} M_{t,\gamma^m}\, Pr(\gamma^m | data)$

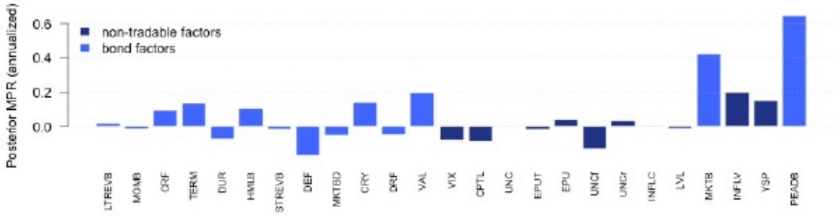
Results

Results - 25 risk factors (bonds and nontrade risk factors)

- Selected risk factors at S.R. = 0.8 (S.R. annualized = 2.4)
- PEADB: post-earnings announcement drift (bond)
- YSP: slope of the yield curve (nontrade?)
- INFL: inflation volatility (nontrade?)
- MKTB: market factor (bond)





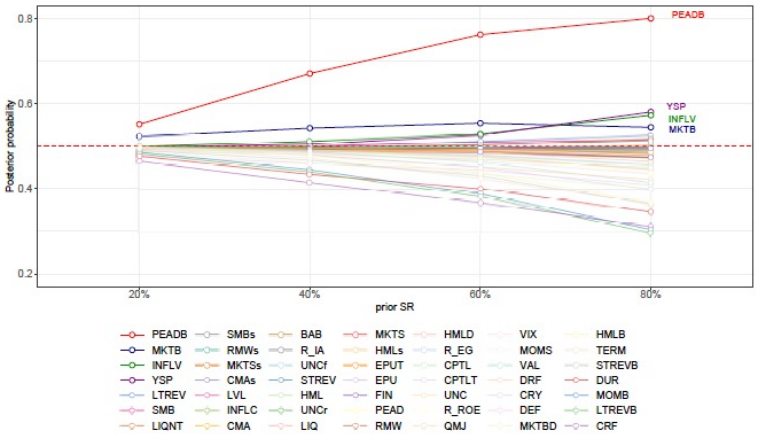


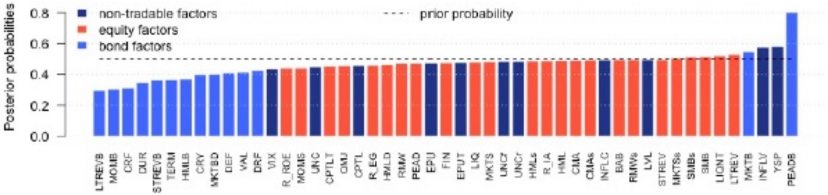
Results - 25 risk factors (bonds and nontrade risk factors)

