Mind the analyst or the brokerage?

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Top 10 financial analysts

Rank	Analyst Name	Firm Name	Total Recommendations	Success rate
1	Moshe Orenbuch	Credit Suisse	425	65%
2	Steve Manaker	Stifel Nicolaus	331	72%
3	Bill Carcache	Wolfe Research	302	71%
4	Bose George	Keefe	344	72%
5	Mark Rothschild	Canaccord Genuity	452	71%
6	Gerard Cassidy	RBC	510	58%
7	Susan Roth Katzke	Credit Suisse	248	67%
8	Mark Dwelle	RBC	495	64%
9	Ken Usdin	Jefferies Co.	462	61%
10	Bobby Griffin	Raymond James	256	61%

Source: TipRanks

CNBC

Popular questions

Do analysts generate abnormal returns?

YES	NO
Womack (1996)	Altinkiliç et al. (2013)
Barber et al. (2001)	Kim and Song (2014)
Green (2006)	
Crawford et al. (2017)	
Crane and Crotty (2020)	

Do analysts exhibit herding behavior?

YES	NO
Graham (1999)	Bernhardt et al. (2006)
Welch (2000)	Brown et al. (2014)
Clement and Tse (2005)	
Jegadeesh and Kim (2010)	*Ashiya (2009)

Data

925,555 analysts' recommendations from I/B/E/S.

4,173 stocks (current or past constituents of the S&P 500, Nasdaq, and NYSE indices)

12,716 analysts or 833 brokerage firms

The sample covers the period from January 1, 1999, to April 30, 2020.

I/B/E/S transforms the analysts' recommendations to numerical scores, namely:

“5”: strong sell	**“4”: sell**	**“3”: hold**	**“2”: buy**	**“1”: strong buy**

If the analyst has no opinion on what to recommend, a ``0'' recommendation is issued.

Data

Recommendations breakdown

All recommendations 925,555	% of recommendations		Initial recommendations 87,492	% of initial recommendations	
Strong buy	23.36	**58.58% are positive**	Strong buy	27.21	**68.4% are positive**
Buy	35.22		Buy	41.19	
Hold	35.76		Hold	27.35	
Sell	4.6		Sell	2.95	
Strong sell	0.97		Strong sell	1.23	
No opinion	0.1		No opinion	0.07	

Womack (1986) reports that the ratio of the new buy recommendations over new sell recommendations is almost 7/1

Data

Transition matrix of analysts' recommendations

Old \ New	Strong sell	Sell	Hold	Buy	Strong buy
Strong sell	0.55	0.04	0.23	0.06	0.06
Sell	0.04	2.42	1.55	0.48	0.29
Hold	0.23	1.5	27.25	4.65	3.04
Buy	0.05	0.46	4.48	27.03	2.61
Strong buy	0.05	0.28	2.83	2.49	17.33

Numbers in %

Jegadeesh and Kim (2010) model

$$ABR_{x,t,t+h} = \prod_{\tau=t}^{t+h}(1+R_{x,\tau}) - \prod_{\tau=t}^{t+h}(1+R_{m,\tau}) = \alpha_h + b_h \times I_{multi} + c_h \times I_{single} + d_h \times NC_{x,t} + u_{t,h}$$

where $h = \{0,1,2\}$ is day after the recommendation announcement,

$$I_{multi}\ (I_{single}) = \begin{cases} 1, \text{if a multi (single)−step upgrade is announced} \\ -1, \text{if a multi (single)−step upgrade is announced.} \\ 0, \text{if the analyst keeps the same recommendation} \end{cases}$$

NC is the *deviation of the analyst's new recommendation from the prevailing consensus*.

If $d > 0$, then analysts ***herd*** close to the consensus. Otherwise, analysts ***exaggerate*** their differences with the consensus. $u_{t,h}$ is the error term.

Sparse Bayesian Estimation

We form the h - day buy-and-hold abnormal returns for the stock x with respect to the market m index returns as

$$ABR = X\beta + u,$$

where the X contains both the dummy variables introduced by Jegadeesh and Kim (2010), and several other variables that capture macroeconomic and financial environment.

Explanatory variables

Analysts' recommendations usually are accompanied by a ***target price (TP)*** for the stock. We model analyst's exaggeration through the ***analyst's target price expected return***

$$TER_t = \frac{TP - P_{t-1}}{P_{t-1}}$$ (Huang et al. (2009)),

the ***analyst's target price revision***

$$DTar_t = \frac{TP_{new} - TP_{old}}{TP_{old}}$$ (Brav and Lehavy (2003)),

and, ***the deviation of analyst's new recommendation from the prevailing consensus***

$$NC_t = New\_rec_t - Consensus_{t-1}$$ (Jegadeesh and Kim (2010))

Explanatory variables

Stock market variables

VIX Index,

Price to earnings (P/E) of S&P 500 Index,

Growth rate of the trailing 12-month sums of earnings of S&P 500 Index,

DEBT/EBITDA ratio of the S&P 500 Index,

Net equity expansion on the NYSE Index,

Macro variables

Yield to maturity for the three-month Treasury bill,

2/10 U.S. Government bond yield spread,

Moody's BAA and AAA-rated corporate bond yields spread,

U.S. inflation,

U.S. ISM Manufacturing Purchasing Managers Index,

Growth rate of the U.S. Conference Board Leading Economic Indicators Index,

U.S. Business Cycle Phase.

Priors

Horseshoe prior (Carvalho et al. 2010)

$$\beta_k|\lambda_k \sim N(0, \lambda_k^2),\ \lambda_k|\tau \sim \mathrm{C}^+(0, \tau),\ \tau|\sigma \sim \mathrm{C}^+(0, \sigma),$$

where $\mathrm{C}^+(0, \sigma)$ is the half-Cauchy distribution with zero location and scale parameter σ defined over positive real numbers, assuming $p(\sigma) \sim 1/\sigma$.

The horseshoe prior has proven to be a noteworthy alternative for sparse Bayesian estimation, but has previously suffered from two problems.

1. No systematic way of specifying a prior for the global shrinkage hyperparameter based on prior information about the degree of sparsity in the parameter vector.
2. There is no possibility of specifying separately information about sparsity and the amount of regularization for the largest coefficients

Priors

Horseshoe-like prior (Bhadra et al. 2019)

$$\beta_k|\lambda_k \sim N(0, \lambda_k^2),\ \lambda_k|c \sim S(\boldsymbol{\alpha}, 1, 0, c),\ \mathrm{c}|\sigma \sim S(\boldsymbol{\alpha}, 1, 0, \sigma),\ \boldsymbol{\alpha} < 1, \mathrm{k} = 1, 2, \cdots, K$$

where $S(\boldsymbol{\alpha}, \beta, d, c)$ is the half-stable distribution, d, c are the location and scale parameters, $0 < \boldsymbol{\alpha} \leq 2$ is the characteristic exponent, and $-1 \leq \beta \leq 1$.

When $\beta = 1$, the distribution is "maximally skewed", and for $\boldsymbol{\alpha} < 1$, the distribution obtained is an ***α −stable distribution***.

