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Shrinking the Cross Sectional

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Agenda

- Motivation
- Methodology
- Dataset
- Results



Motivation

Motivation

Harvey et al. (2016): ... and the Cross-Section of Expected Returns

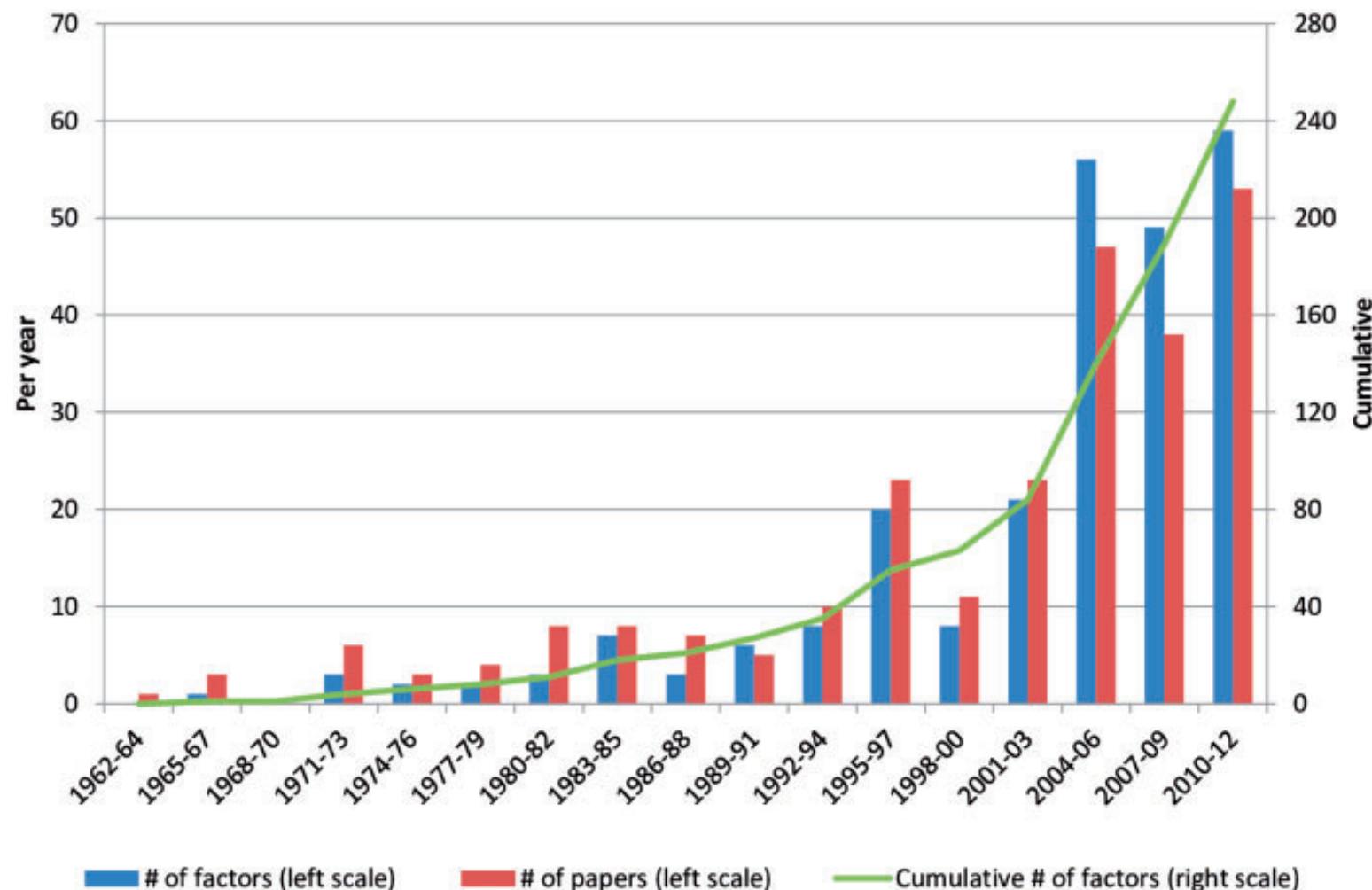


Figure 2
Factors and publications.

Motivation



- Asset pricing seek to find a *characteristics-sparse* SDF representation which is linear in only a few such factors
- Cochrane (2011): the “zoo” factors problem
- High dimension environment

“(… we seek a method that allows us to estimate the SDF’s loadings on potentially dozens or hundreds of characteristics-based factors without imposing that the SDF is necessarily characteristics-sparse.”



Methodology

Methodology



Hansen & Jagannathan (1991):

- Exist one SDF in the linear span of excess returns such that:
 - $M_t = 1 - b_{t-1}^T(R_t - \mathbb{E}R_t)$
 - $\mathbb{E}(M_t R_t) = 0$

Characteristics-based factor SDF:

- $b_{t-1} = Z_{t-1}b$, where Z_{t-1} is a matrix of assets characteristics
- $F_t = Z_{t-1}^T R_t$, where F_t is a vector of factors
- and we have:
 - $M_t = 1 - b^T(F_t - \mathbb{E}F_t)$

Methodology



- By solving $M_t = 1 - b^T(F_t - \mathbb{E}F_t)$:
 - $\mu = \Sigma b$, where $\mu = \mathbb{E}F_t$ and $\Sigma = \mathbb{E}[(F_t - \mathbb{E}F_t)(F_t - \mathbb{E}F_t)^T]$
 - $\mu = \Sigma b$ gives the moment conditions to find \hat{b}
 - GMM present overfitting or is unfishable due to high dimension
- GMM with L1 and L2 penalization:
 - $\hat{b} = \text{argmin}\{(\bar{\mu} - \bar{\Sigma}b)^T \bar{\Sigma}^{-1} (\bar{\mu} - \bar{\Sigma}b) + \gamma_1 b^T b + \gamma_2 |b|\}$

where: $\bar{\mu}$ is the factor estimated average excess returns
 $\bar{\Sigma}$ is the estimated covariance matrix from factor