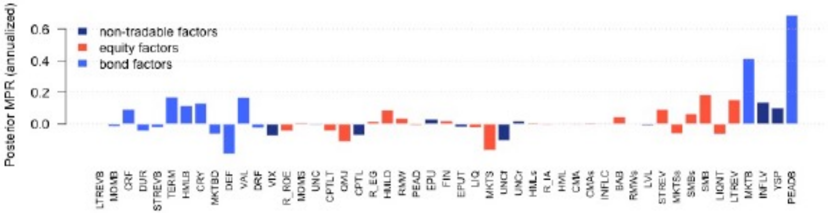
	Factor prob., $\mathbb{E}[\gamma_j \mid \text{data}]$				Price of risk, $\mathbb{E}[\lambda_j \mid \text{data}]$			
	Total prior Sharpe ratio				Total prior Sharpe ratio			
Factors:	20%	40%	60%	80%	20%	40%	60%	80%
PEADB	0.564	0.697	0.764	0.757	0.073	0.285	0.511	0.646
YSP	0.501	0.511	0.541	0.613	0.004	0.016	0.048	0.150
INFLV	0.499	0.513	0.545	0.604	0.006	0.026	0.072	0.199
MKTB	0.529	0.544	0.548	0.519	0.066	0.171	0.291	0.423
INFLC	0.497	0.495	0.496	0.495	0.000	0.000	0.000	0.001
LVL	0.495	0.494	0.495	0.496	0.000	−0.002	−0.004	−0.012
UNCf	0.497	0.505	0.500	0.475	−0.010	−0.035	−0.074	−0.133
UNCr	0.490	0.490	0.487	0.480	0.000	0.003	0.010	0.032
EPU	0.495	0.491	0.487	0.472	0.001	0.005	0.014	0.038
EPUT	0.493	0.492	0.488	0.467	0.000	0.001	−0.005	−0.018
UNC	0.494	0.487	0.471	0.439	−0.003	−0.009	−0.011	−0.001
CPTL	0.493	0.483	0.468	0.422	−0.006	−0.028	−0.058	−0.087
VAL	0.495	0.482	0.455	0.404	0.041	0.094	0.148	0.196
VIX	0.490	0.476	0.456	0.415	−0.008	−0.021	−0.049	−0.081
DRF	0.496	0.469	0.445	0.402	0.026	0.033	0.010	−0.049
CRY	0.497	0.474	0.437	0.378	0.040	0.083	0.115	0.140
MKTBD	0.478	0.453	0.424	0.377	0.019	0.016	−0.007	−0.054
DEF	0.476	0.455	0.427	0.369	−0.017	−0.071	−0.130	−0.17
HMLB	0.497	0.474	0.420	0.332	0.047	0.097	0.117	0.104
STREVB	0.485	0.459	0.416	0.343	0.001	−0.003	−0.009	−0.017
TERM	0.495	0.457	0.398	0.324	0.075	0.137	0.151	0.135
DUR	0.477	0.429	0.386	0.325	0.020	0.004	−0.035	−0.073
MOMB	0.480	0.434	0.364	0.276	−0.020	−0.032	−0.027	−0.014
LTREVB	0.480	0.432	0.361	0.267	0.021	0.036	0.030	0.018
CRF	0.456	0.398	0.350	0.280	0.009	0.036	0.074	0.095

Results - 49 risk factors (bonds, nontrade and equity risk factors)

- Selected risk factors at S.R. = 0.8 (S.R. annualized = 2.4)
- PEADB, YSP, INFL, MKTB and
- LTREV: long-term reversal (equity)
- SMB: small minus big (equity)
- SMBs: small minus big without its unpriced component (equity)
- LIQNT: liquidity (equity)