The joint prior of the regression coefficients is the following:

$$\mathrm{p}(\boldsymbol{\beta}, \lambda, \boldsymbol{\alpha}, c) = \left\{\prod_{k=1}^{K} (2\pi\lambda_k^2)^{-\frac{1}{2}} e^{-\beta_k^2\left(\frac{2}{\lambda_k^2}\right)} f(\lambda_k; \alpha, c)\right\} f(c; \boldsymbol{\alpha}, \sigma)^{\mathrm{K}}$$

where $f(\lambda_k; \boldsymbol{\alpha}, c)$ the density of the ***α −stable distribution*** family.

Model

$$ABR_{x,t,t+h} =$$

$$X'_t\beta_1 + \left(\underbrace{TER_t, DTAR_t, NC_t, I_{R_{t-1}}, I_{R_t}}_{analyst\ 1}, \cdots, \underbrace{TER_t, DTAR_t, NC_t, I_{R_{t-1}}, I_{R_t}}_{analyst\ G}\right)\beta_2 + u_{t,h}$$

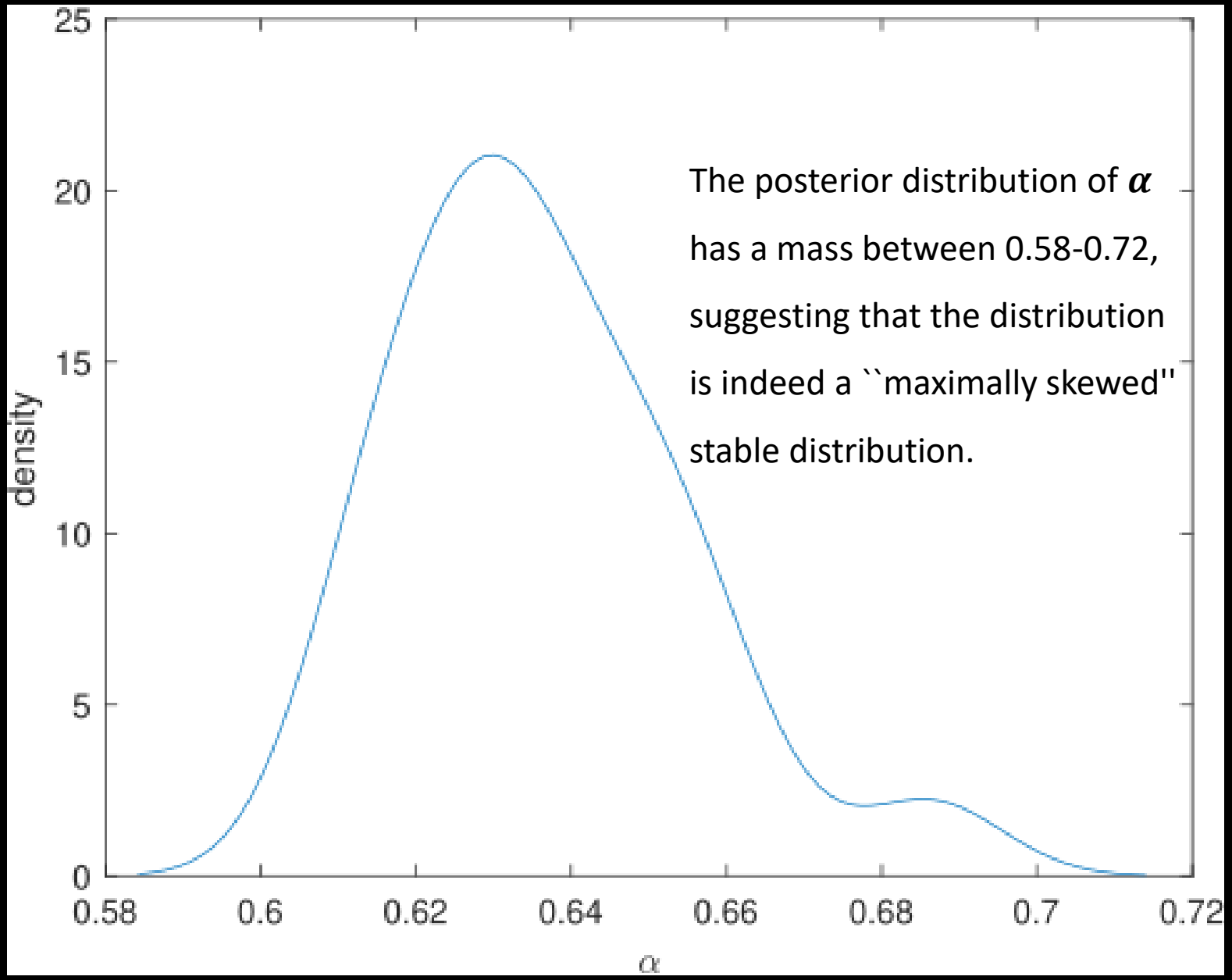
where X_t contains the explanatory variables, $I_{R_{t-1}} \equiv I(R_{t-1} = i)$ = 1, $I_{R_t} \equiv I(R_t = j)$, for $i, j = \{-2, -1, 0, 1, 2\}$. Next, we assume a time-varying Markov switching model for R_t and R_{t-1}, that is

$$p_{ij,t} = \Pr(R_t = j | R_{t-1} = i) = \frac{\Phi(z'_{i,t}\gamma_{i,j})}{\sum_{m=1}^{M}\Phi(z'_{i,t}\gamma_{i,m})}$$

where z_t includes the variables *TER*, *DTar*, and *NC*. To model endogeneity, we include $u_t$and u_{t-1} among the regressors z_t that determine the transition probabilities.

Results

Marginal posterior density of the α–stable distribution characteristic exponent



The posterior distribution of α has a mass between 0.58-0.72, suggesting that the distribution is indeed a ``maximally skewed'' stable distribution.

Cross-sectional regression results

TER	0.038***
DTar	0.012***
NC	0.010***
S&P 500 P/E Index	0.017***
2/10 U.S. Government bond yield spread	-0.008***
U.S. inflation	-0.004***
U.S. ISM Manufacturing Purchasing Managers Index	-0.015***
$I(R_{t-1}$=-2)	-0.004**
$I(R_{t-1}$=-1)	-0.004***
$I(R_{t-1}$=0)	0.003**
$I(R_{t-1}$=1)	0.002**
$I(R_{t-1}$=2)	0.004**
$I(R_t$=-2)	-0.015***
$I(R_t$=-1)	-0.0073***
$I(R_t$=0)	0.020***
$I(R_t$=1)	0.015***
$I(R_t$=2)	0.018***

Analysts

$$P = \begin{array}{c} \\ \text{Strong sell} \\ \text{Sell} \\ \text{Hold} \\ \text{Buy} \\ \text{Strong buy} \end{array} \begin{array}{c} \begin{array}{ccccc} \text{Strong sell} & \text{Sell} & \text{Hold} & \text{Buy} & \text{Strong buy} \end{array} \\ \begin{pmatrix} 0.161^{***} & 0.272^{***} & 0.252^{***} & 0.310^{***} & 0.005^{*} \\ (0.021) & (0.014) & (0.044) & (0.019) & (0.003) \\ 0.108 & 0.410^{***} & 0.278^{***} & 0.189^{***} & 0.015 \\ (0.033) & (0.045) & (0.017) & (0.015) & (0.020) \\ 0.254^{***} & 0.271^{***} & 0.214^{***} & 0.006 & 0.255^{***} \\ (0.076) & (0.049) & (0.055) & (0.004) & (0.048) \\ 0.108^{*} & 0.178^{*} & 0.230^{***} & 0.302^{***} & 0.182^{**} \\ (0.065) & (0.098) & (0.047) & (0.092) & (0.081) \\ 0.228^{*} & 0.220 & 0.244^{***} & 0.205^{***} & 0.103^{***} \\ (0.133) & (0.155) & (0.016) & (0.033) & (0.017) \end{pmatrix} \end{array}$$