Dataset



Dataset

Fama-French SZ/BM portfolios:

- 25 Fama-French ME/BM-sorted portfolios
- Orthogonalized w.r.t. to the market index return
- 07/01/1926 to 12/29/2017 with daily frequency

50 characteristics factors (literature):

- U.S. firms in CRSP (cut off at 0.01% market cap)
- 11/01/1973 to 12/29/2017 with daily frequency

80 WFR industry financial ratios factors:

- U.S. firms in CRSP (cut off at 0.01% market cap)
- 09/01/1964 to 12/29/2017 with daily frequency

First-order interactions

- 50 characteristics portfolios turns = 1,375
- 70 WRDS industry financial ratios portfolios turns = 3,400



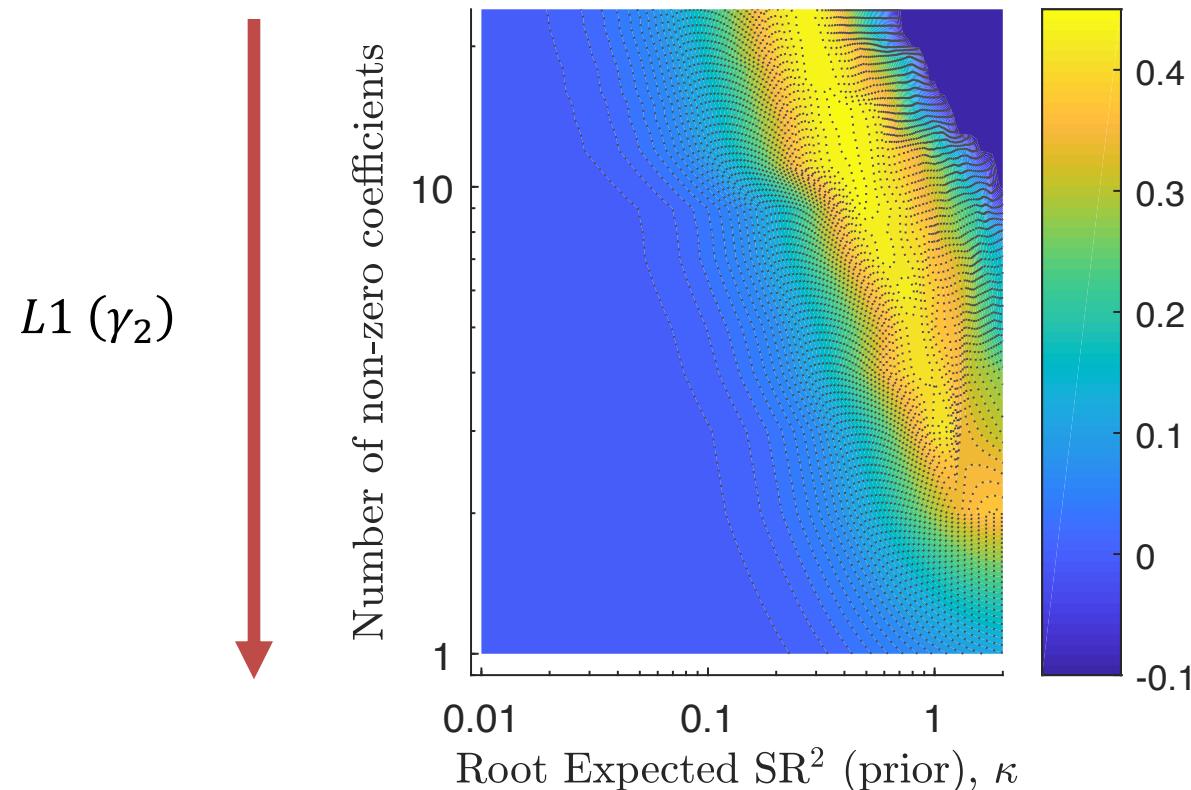
Results

Results

Fama-French SZ/BM portfolios:



(γ_1, γ_2) and OOS R^2 (31Y)



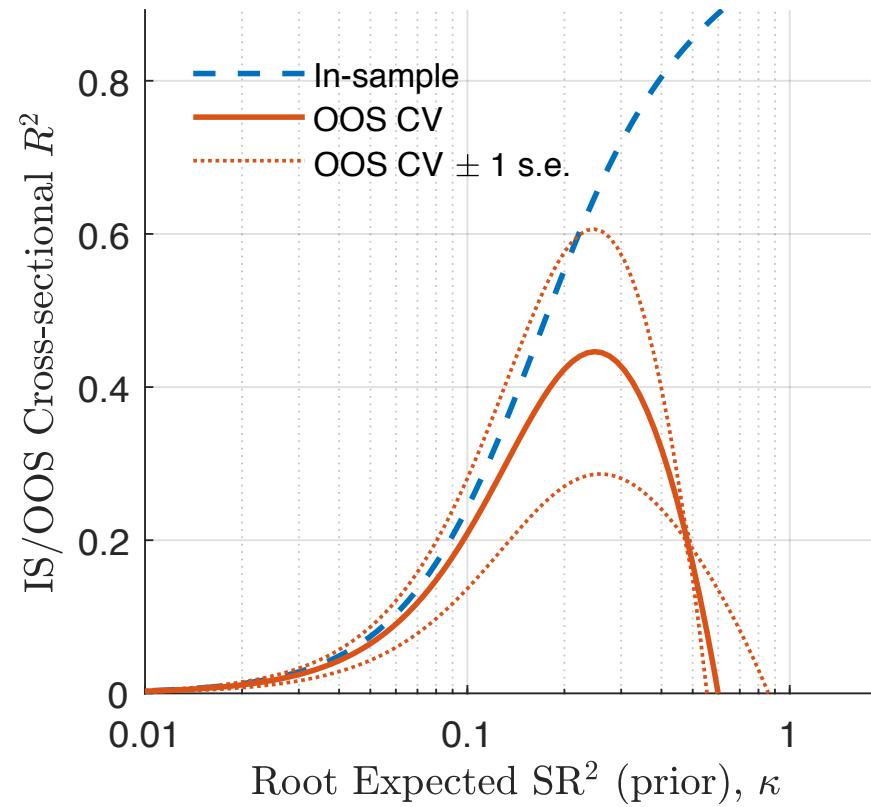
$L2 (\gamma_1)$

Results

Fama-French SZ/BM portfolios:



Without L1 (γ_2)



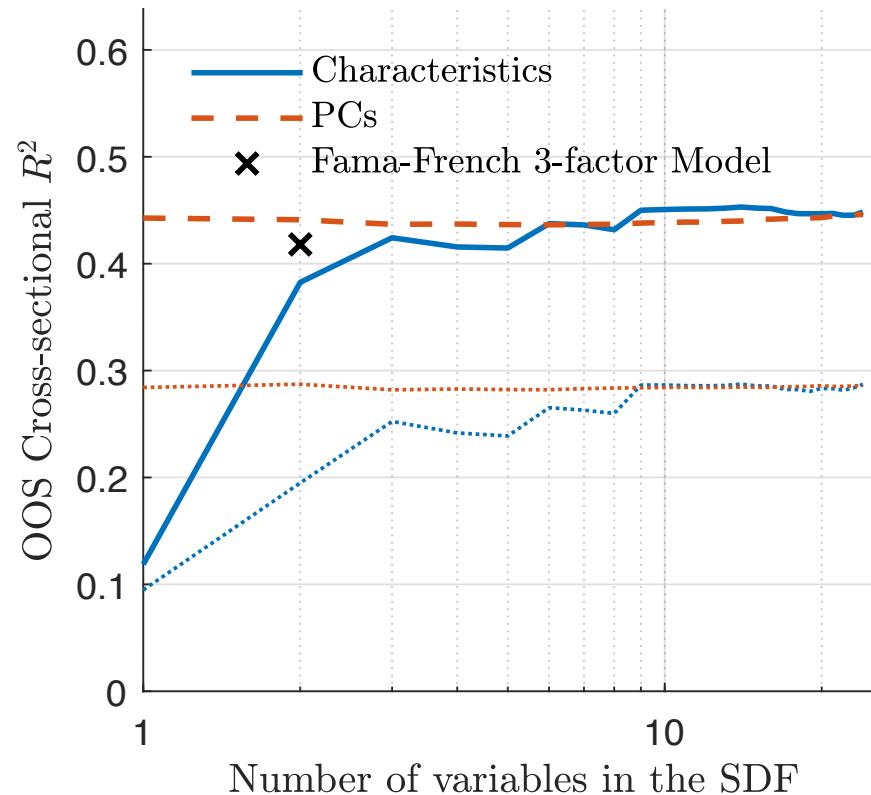
$L2 (\gamma_1)$

Results

Fama-French SZ/BM portfolios:

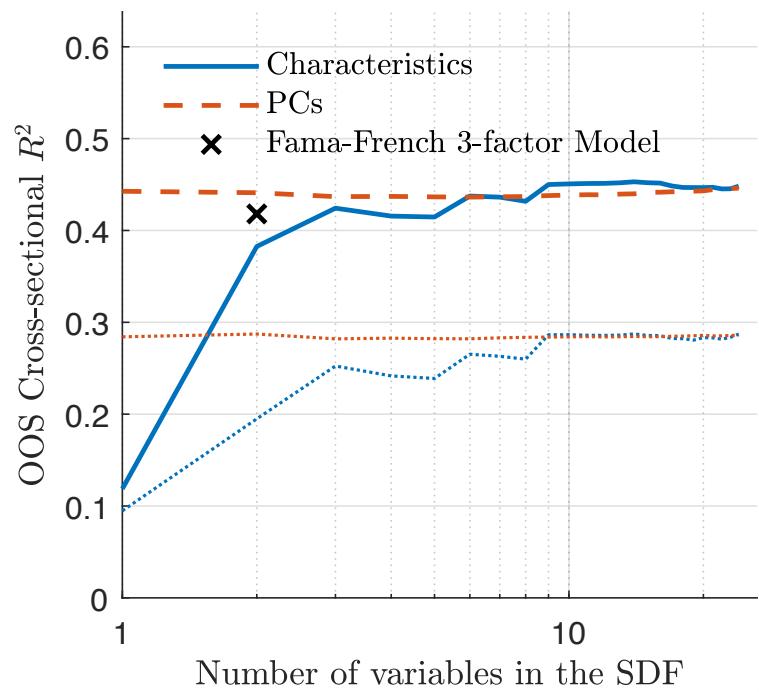
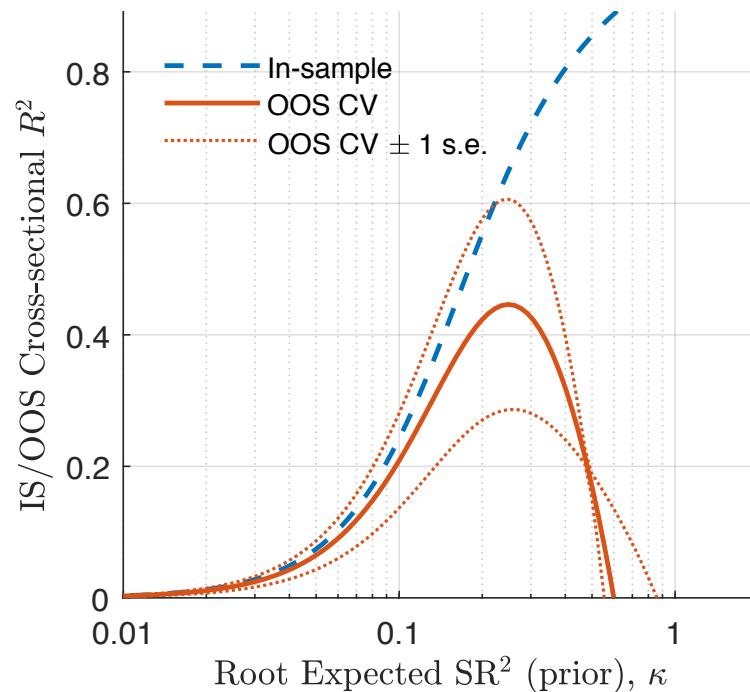
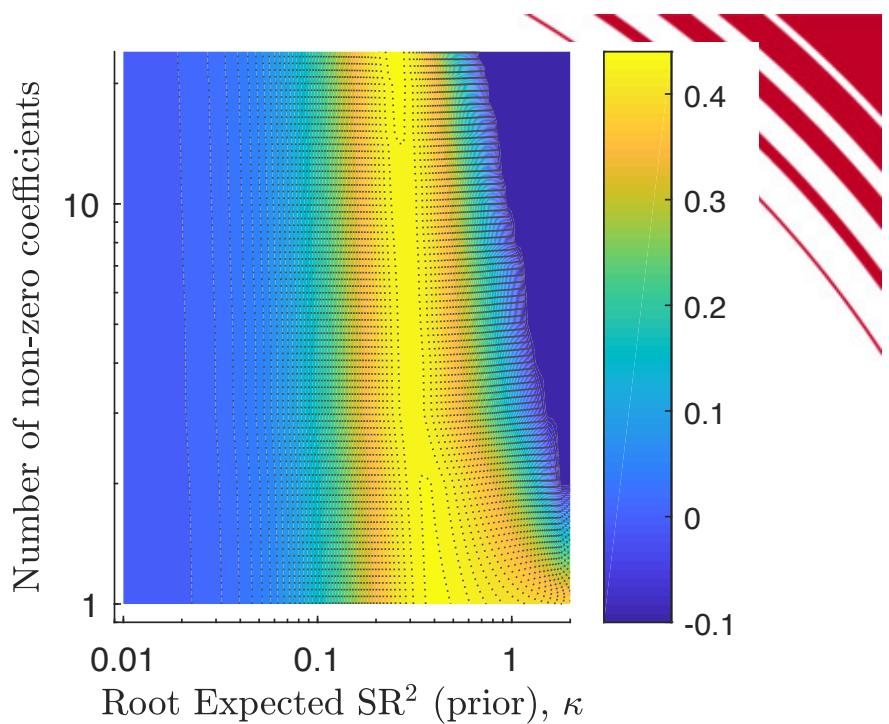
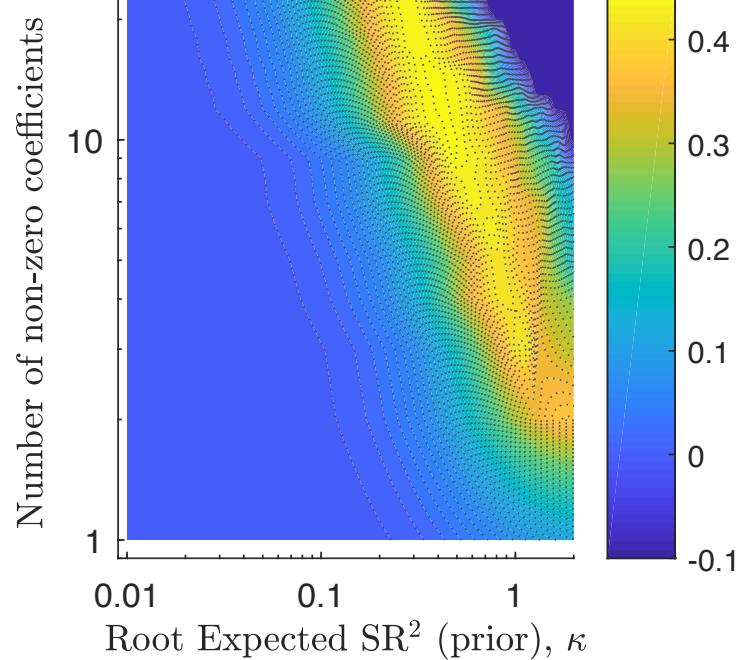


Given the optimal L2 (γ_1)