Results - 49 risk factors

	Factor prob., $\mathbb{E}[\gamma_j \mid \text{data}]$				Price of risk, $\mathbb{E}[\lambda_j \mid \text{data}]$			
	Total prior Sharpe ratio				Total prior Sharpe ratio			
Factors:	20%	40%	60%	80%	20%	40%	60%	80%
PEADB	0.552	0.671	0.762	0.801	0.055	0.228	0.463	0.685
MKTB	0.523	0.543	0.554	0.545	0.053	0.144	0.260	0.413
INFLV	0.500	0.512	0.529	0.573	0.005	0.020	0.052	0.137
YSP	0.498	0.505	0.526	0.581	0.003	0.012	0.034	0.101
LTREV	0.493	0.500	0.512	0.526	0.005	0.023	0.064	0.151
SMB	0.494	0.501	0.510	0.516	0.008	0.033	0.088	0.185
LIQNT	0.496	0.498	0.503	0.518	−0.002	−0.008	−0.022	−0.062
SMBs	0.495	0.499	0.504	0.514	0.002	0.010	0.026	0.064
RMWs	0.499	0.500	0.499	0.497	0.000	0.000	0.000	0.000
MKTSs	0.497	0.498	0.497	0.502	−0.002	−0.009	−0.025	−0.06
CMAs	0.498	0.496	0.496	0.495	0.000	0.001	0.002	0.004
LVL	0.495	0.493	0.497	0.498	0.000	−0.001	−0.003	−0.008
INFLC	0.496	0.495	0.496	0.494	0.000	0.000	0.000	0.001
CMA	0.496	0.497	0.493	0.494	0.000	0.001	0.001	−0.002
BAB	0.494	0.497	0.494	0.492	0.002	0.008	0.020	0.045
R_IA	0.497	0.497	0.494	0.489	0.000	0.000	−0.001	−0.005
UNCf	0.496	0.499	0.497	0.482	−0.008	−0.028	−0.059	−0.104
STREV	0.496	0.491	0.494	0.494	0.003	0.012	0.035	0.092
HML	0.496	0.496	0.494	0.488	0.000	0.001	0.002	0.002
UNCr	0.496	0.498	0.493	0.483	0.000	0.002	0.007	0.021
LIQ	0.496	0.495	0.492	0.482	−0.001	−0.005	−0.012	−0.023
MKTS	0.493	0.492	0.493	0.486	−0.006	−0.032	−0.081	−0.165
HMLs	0.492	0.491	0.492	0.487	0.000	0.001	0.003	0.006
EPUT	0.496	0.495	0.489	0.478	0.000	0.000	−0.003	−0.019
EPU	0.495	0.492	0.487	0.475	0.001	0.004	0.011	0.031
FIN	0.493	0.491	0.487	0.474	0.000	0.004	0.011	0.022
PEAD	0.494	0.491	0.486	0.470	−0.001	−0.002	−0.005	−0.008
RMW	0.494	0.489	0.484	0.473	0.001	0.006	0.016	0.038
HMLD	0.494	0.490	0.485	0.465	0.006	0.021	0.049	0.088
R_EG	0.492	0.489	0.480	0.458	0.001	0.005	0.008	0.018
CPTL	0.494	0.491	0.477	0.456	−0.005	−0.022	−0.044	−0.07
CPTLT	0.495	0.485	0.475	0.447	−0.003	−0.018	−0.035	−0.043
UNC	0.492	0.487	0.476	0.446	−0.002	−0.007	−0.01	−0.005
R_ROE	0.496	0.487	0.472	0.440	−0.006	−0.015	−0.028	−0.044
QMJ	0.488	0.481	0.469	0.451	−0.008	−0.021	−0.05	−0.111
VIX	0.493	0.484	0.466	0.437	−0.006	−0.017	−0.039	−0.073
MOMS	0.490	0.481	0.466	0.436	−0.003	−0.005	−0.004	0.007
VAL	0.500	0.487	0.463	0.416	0.033	0.079	0.124	0.167
DRF	0.497	0.479	0.453	0.423	0.022	0.034	0.02	−0.024
CRY	0.499	0.478	0.452	0.400	0.033	0.071	0.103	0.132
DEF	0.477	0.460	0.446	0.410	−0.012	−0.058	−0.122	−0.19
MKTBD	0.485	0.462	0.437	0.402	0.016	0.017	−0.005	−0.061
HMLB	0.498	0.479	0.439	0.368	0.038	0.086	0.115	0.117
TERM	0.496	0.472	0.425	0.366	0.062	0.13	0.161	0.168
STREVB	0.490	0.467	0.432	0.364	0.001	−0.002	−0.01	−0.021
DUR	0.476	0.436	0.401	0.345	0.018	0.013	−0.015	−0.044
MOMB	0.486	0.446	0.389	0.305	−0.016	−0.03	−0.027	−0.017
LTREVB	0.482	0.441	0.382	0.297	0.017	0.031	0.023	−0.001
CRF	0.465	0.416	0.367	0.312	0.006	0.027	0.061	0.093

Results - 25 risk factors (bonds and nontrade risk factors)

- Selected risk factors at S.R. = 0.8 (SR annualized = 2.4) – no results for other SR priors

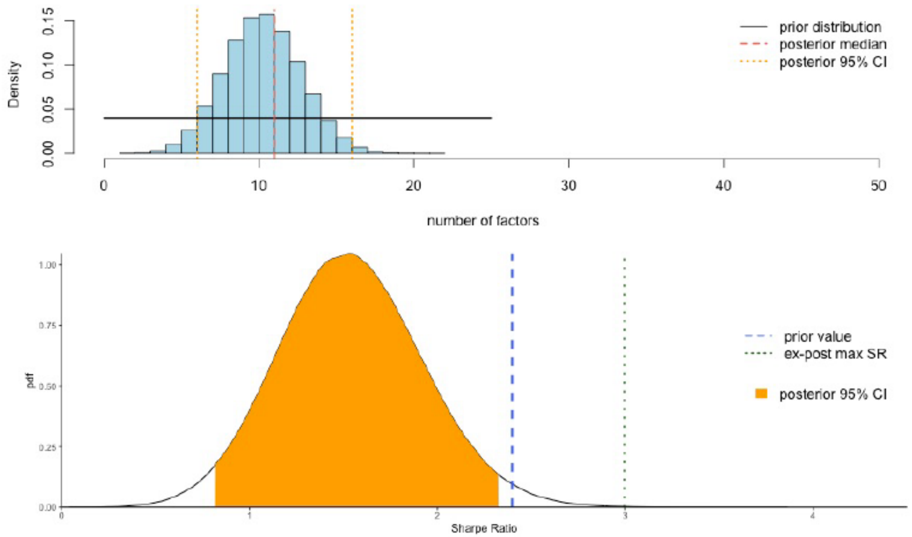


Figure 4: Posterior SDF dimension and Sharpe ratio – bond factor zoo.