Brokerages

$$\mathbf{P} = \begin{bmatrix} 0.250^{*} & 0.296^{*} & 0.223^{*} & 0.001 & 0.229 \\ (0.138) & (0.172) & (0.127) & (0.089) & (0.151) \\ 0.380^{*} & 0.204^{**} & 0.065^{***} & 0.187 & 0.164^{**} \\ (0.200) & (0.081) & (0.021) & (0.169) & (0.071) \\ 0.292^{***} & 0.058^{***} & 0.087^{***} & 0.400 & 0.164^{**} \\ (0.029) & (0.019) & (0.026) & (0.385) & (0.078) \\ 0.723 & 0.037 & 0.008 & 0.074 & 0.159^{***} \\ (0.620) & (0.145) & (0.136) & (0.118) & (0.043) \\ 0.273^{**} & 0.278 & 0.304 & 0.089^{***} & 0.056 \\ (0.112) & (0.192) & (0.250) & (0.021) & (0.043) \end{bmatrix}$$

Transition Probability Mechanism

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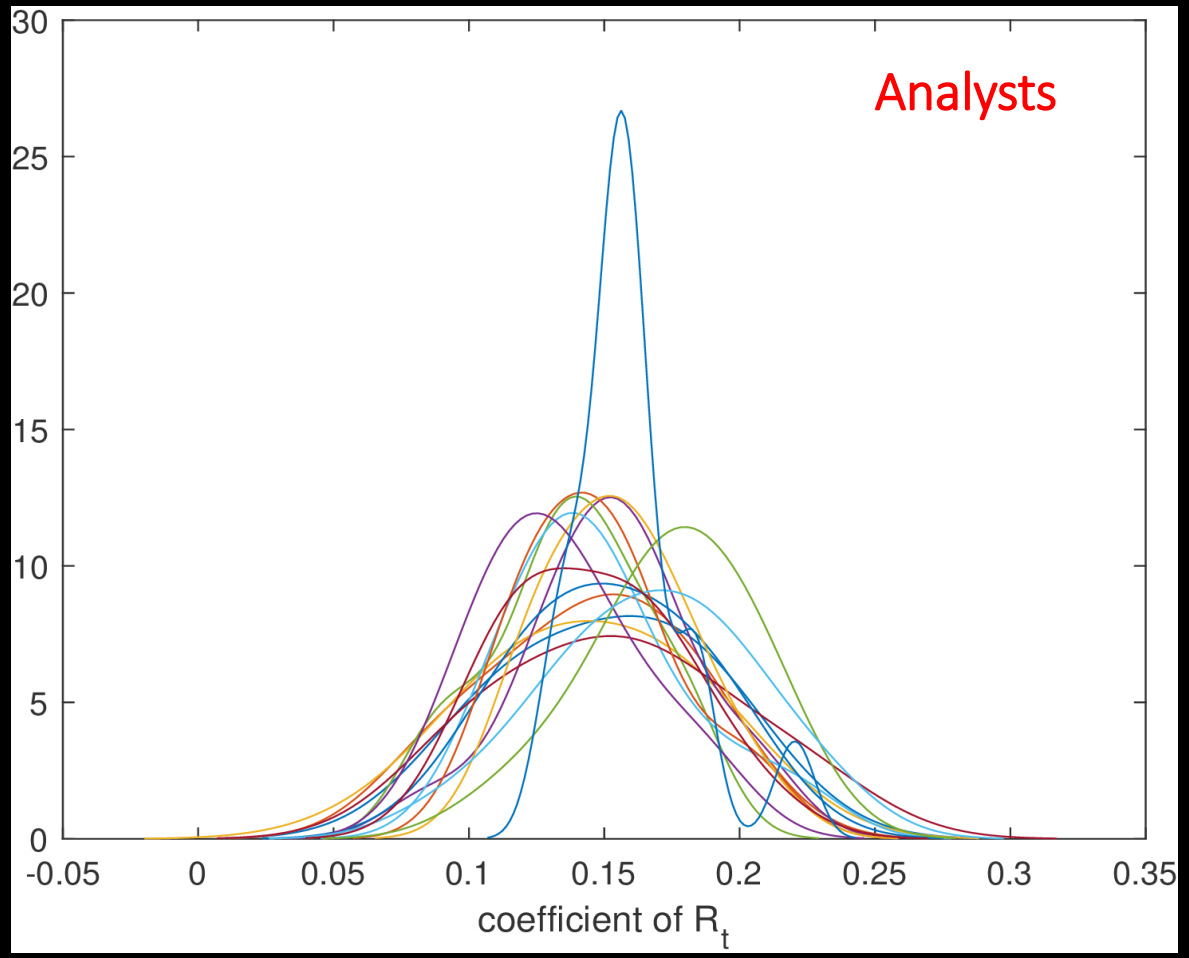
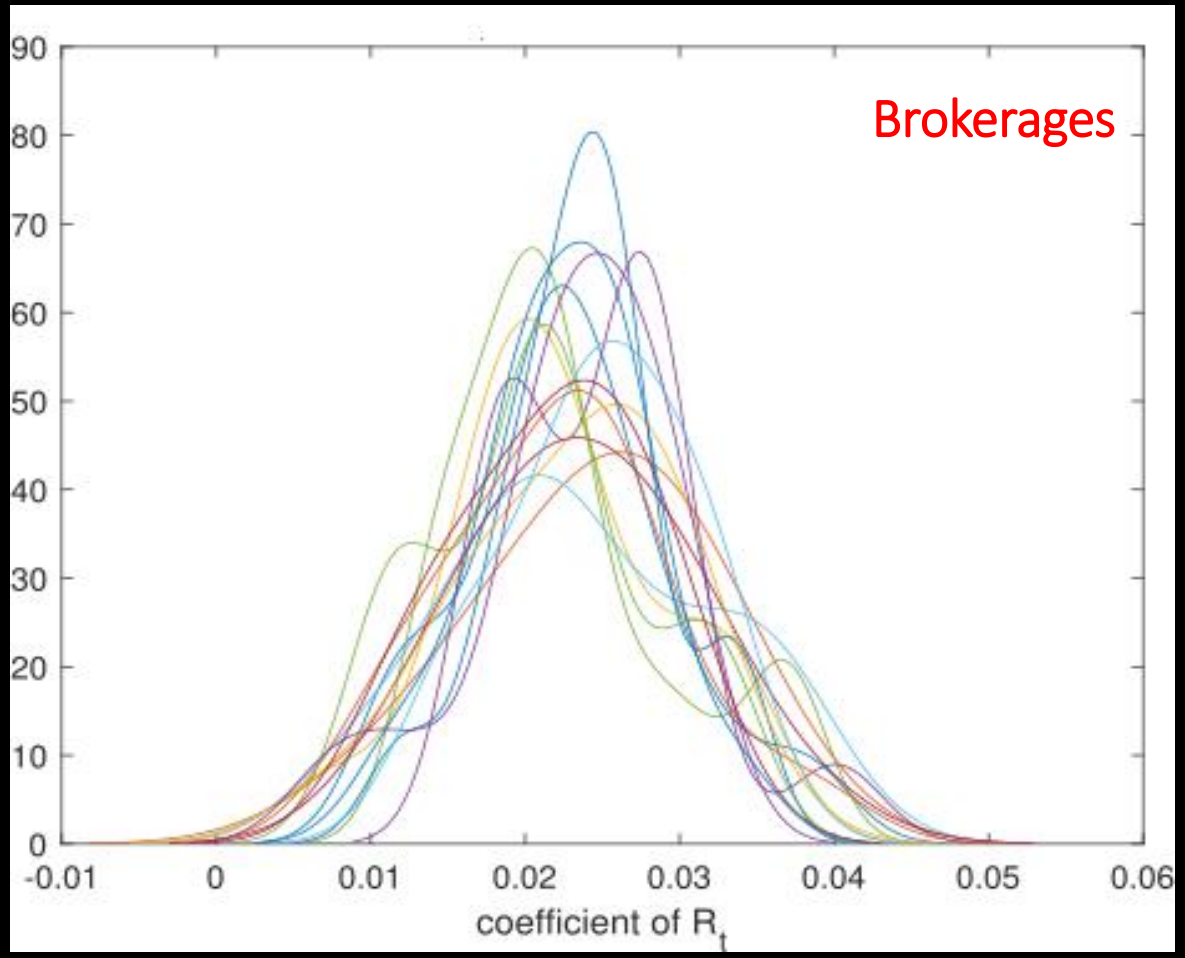
The tables report the sample means (with sample standard deviations in parentheses) of posterior mean estimates across the sample for the transition probabilities assuming h = 0.