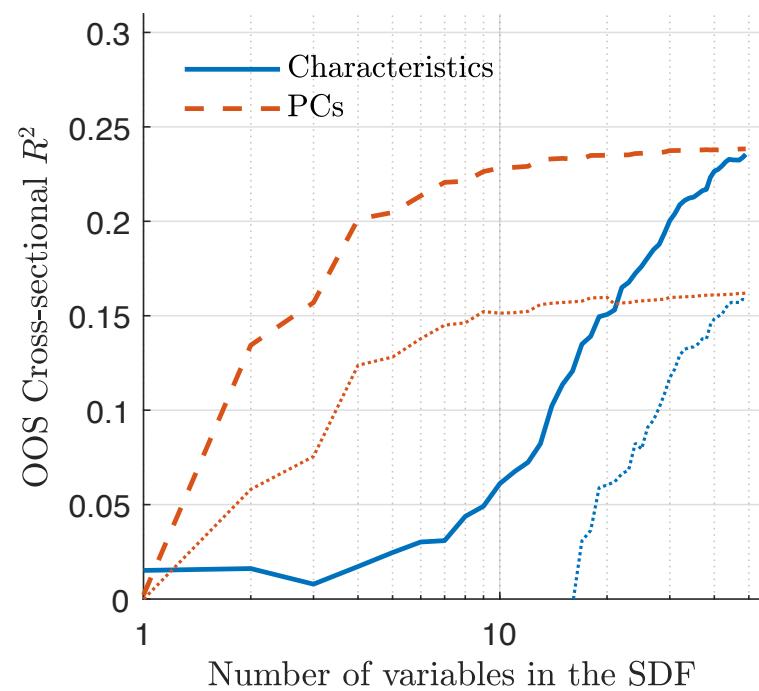
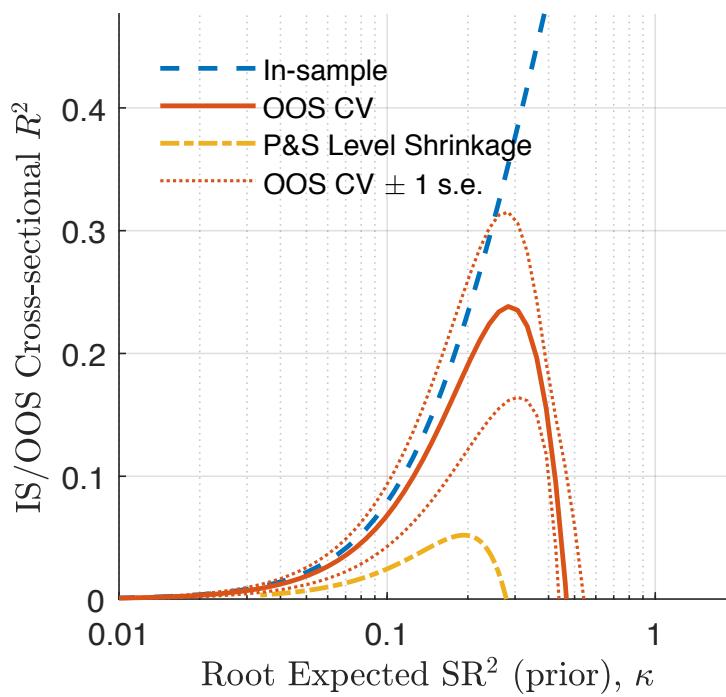
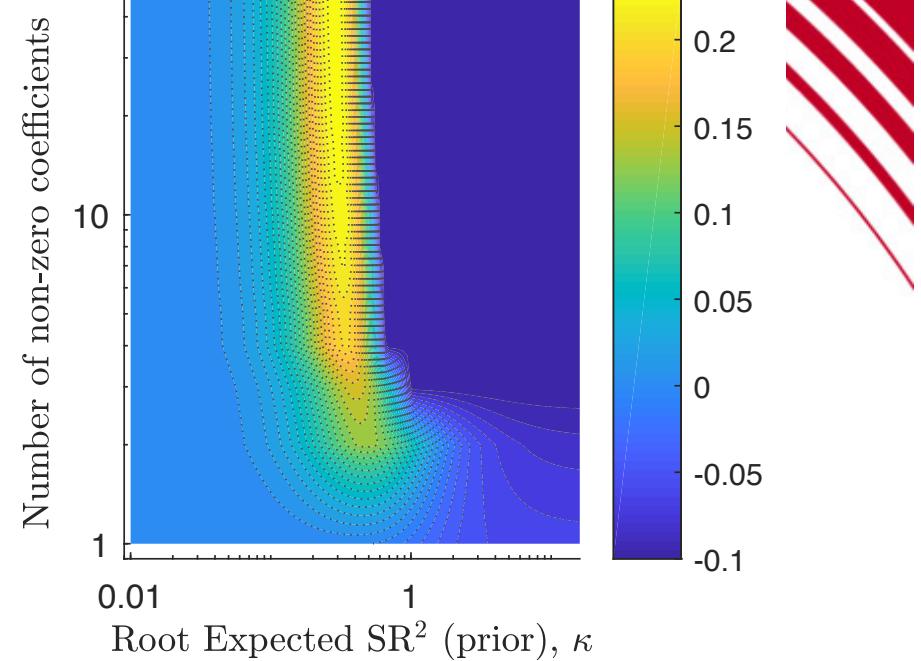
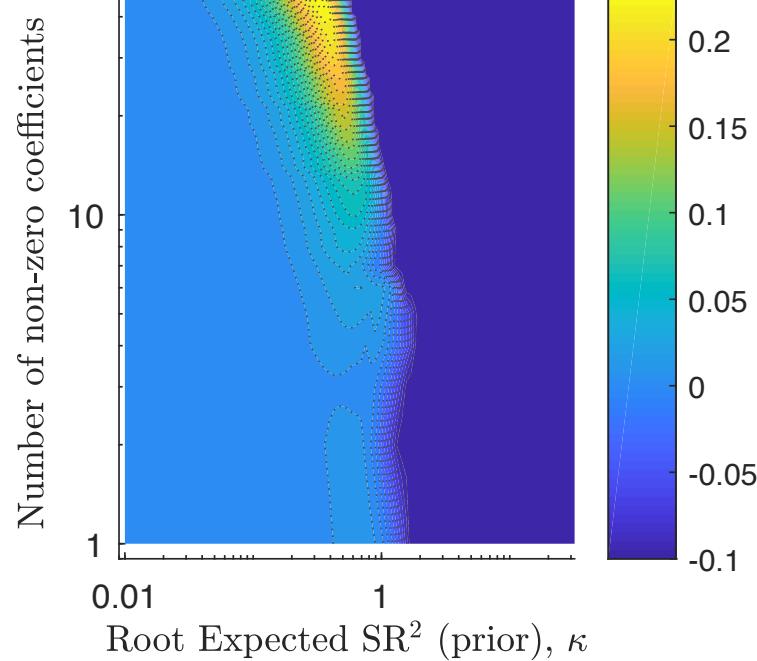


$L1 (\gamma_2)$

FF 25



50 C



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50 characteristics factors



Considering the Factors:

- Substantial regularization is needed to get good OOS performance
- Substantial L2 but no L1
- Almost no redundancy among the 50 anomalies
- No sparsity SDF

Considering the PCs:

- Substantial L1 (Sparsity) but also needs L2

50 characteristics factors



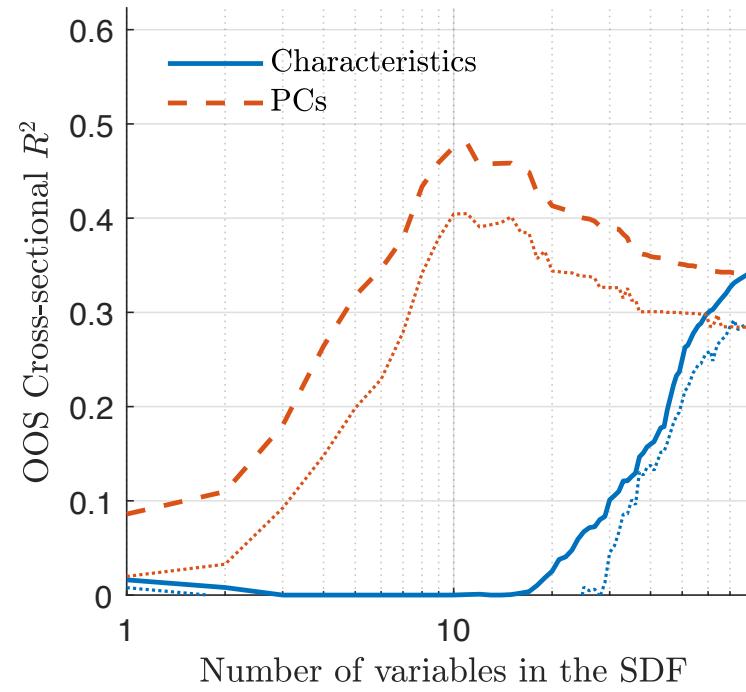
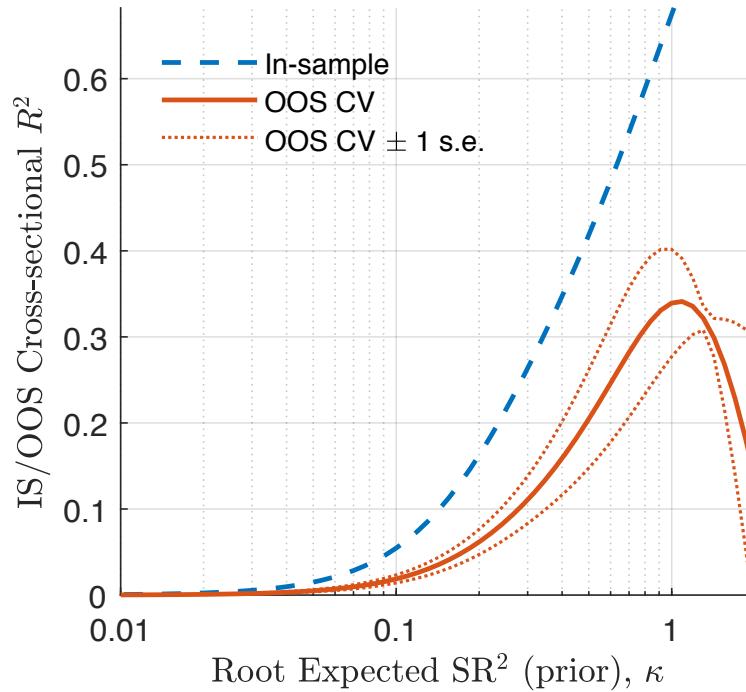
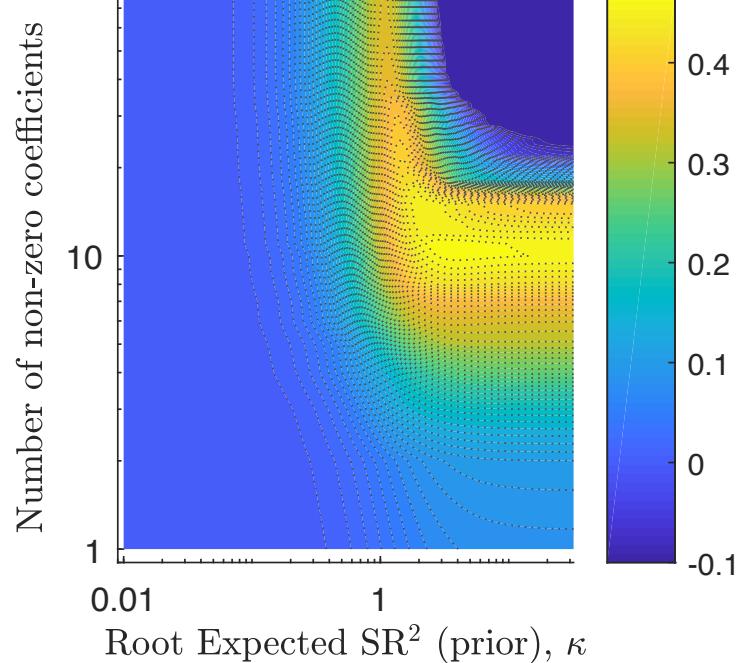
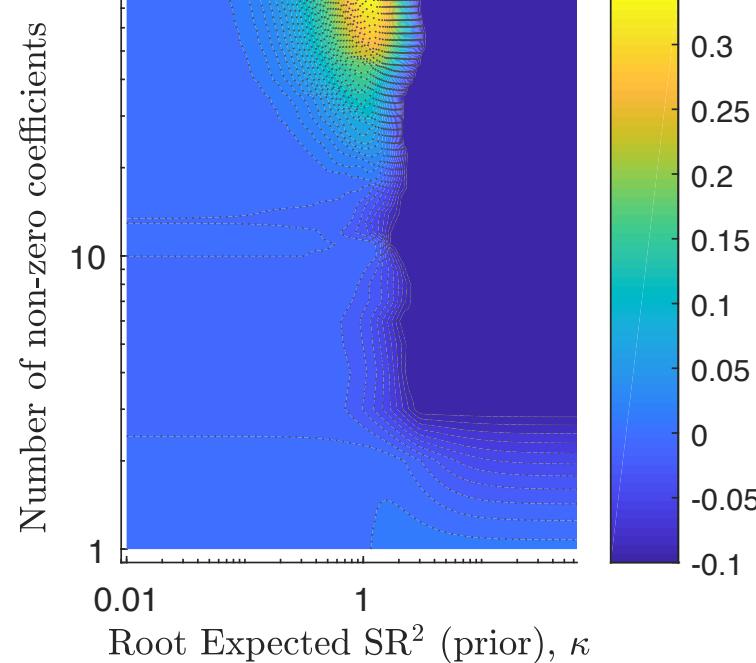
Table 1: Largest SDF factors (50 anomaly portfolios)

Coefficient estimates and absolute t -statistics at the optimal value of the prior root expected SR^2 (based on cross-validation). Panel (a) focuses on the original 50 anomaly portfolios. Panel (b) pre-rotates returns into PC space and shows coefficient estimates corresponding to these PCs. Coefficients are sorted descending on their absolute t -statistic values.