Posterior distributions of the number of factors to be included in the SDF (top panel) and of the SDF-implied Sharpe ratio (bottom panel), computed using 25 bond related factors described in Appendix B. Test assets include 50 bond portfolios sorted on credit spreads, size, rating and maturity, with returns computed in excess of the one-month risk-free rate, and the 14 traded bond factors ($N = 64$). The prior distribution for the j^{th} factor inclusion is a Beta(1, 1), yielding a 0.5 prior expectation for γ_j. The prior Sharpe ratio is set to 80% of the ex post maximum Sharpe ratio of the 64 bond portfolios and traded factors. Sample period: 1986:01 to 2021:09 ($T = 429$).

Results - 49 risk factors (bonds, nontrade and equity risk factors)

- Selected risk factors at S.R. = 0.8 (SR annualized = 2.4) – no results for other SR priors
-

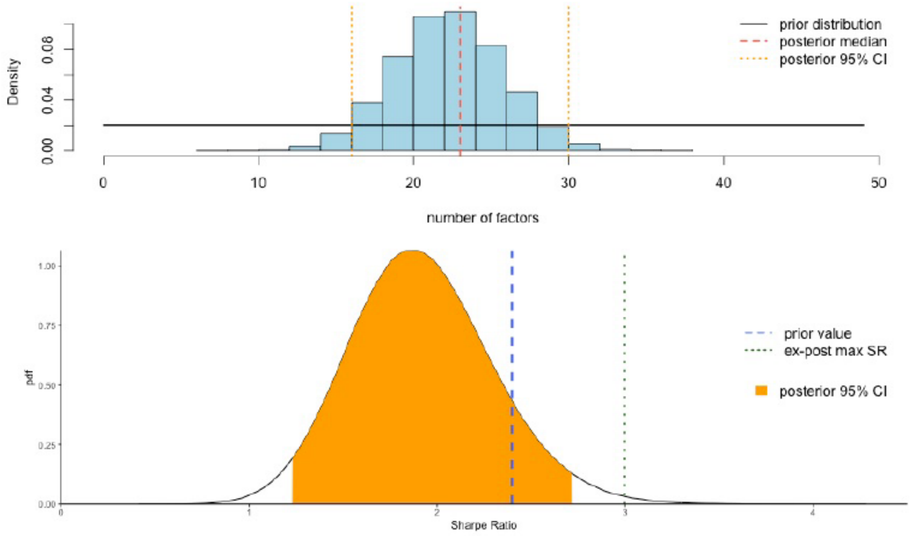


Figure 6: Posterior SDF dimension and Sharpe Ratio – bond and equity factor zoo.

Posterior distributions of the number of factors to be included in the SDF (top panel) and of the SDF-implied Sharpe ratio (bottom panel), computed using the 49 bond and equity factors described in Appendix B. Test assets include 50 bond portfolios sorted on credit spreads, size, rating and maturity, with returns computed in excess of the one-month risk-free rate, and the 14 traded bond factors ($N = 64$). The prior distribution for the j^{th} factor inclusion is a Beta(1, 1), yielding a 0.5 prior expectation for γ_j. The prior Sharpe ratio is set to 80% of the ex post maximum Sharpe ratio of the 64 bond portfolios and traded factors. Sample period: 1986:01 to 2021:09 ($T = 429$).

Results – BMS-SDF vs other models (oos n=77)

Table 3: Cross-sectional asset pricing.