Marginal posterior densities of coefficients of $I(R_t=1)$

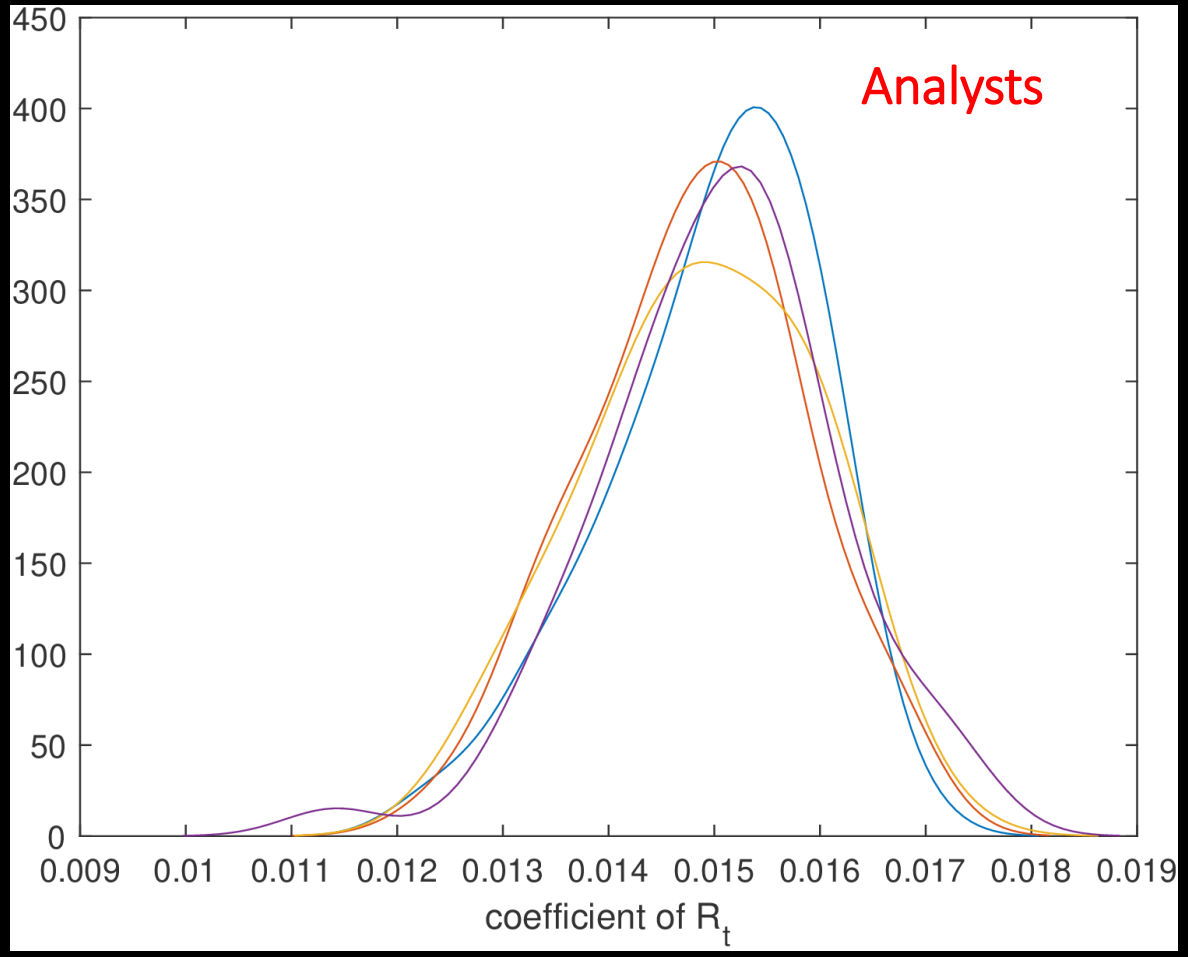


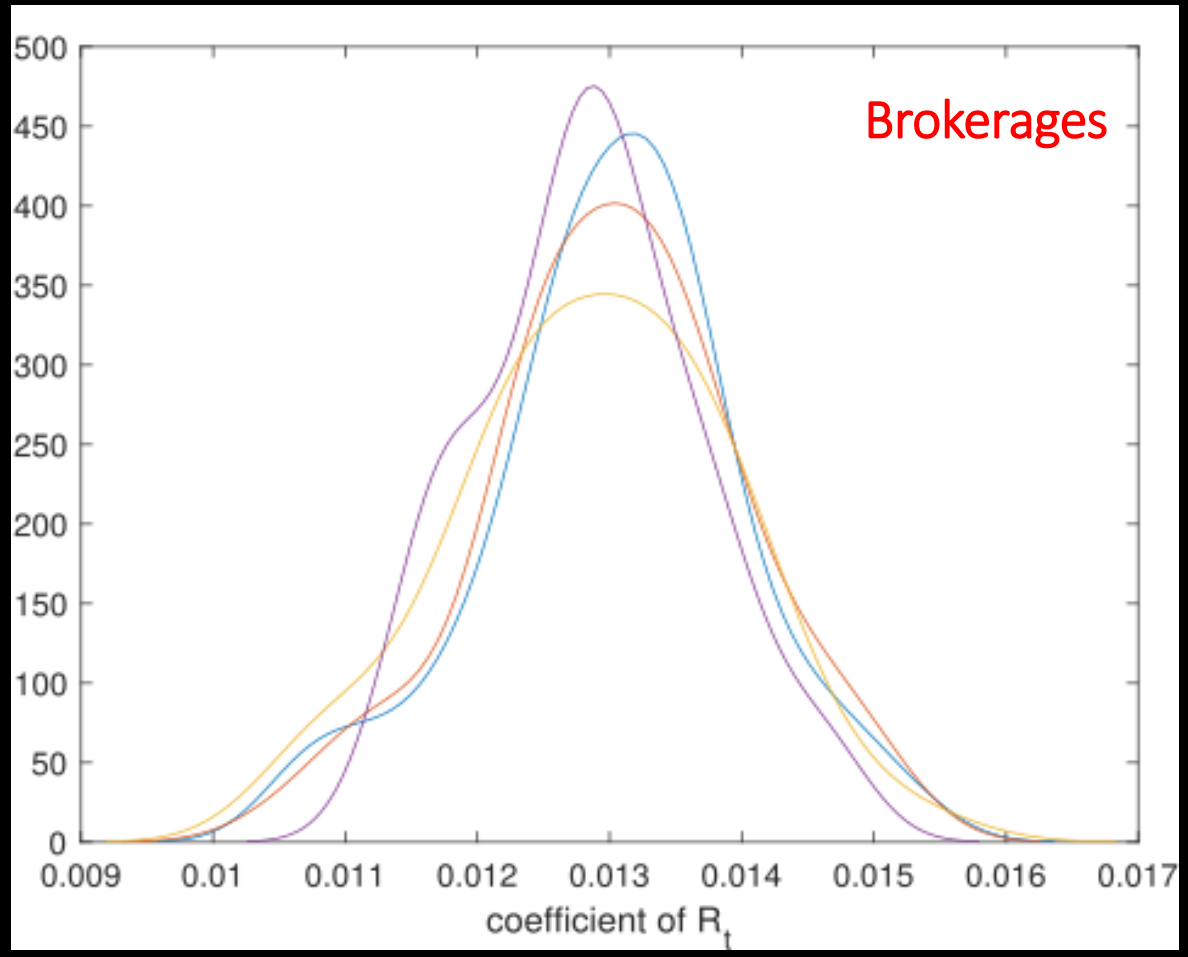


$$h = 0$$

α–stable distribution prior is used. Only the not zero mass marginal posterior densities are plotted.