(a) Raw 50 anomaly portfolios			(b) PCs of 50 anomaly portfolios		
	b	t -stat		b	t -stat
Industry Rel. Rev. (L.V.)	-0.88	3.53	PC 4	1.01	4.25
Ind. Mom-Reversals	0.48	1.94	PC 1	-0.54	3.08
Industry Rel. Reversals	-0.43	1.70	PC 2	-0.56	2.65
Seasonality	0.32	1.29	PC 9	-0.63	2.51
Earnings Surprises	0.32	1.29	PC 15	0.32	1.27
Value-Profitability	0.30	1.18	PC 17	-0.30	1.18
Return on Market Equity	0.30	1.18	PC 6	-0.29	1.18
Investment/Assets	-0.24	0.95	PC 11	-0.19	0.74
Return on Equity	0.24	0.95	PC 13	-0.17	0.65
Composite Issuance	-0.24	0.95	PC 23	0.15	0.56
Momentum (12m)	0.23	0.91	PC 7	0.14	0.56

“The t-statistics are quite low, but it is important to keep in mind that what matters for the SDF is the joint significance of linear combinations of 50 of these factors.”

80 W



80 WFR industry financial ratios factors



Considering the Factors:

- Very similar to 50 characteristics factors
- Substantial L2 but no L1
- No sparsity SDF

Considering the PCs:

- Substantial L1 (Sparsity) **without much L2**

"(...) the data mining and publication bias towards in-sample significant factors may play a bigger role in the anomalies data set, which is based on published anomalies, than in the WFR data set."

Better OOS R2 and smaller standard errors

80 WFR industry financial ratios factors

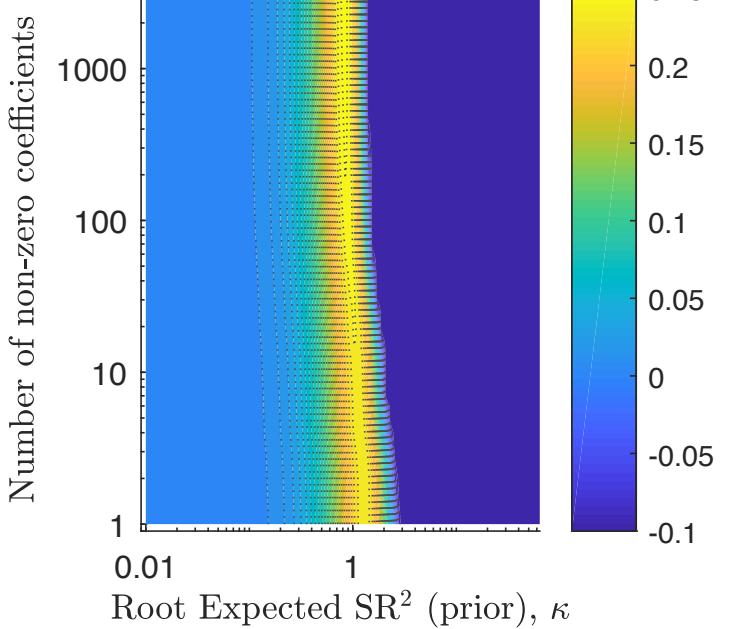
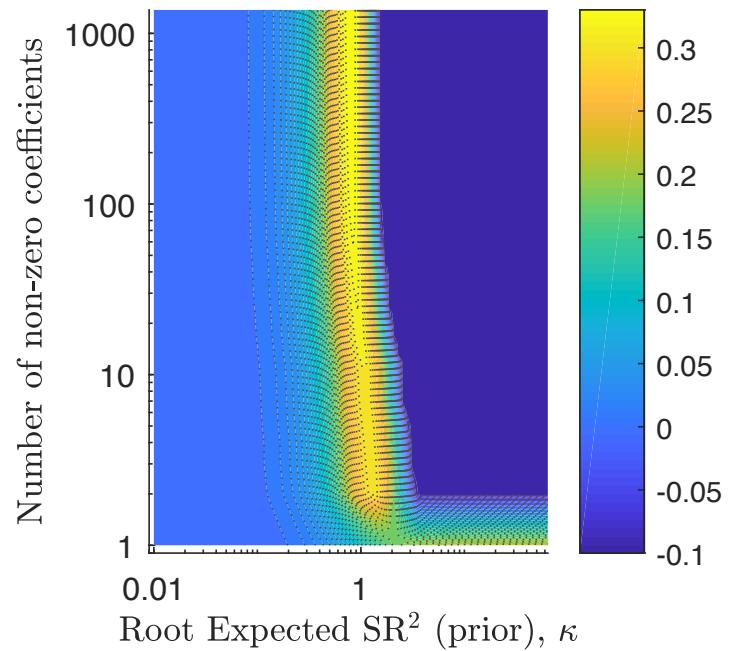
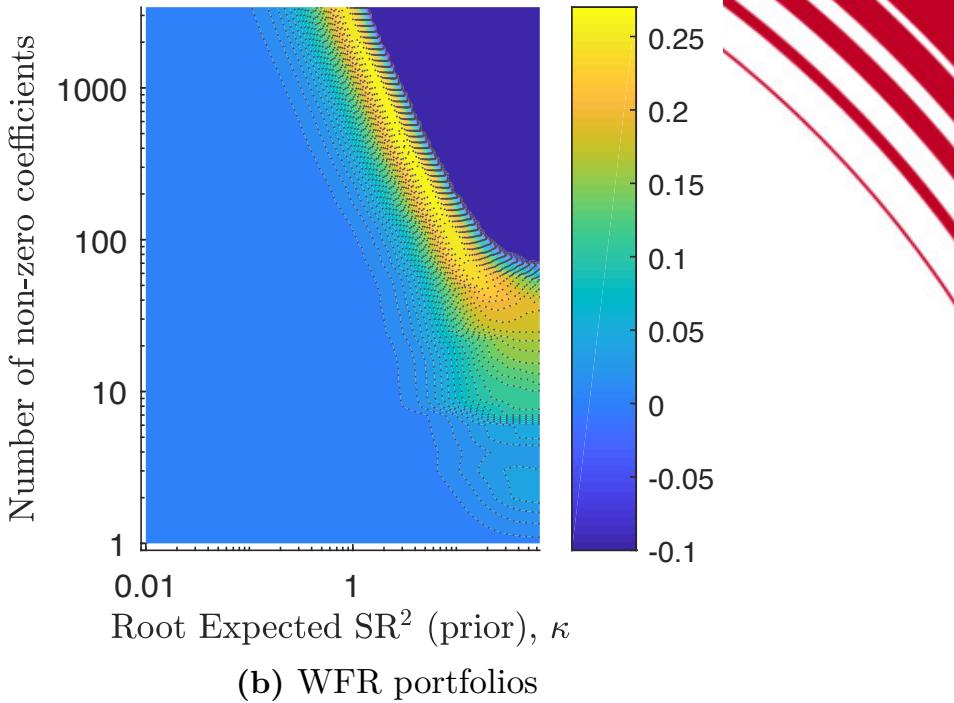
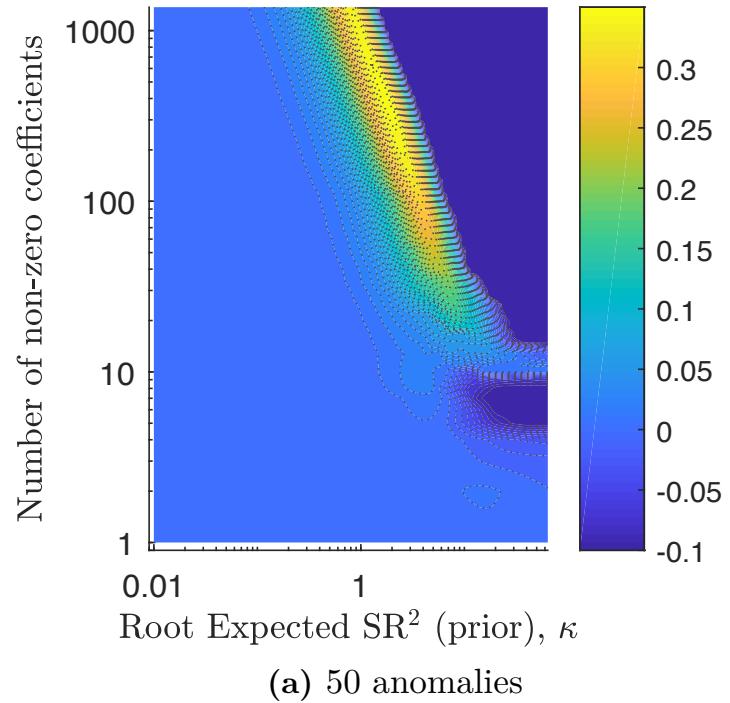