	In-sample				Out-of-sample			
	RMSE	MAPE	R^2_{OLS}	R^2_{GLS}	RMSE	MAPE	R^2_{OLS}	R^2_{GLS}
Panel A: BMA-SDF with 25 bond factors (33.6 mn models)								
prior SR = 20%	0.192	0.144	0.240	0.125	0.127	0.091	0.088	0.035
prior SR = 40%	0.163	0.127	0.450	0.194	0.119	0.087	0.197	0.060
prior SR = 60%	0.144	0.112	0.574	0.252	0.113	0.085	0.272	0.075
prior SR = 80%	0.130	0.100	0.651	0.308	0.108	0.083	0.336	0.092
Panel B: BMA-SDF with 49 bond and stock factors (563 tn models)								
prior SR = 20%	0.198	0.147	0.195	0.117	0.128	0.092	0.068	0.031
prior SR = 40%	0.171	0.132	0.399	0.187	0.121	0.087	0.176	0.062
prior SR = 60%	0.150	0.117	0.539	0.261	0.114	0.083	0.272	0.086
prior SR = 80%	0.132	0.102	0.641	0.348	0.106	0.080	0.368	0.112
Panel C: Benchmark models and most likely factors								
CAPMB	0.176	0.115	0.365	0.137	0.125	0.094	0.113	0.056
CAPM	0.261	0.207	−0.401	0.032	0.156	0.110	−0.368	−0.023
FF5	0.205	0.147	0.138	0.180	0.142	0.106	−0.146	0.011
PEADB	0.255	0.173	−0.337	0.156	0.118	0.087	0.217	−0.027
Top factors bond	0.135	0.095	0.627	0.490	0.122	0.104	0.154	0.026
Top factors all	0.136	0.099	0.618	0.574	0.111	0.091	0.307	0.097

Results – BMS-SDF vs other models (oos n=127)

	RMSE	MAPE	R^2_{OLS}	R^2_{GLS}
Panel A: BMA-SDF with 25 bond factors (33.6 mn models)				
prior SR = 20%	0.122	0.091	0.075	0.109
	[0.021]	[0.015]	[0.085]	[0.075]
prior SR = 40%	0.116	0.086	0.170	0.159
	[0.020]	[0.015]	[0.125]	[0.098]
prior SR = 60%	0.111	0.084	0.238	0.180
	[0.018]	[0.014]	[0.123]	[0.105]
prior SR = 80%	0.106	0.082	0.299	0.202
	[0.015]	[0.012]	[0.120]	[0.110]
Panel B: BMA-SDF with 49 bond and stock factors (563 tn models)				
prior SR = 20%	0.124	0.092	0.059	0.098
	[0.020]	[0.015]	[0.072]	[0.068]
prior SR = 40%	0.117	0.087	0.151	0.158
	[0.020]	[0.015]	[0.119]	[0.093]
prior SR = 60%	0.110	0.083	0.238	0.193
	[0.018]	[0.014]	[0.124]	[0.101]
prior SR = 80%	0.103	0.080	0.330	0.229
	[0.015]	[0.011]	[0.120]	[0.107]
Panel C: Benchmark models and most likely factors				
CAPMB	0.121	0.091	0.090	0.188
	[0.025]	[0.022]	[0.242]	[0.131]
CAPM	0.148	0.110	−0.345	0.035
	[0.031]	[0.024]	[0.244]	[0.109]
FF5	0.137	0.104	−0.225	0.062
	[0.025]	[0.020]	[0.476]	[0.108]
PEADB	0.114	0.086	0.159	−0.085
	[0.014]	[0.011]	[0.242]	[0.070]
Top factors bond	0.120	0.102	0.040	0.121
	[0.013]	[0.013]	[0.389]	[0.160]
Top factors all	0.109	0.090	0.193	0.234
	[0.013]	[0.012]	[0.338]	[0.169]

Results – BMS-SDF vs other models (oos n=77 and duration adjusted returns)

Table 5: Cross-sectional asset pricing – duration adjusted returns

	In-sample				Out-of-sample			
	RMSE	MAPE	R^2_{OLS}	R^2_{GLS}	RMSE	MAPE	R^2_{OLS}	R^2_{GLS}
Panel A: BMA-SDF with 25 bond factors (33.6 mn models)								
prior SR = 20%	0.137	0.085	0.142	0.118	0.091	0.066	0.129	0.006
prior SR = 40%	0.118	0.083	0.362	0.205	0.089	0.066	0.165	0.011
prior SR = 60%	0.108	0.083	0.467	0.271	0.092	0.068	0.114	0.005
prior SR = 80%	0.103	0.082	0.513	0.322	0.093	0.069	0.089	0.009
Panel B: BMA-SDF with 49 bond and stock factors (563 tn models)								
prior SR = 20%	0.140	0.085	0.110	0.108	0.092	0.066	0.114	0.006
prior SR = 40%	0.122	0.081	0.322	0.189	0.088	0.065	0.177	0.017
prior SR = 60%	0.109	0.081	0.463	0.266	0.089	0.067	0.156	0.022
prior SR = 80%	0.100	0.078	0.542	0.338	0.090	0.067	0.141	0.038
Panel C: Benchmark models and most likely factors								
CAPMB	0.170	0.104	−0.318	0.074	0.098	0.072	−0.006	−0.002
CAPM	0.160	0.098	−0.162	0.066	0.099	0.074	−0.042	−0.015
FF5	0.156	0.102	−0.114	0.132	0.104	0.075	−0.145	−0.037
PEADB	0.186	0.134	−0.580	0.153	0.098	0.072	−0.005	−0.086
Top factors bond	0.157	0.122	−0.125	0.458	0.116	0.097	−0.433	−0.152
Top factors all	0.135	0.110	0.165	0.511	0.131	0.106	−0.804	−0.083