Marginal posterior densities of coefficients of $I(R_t=1)$

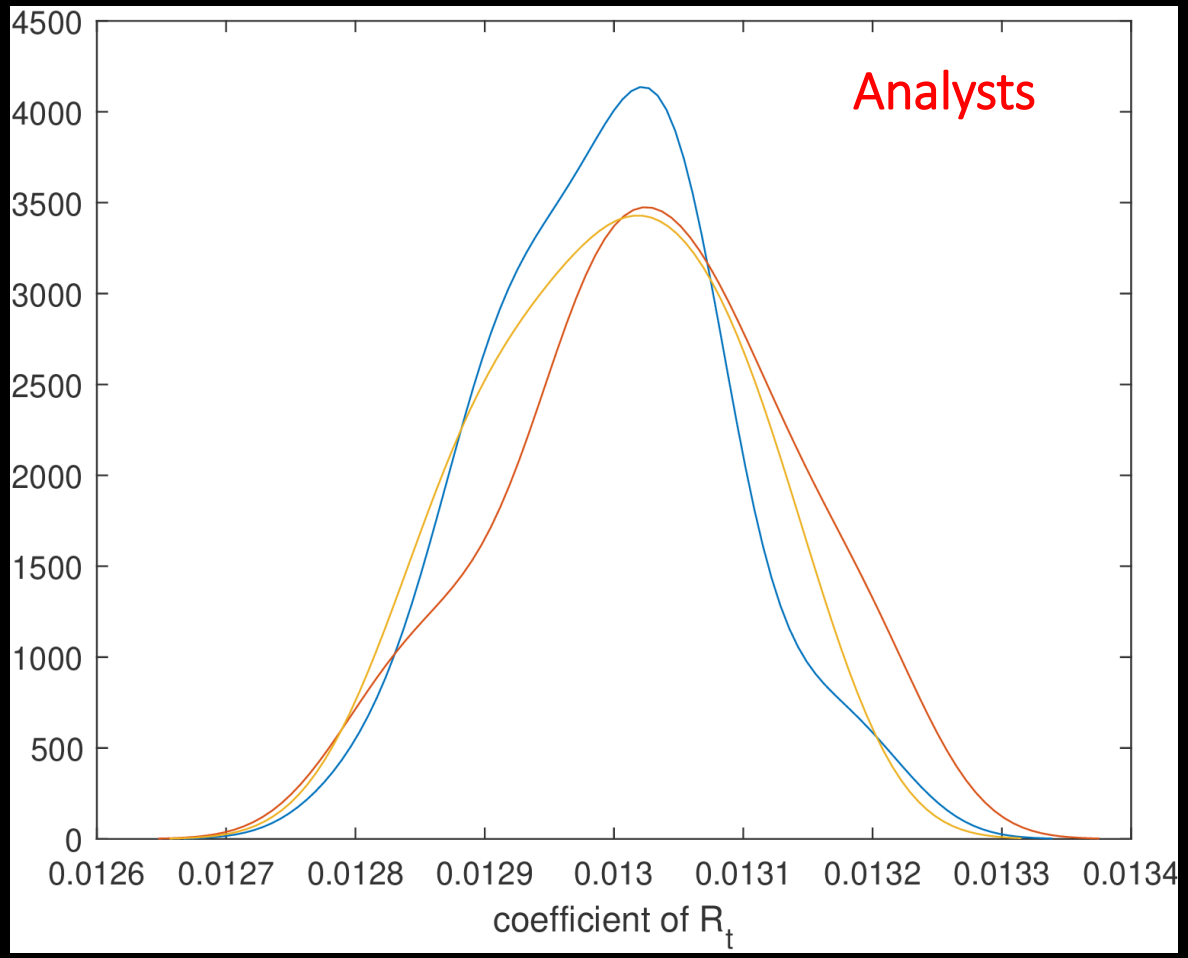


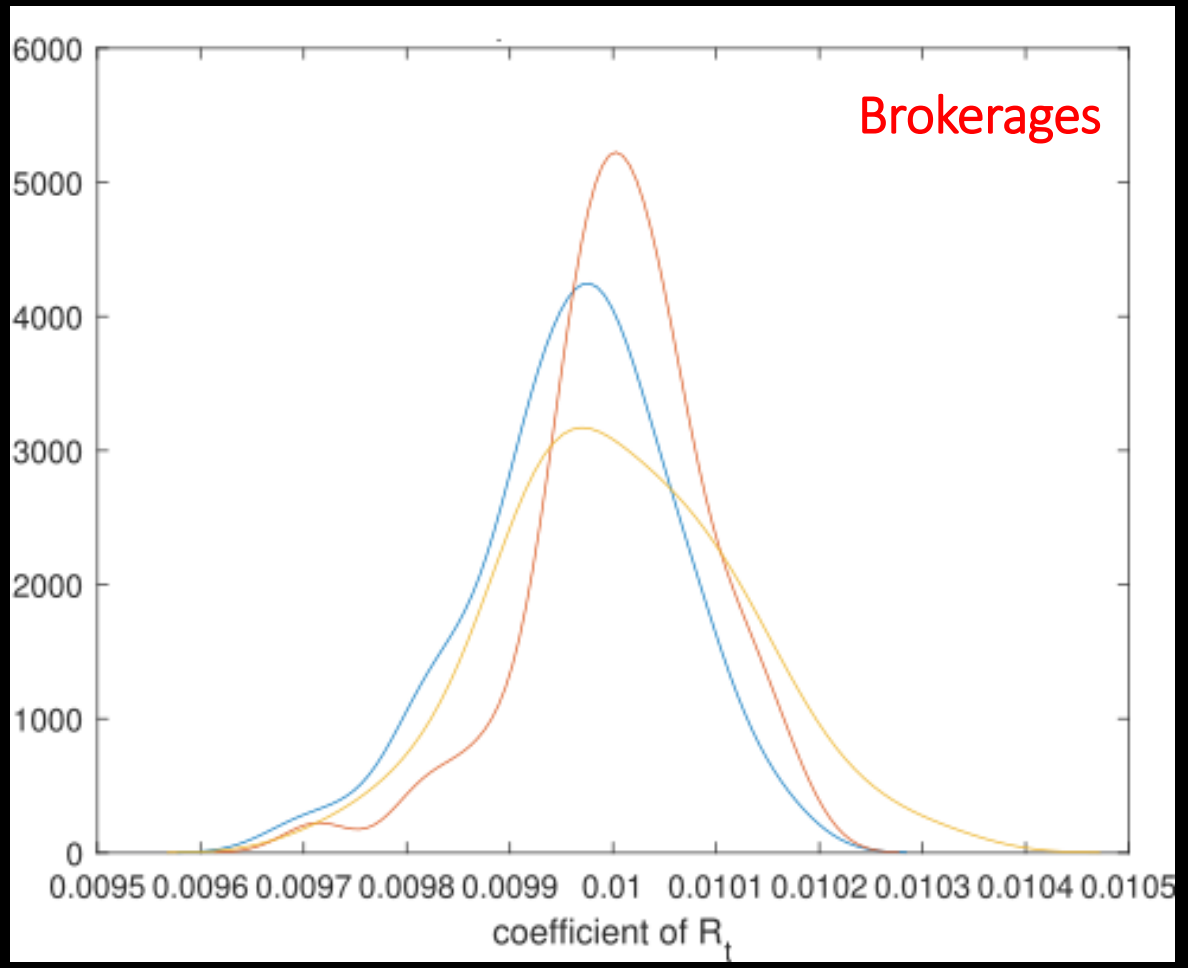


$h = 1$

α–stable distribution prior is used. Only the not zero mass marginal posterior densities are plotted.

Marginal posterior densities of coefficients of $I(R_t=1)$

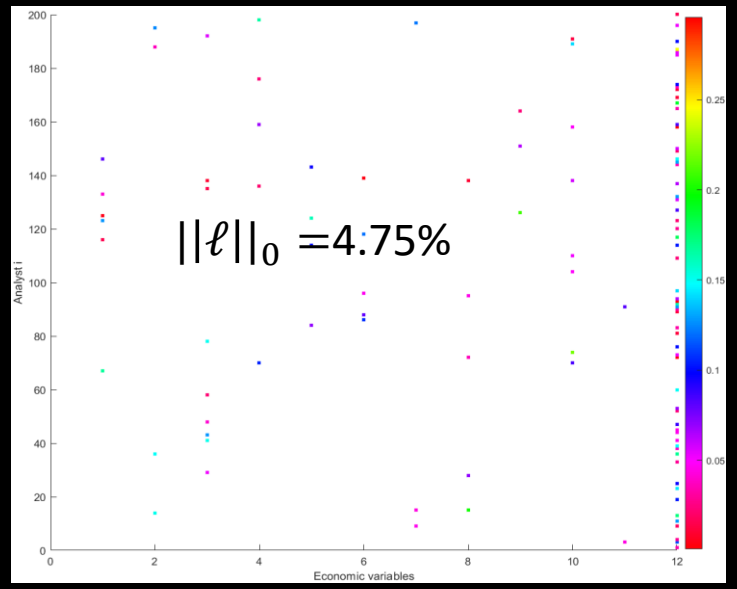




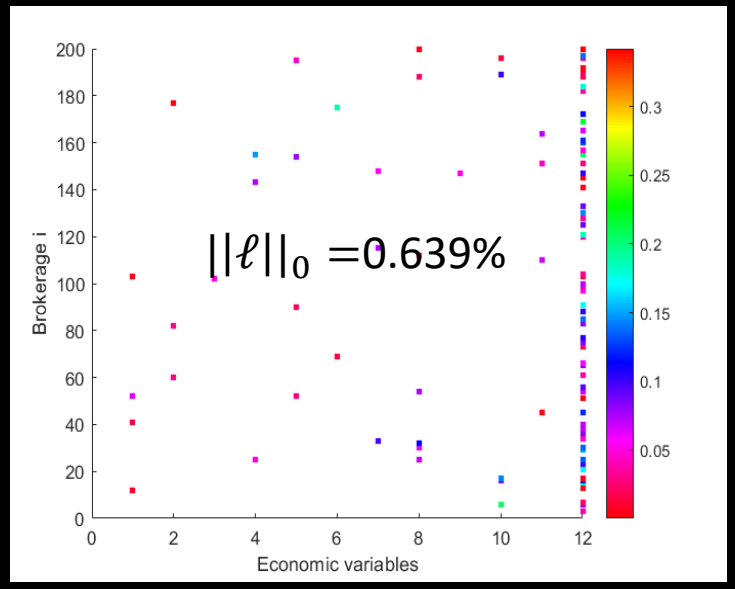
$$h = 2$$

α–stable distribution prior is used. Only the not zero mass marginal posterior densities are plotted.

Posterior mean estimates of the coefficients of the market conditions variables



Analysts



Brokerages

α-stable distribution prior

x-axis:

1. VIX Index
2. Price to earnings (P/E) of S&P 500 Index
3. Growth rate of the trailing 12-month sums of earnings of S&P 500 Index
4. DEBT/EBITDA ratio of the S&P 500 Index
5. Net equity expansion on the NYSE Index
6. Yield to maturity for the three-month Treasury bill
7. 2/10 U.S. Government bond yield spread
8. Moody's BAA and AAA-rated corporate bond yields spread
9. U.S. inflation
10. U.S. ISM Manufacturing Purchasing Managers Index
11. Growth rate of the U.S. Conference Board Leading Economic Indicators Index
12. U.S. business cycle phase

y-axis: 200 randomly chosen analyst

Conclusions

α-stable distribution performs better than **LASSO**, **elastic net**, and the horseshoe prior, both in-sample and out-of-sample.

Very few analysts' recommendations generate abnormal returns, yet profitable investment strategies based on analysts' recommendations exist.

The ***brokerage behavior differs*** from that of ***individual analysts***, suggesting that the mechanism of its and analysts recommendations is other.