Table 2: Largest SDF factors (WFR portfolios)

Coefficient estimates and t -statistics at the optimal value of the prior root expected SR² (based on cross-validation). Panel (a) focuses on the original WFR portfolios. Panel (b) pre-rotates returns into PC space and shows coefficient estimates corresponding to these PCs. Coefficients are sorted descending on their absolute t -statistic values.

	(a) Raw WFR portfolios	b	t -stat		(b) PCs of WFR portfolios	b	t -stat
Free Cash Flow/Operating Cash Flow	3.64	5.49		PC 7	-3.39	6.64	
Accruals/Average Assets	2.85	4.13		PC 19	-3.69	6.00	
P/E (Diluted, Incl. EI)	-2.46	3.51		PC 6	2.48	5.06	
Month $t - 9$	1.83	3.03		PC 20	-2.83	4.59	
Month $t - 11$	1.64	2.71		PC 26	2.78	4.20	
Operating CF/Current Liabilities	1.89	2.65		PC 10	1.61	2.85	
Cash Flow/Total Debt	1.80	2.48		PC 2	-0.59	2.66	
Trailing P/E to Growth (PEG) ratio	-1.63	2.47		PC 8	1.38	2.56	
P/E (Diluted, Excl. EI)	-1.72	2.43		PC 5	0.98	2.44	
Month $t - 1$	-1.40	2.31		PC 36	1.47	2.05	
Enterprise Value Multiple	-1.43	2.11		PC 25	1.31	2.00	

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Performance compared with Sparse Models



- Pure OOS Test (2005-2017)
- Implied MVE: $P_t = \hat{b}^T F_t$
- FF6 = FF5 + MOM and $\hat{w} = \hat{\Sigma}^{-1} \hat{\mu}$
- Characteristic Sparse: 6 factor by L1
- PCs Sparse: first 5 factors selected by L1 and L2

Table 4: MVE portfolio's annualized OOS α in the withheld sample (2005-2017), %

The table shows annualized alphas (in %) computed from the time-series regression of the SDF-implied OOS-MVE portfolio's returns (based on L^2 shrinkage only) relative to four restricted benchmarks: CAPM, Fama-French 6-factor model, optimal sparse model with 5 factors, and optimal PC-sparse model with at most 5 PC-based factors. MVE portfolio returns are normalized to have the same standard deviation as the aggregate market. Standard errors in parentheses.

SDF factors \ Benchmark	CAPM	FF 6-factor	Char.-sparse	PC-sparse
50 anomaly portfolios	12.35 (5.26)	8.71 (4.94)	9.55 (3.95)	4.60 (2.22)
80 WFR portfolios	20.05 (5.26)	19.77 (5.29)	17.08 (5.05)	3.63 (2.93)
1,375 interactions of anomalies	25.00 (5.26)	22.79 (5.18)	21.68 (5.03)	12.41 (3.26)