Conclusion

Conclusion

- Findings:
  1. The SDF is dense
  2. The majority of bond risk factors are disposable
  3. Equity and nontraded are not disposable
  4. Bayesian model averaging (BMA-SDF) explain excess bonds returns better than any other individual model

Appendix

Appendix – Factor zoo

Factor ID	Factor name and description	Reference	Source
	Panel A: Traded corporate bond factors		
CRF	Credit risk factor. Equally-weighted average return on two 'credit portfolios': CRF_{VaR}, and CRF_{REV}. CRF_{VaR} is the average return difference between the lowest-rating (i.e., highest credit risk) portfolio and the highest-rating (i.e., lowest credit risk) portfolio across the VaR95 portfolios. CRF_{REV} is the average return difference between the lowest-rating portfolio and the highest-rating portfolio across quintiles sorted on bond short-term reversal.	Bai, Bali, and Wen (2019)	Open Source Bond Asset Pricing
CRY	Bond carry factor. Independent sort (5 × 5) to form 25 portfolios according to ratings and bond credit spreads (CS). For each rating quintile, calculate the weighted average return difference between the highest CS quintile and the lowest CS quintile. CRY is computed as the average long-short portfolio return across all rating quintiles.	Houweling and Van Zundert (2017)	Open Source Bond Asset Pricing
DEF	Bond default risk factor. The difference between the return on the market portfolio of long-term corporate bond returns (the Composite portfolio on the corporate bond module of Ibbotson Associates) and the long-term government bond return.	Fama and French (1992)	Amit Goyal website
DRF	Downside risk factor. Independent sort (5 × 5) to form 25 portfolios according to ratings and 95% value-at-risk (VaR95). For each rating quintile, calculate the weighted average return difference between the highest VaR5 quintile and the lowest VaR5 quintile. DRF is computed as the average long-short portfolio return across all rating quintiles.	Bai, Bali, and Wen (2019)	Open Source Bond Asset Pricing
DUR	Bond duration factor. Independent sort (5 × 5) to form 25 portfolios according to ratings and bond duration (DUR^B). For each rating quintile, calculate the weighted average return difference between the highest DUR^B quintile and the lowest DUR^B quintile. DUR is computed as the average long-short portfolio return across all rating quintiles.	Dang, Hollstein, and Prokopczuk (2023)	Open Source Bond Asset Pricing
HMLB	Bond book-to-market factor. Independent sort (2 × 3) to form 6 portfolios according to bond size and bond book-to-market (BBM), defined as bond principal value scaled by market value. For each size portfolio, calculate the weighted average return difference between the lowest BBM tercile and the highest BBM tercile. HMLB is computed as the average long-short portfolio return across the two size portfolios.	Bartram, Grinblatt, and Nozawa (2020)	Open Source Bond Asset Pricing
LTREVB	Bond long-term reversal factor. Dependent sort (3 × 3 × 3) to form 27 portfolios according to ratings, maturity, and the 48-13 cumulative previous bond return ($LTREV^B$). For each rating quintile, the factor is computed as the average return differential between the portfolio with the lowest $LTREV^B$ and the one with the highest $LTREV^B$ within the rating and maturity portfolios. LTREVB is computed as the average long-short portfolio return across the nine rating-maturity terciles.	Bali, Subrahmanyam, and Wen (2021)	Open Source Bond Asset Pricing
MKTB	Corporate Bond Market excess return. Constructed using bond returns in excess of the one-month risk-free rate of return.	Dickerson, Mueller, and Robotti (2023)	Open Source Bond Asset Pricing
MKTBD	Corporate Bond Market duration adjusted return. Constructed using bond returns in excess of their duration-matched U.S. Treasury bond rate of return.	van Binsbergen, Nozawa, and Schwert (2023)	Open Source Bond Asset Pricing
MOMB	Bond momentum factor. Independent sort (5 × 5) to form 25 portfolios according to ratings and the 12-2 cumulative previous bond return (MOM). For each rating quintile, calculate the weighted average return difference between the highest MOM quintile and the lowest MOM quintile. MOMB is computed as the average long-short portfolio return across all rating quintiles.	Bali, Subrahmanyam, and Wen (2017)	Open Source Bond Asset Pricing
PEADB	Bond earnings announcement drift factor. Independent sort (2 × 3) to form 6 portfolios according to market equity and earnings surprises (CAR), computed according to Chan, Jegadeesh, and Lakonishok (1996). For each firm size portfolio, calculate the weighted average return difference between the highest CAR terciles and the lowest CAR tercile. PEADB is computed as the average long-short portfolio return across the two firm size portfolios.	Nozawa, Qiu, and Xiong (2023)	Open Source Bond Asset Pricing
STREVB	Bond short-term reversal factor. Independent sort (5 × 5) to form 25 portfolios according to ratings and the prior month's bond return (REV). For each rating quintile, calculate the weighted average return difference between the lowest REV quintile and the highest REV quintile. STREVB is computed as the average long-short portfolio return across all rating quintiles.	Bali, Subrahmanyam, and Wen (2021)	Open Source Bond Asset Pricing
TERM	Bond term structure risk factor. The difference between the monthly long-term government bond return and the one-month T-Bill rate of return.	Fama and French (1992)	Amit Goyal website
VAL	Bond value factor. Independent sort (2 × 3) to form 6 portfolios according to bond size and bond value (VAL^B). VAL^B is computed via cross-sectional regressions of credit spreads on ratings, maturity, and the 3-month change in credit spread. The percentage difference between the actual credit spread and the fitted ('fair') credit spread for each bond is the VAL^B characteristic. For each size portfolio, calculate the weighted average return difference between the highest VAL^B tercile and the lowest VAL^B tercile. VAL is computed as the average long-short portfolio return across the two size portfolios.	Houweling and Van Zundert (2017)	Open Source Bond Asset Pricing