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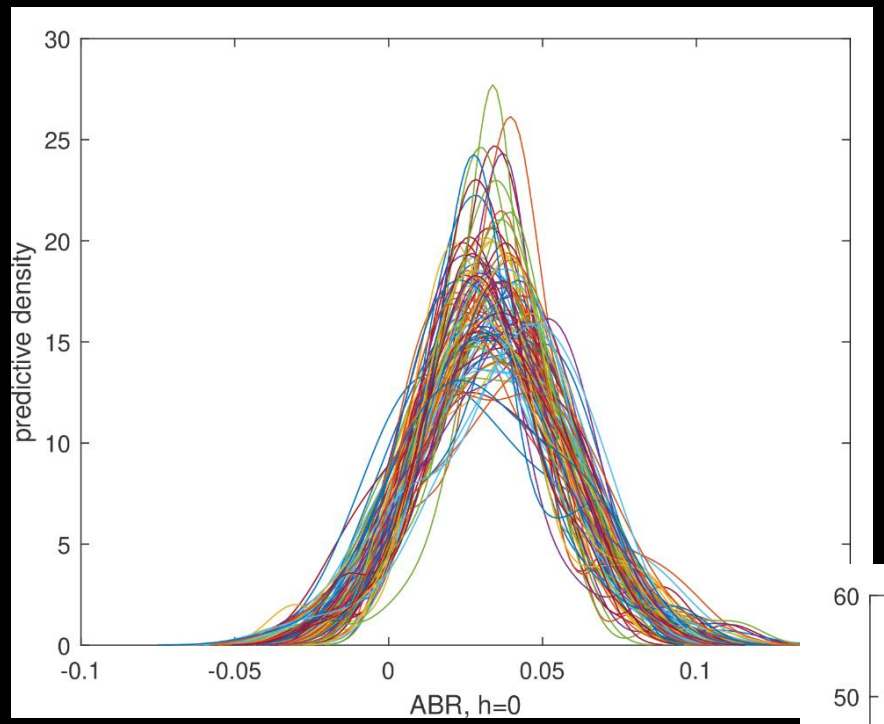
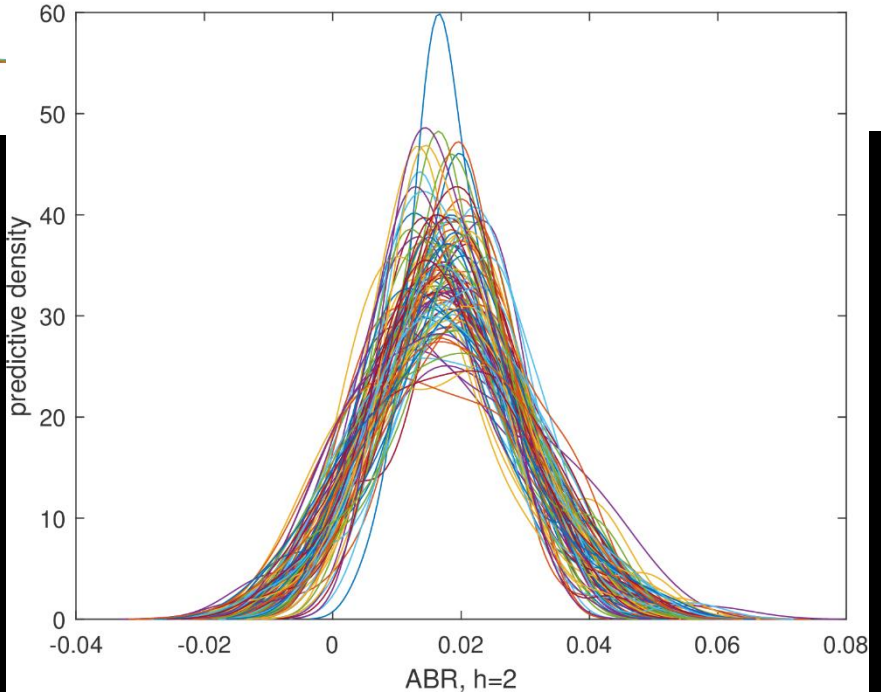
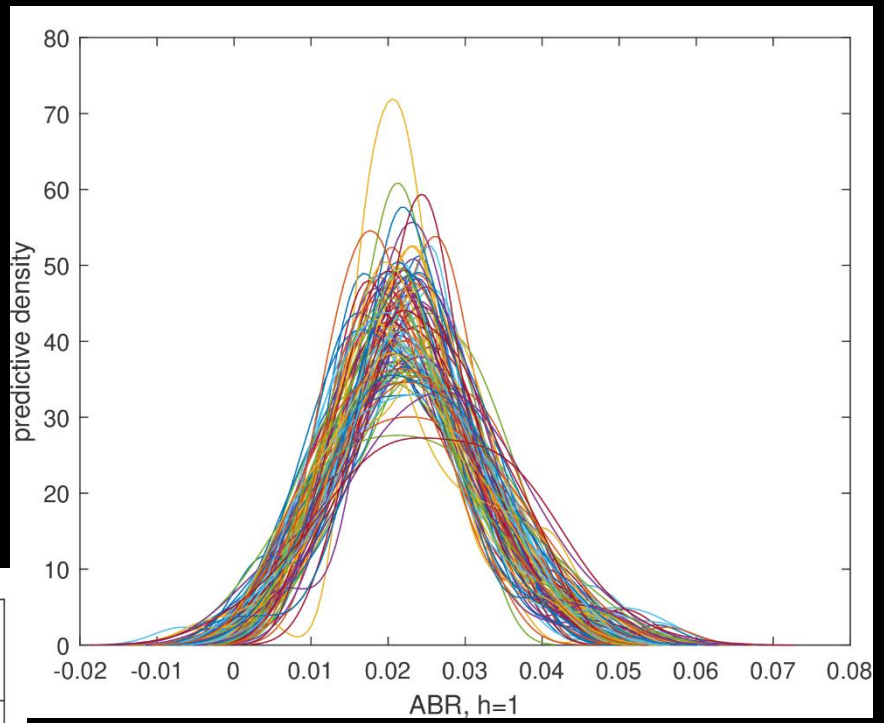
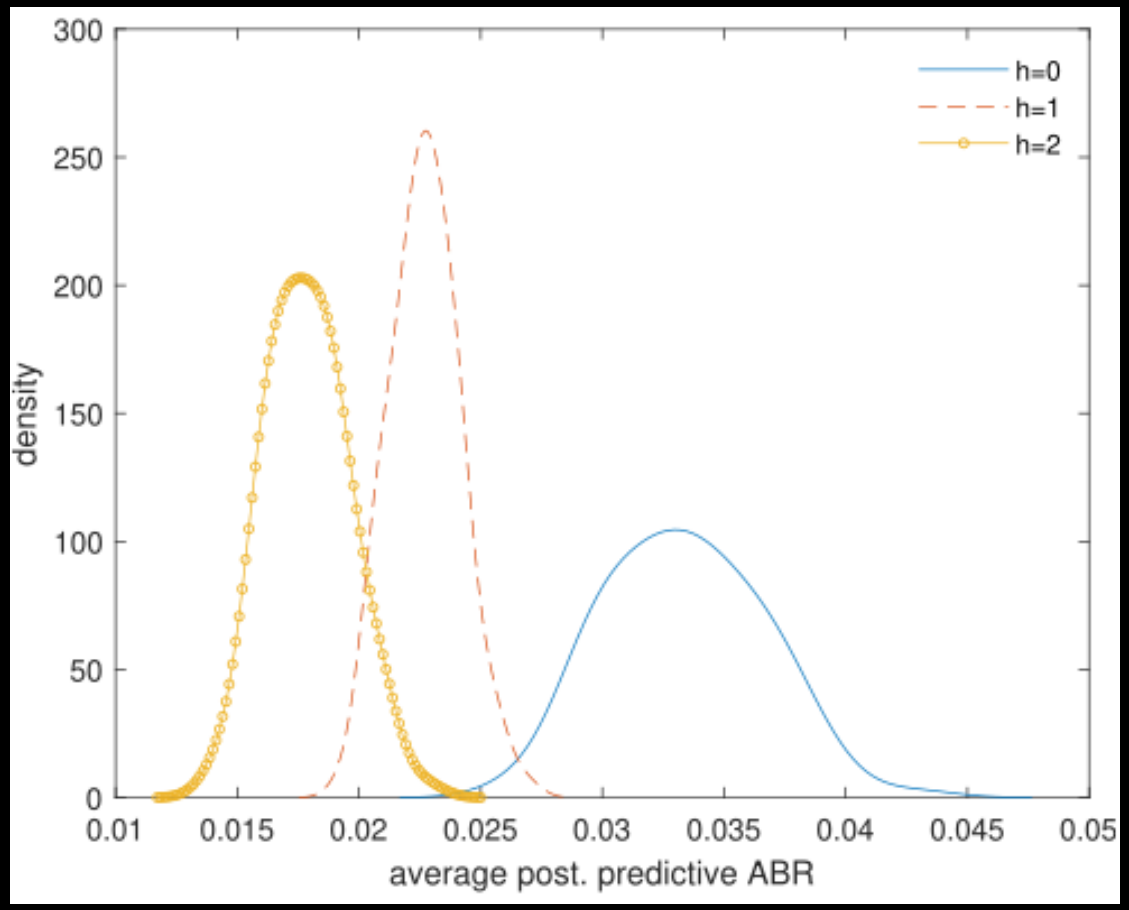
Individual analyst's posterior predictive density of abnormal returns assuming the α–stable distribution prior