Appendix – Factor zoo

Panel B: Nontraded corporate bond and equity factors			
CPTL	Intermediary capital nontraded risk factor. Constructed using AR(1) innovations to the market-based capital ratio of primary dealers, scaled by the lagged capital ratio.	He, Kelly, and Manela (2017)	Zhiguo He website
EPU	Economic Policy Uncertainty. First difference in the economic policy uncertainty index.	Dang, Hollstein, and Prokopczuk (2023)	FRED
EPUT	Economic Tax Policy Uncertainty. First difference in the economic tax policy uncertainty index.	Dang, Hollstein, and Prokopczuk (2023)	FRED
INFLC	Shocks to core inflation. Unexpected core inflation component captured by an ARMA(1,1) model. Monthly core inflation is calculated as the percentage change in the seasonally adjusted Consumer Price Index for All Urban Consumers: All Items Less Food and Energy which is lagged by one-month to account for the inflation data release lag.	Fang, Liu, and Roussanov (2022)	FRED
INFLV	Inflation volatility. Computed as the 6-month volatility of the unexpected inflation component captured by an ARMA(1,1) model. Monthly inflation is calculated as the percentage change in the seasonally adjusted Consumer Price Index for All Urban Consumers (CPI) which is lagged by one-month to account for the inflation data release lag.	Kang and Pflueger (2015) and Ceballos (2022)	FRED
LVL	Level term structure factor. Constructed as the first principal component of the one- through 30-year CRSP Fixed Term Indices U.S. Treasury Bond yields.	Koijen, Lustig, and Van Nieuwerburgh (2017)	CRSP Indices
LIQNT	Liquidity factor, computed as the average of individual-stock measures estimated with daily data (residual predictability, controlling for the market factor)	Pástor and Stambaugh (2003)	Robert Stambaugh website
UNC	First difference in the Macroeconomic uncertainty index, which is lagged by one-month to align the forecast to the returns observed in month t.	Koijen, Lustig, and Van Nieuwerburgh (2017)	Sydney Ludvigson website
UNCf	First difference in the Financial economic uncertainty index, which is lagged by one-month to align the forecast to the returns observed in month t.	Koijen, Lustig, and Van Nieuwerburgh (2017)	Sydney Ludvigson website
UNCr	First difference in the Real economic uncertainty index, which is lagged by one-month to align the forecast to the returns observed in month t.	Koijen, Lustig, and Van Nieuwerburgh (2017)	Sydney Ludvigson website
VIX	First difference in the CBOE VIX.	Chung, Wang, and Wu (2019)	FRED
YSP	Slope term structure factor. Constructed as the difference in the five and one-year U.S. Treasury Bond yields.	Koijen, Lustig, and Van Nieuwerburgh (2017)	CRSP Indices

Panel C: Traded equity factors			
BAB	Betting-against-beta factor, constructed as a portfolio that holds low-beta assets, leveraged to a beta of 1, and that shorts high-beta assets, de-leveraged to a beta of 1	Frazzini and Pedersen (2014)	AQR data library
CMA	Investment factor, constructed as a long-short portfolio of stocks sorted by their investment activity	Fama and French (2015)	Ken French website
CMAs	CMA with a hedged unpriced component	Daniel, Mota, Rottke, and Santos (2020)	Kent Daniel website
CPTLT	The value-weighted equity return for the New York Fed's primary dealer sector not including new equity issuance	He, Kelly, and Manela (2017)	Zhiguo He website
FIN	Long-term behavioral factor, predominantly capturing the impact of share issuance and correction	Daniel, Hirshleifer, and Sun (2020)	Kent Daniel website
HML	Value factor, constructed as a long-short portfolio of stocks sorted by their book-to-market ratio	Fama and French (1992)	Ken French website
HML_DEV	A version of the HML factor that relies on the current price level to sort the stocks into long and short legs	Asness and Frazzini (2013)	AQR data library
HMLs	HML with a hedged unpriced component	Daniel, Mota, Rottke, and Santos (2020)	Kent Daniel website
LIQ	Liquidity factor, constructed as a long-short portfolio of stocks sorted by their exposure to LIQ_NT	Pástor and Stambaugh (2003)	Robert Stambaugh website
LTREV	Long-term reversal factor, constructed as a long-short portfolio of stocks sorted by their cumulative return accrued in the previous 60-13 months	Jegadeesh and Titman (2001)	Ken French website
MKTS	Market excess return	Sharpe (1964) and Lintner (1965)	Ken French website
MKTSs	Market factor with a hedged unpriced component	Daniel, Mota, Rottke, and Santos (2020)	Kent Daniel website
MOMS	Momentum factor, constructed as a long-short portfolio of stocks sorted by their 12-2 cumulative previous return	Carhart (1997), Jegadeesh and Titman (1993)	Ken French website
PEAD	Short-term behavioral factor, reflecting post-earnings announcement drift	Daniel, Hirshleifer, and Sun (2020)	Kent Daniel website
QMJ	Quality-minus-junk factor, constructed as a long-short portfolio of stocks sorted by the combination of their safety, profitability, growth, and the quality of management practices	Asness, Frazzini, and Pedersen (2019)	AQR data library
RMW	Profitability factor, constructed as a long-short portfolio of stocks sorted by their profitability	Fama and French (2015)	Ken French website
RMWs	RMW with a hedged unpriced component	Daniel, Mota, Rottke, and Santos (2020)	Kent Daniel website
R_EG	Expected growth factor, constructed as a long-short portfolio of stocks sorted by their forecasted growth rates	Hou, Mo, Xue, and Zhang (2021)	Lu Zhang website
R_IA	Investment factor, constructed as a long-short portfolio of stocks sorted by their investment-to-capital	Hou, Xue, and Zhang (2015)	Lu Zhang website
R_ROE	Profitability factor, constructed as a long-short portfolio of stocks sorted by their return on equity	Hou, Xue, and Zhang (2015)	Lu Zhang website
SMB	Size factor, constructed as a long-short portfolio of stocks sorted by their market cap	Fama and French (1992)	Ken French website
SMBs	SMB with a hedged unpriced component	Daniel, Mota, Rottke, and Santos (2020)	Kent Daniel website
STREV	Short-term reversal factor, constructed as a long-short portfolio of stocks sorted by their previous month return	Jegadeesh and Titman (1993)	Ken French website

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