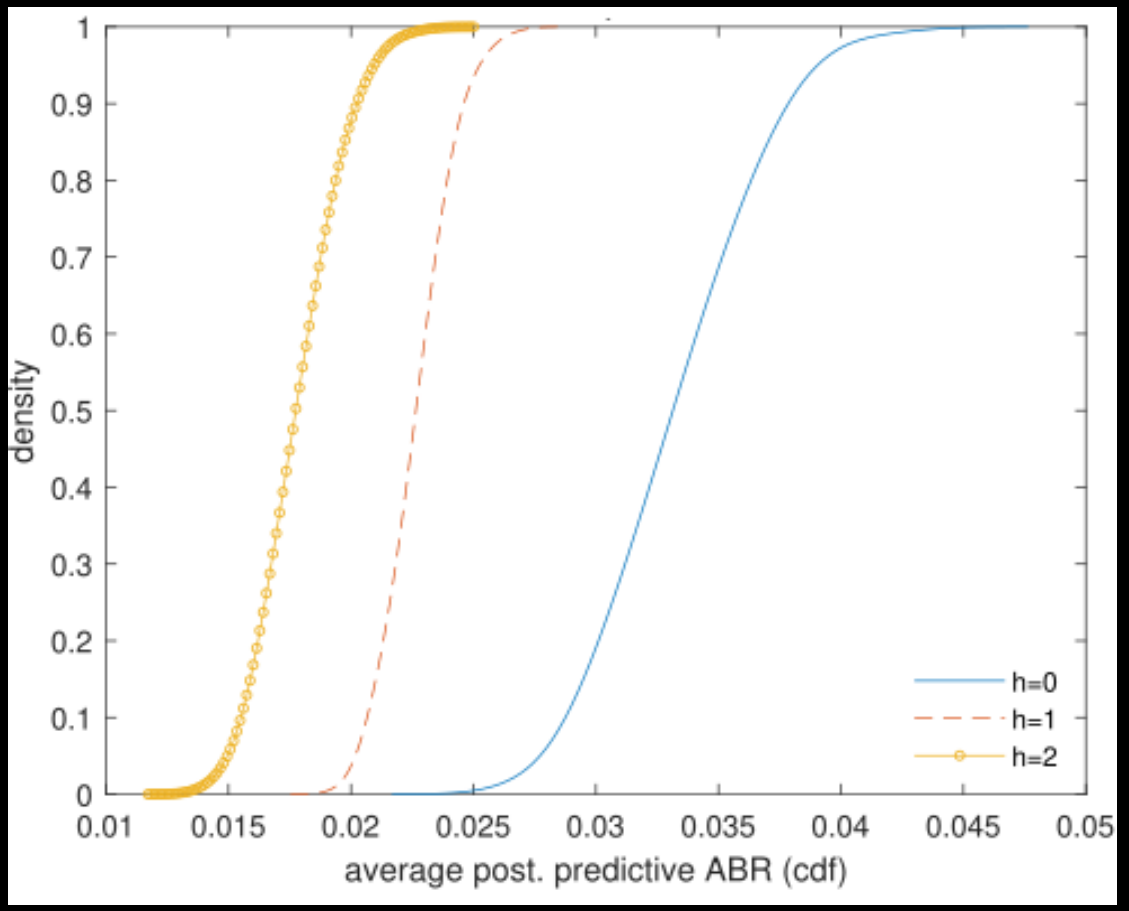






Average posterior predictive densities and cumulative distribution functions of abnormal returns



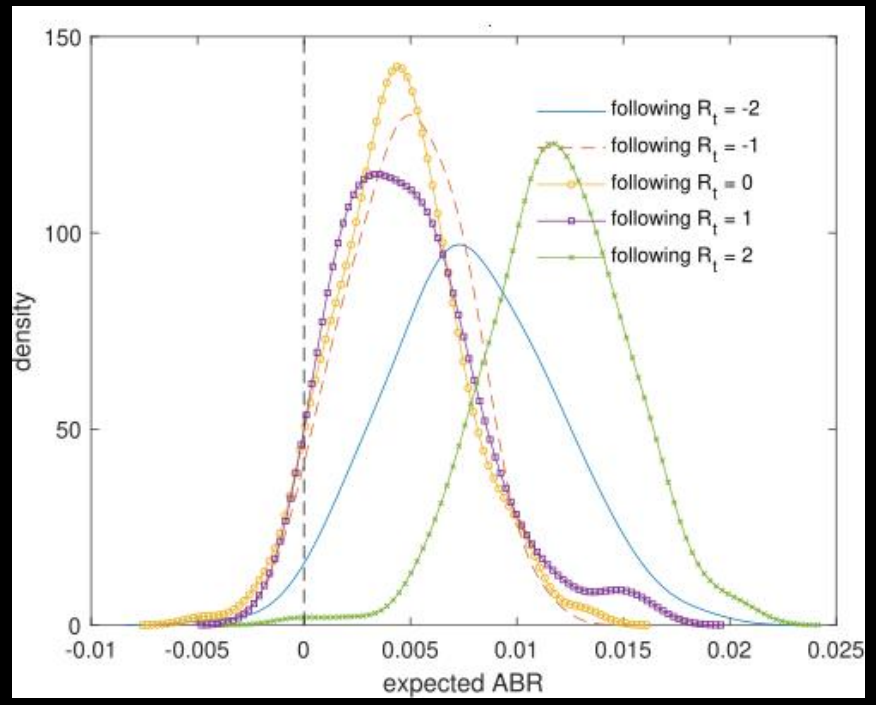


The densities are obtained using the α–stable distribution prior, for h= 0,1,2 days after the recommendation revision.

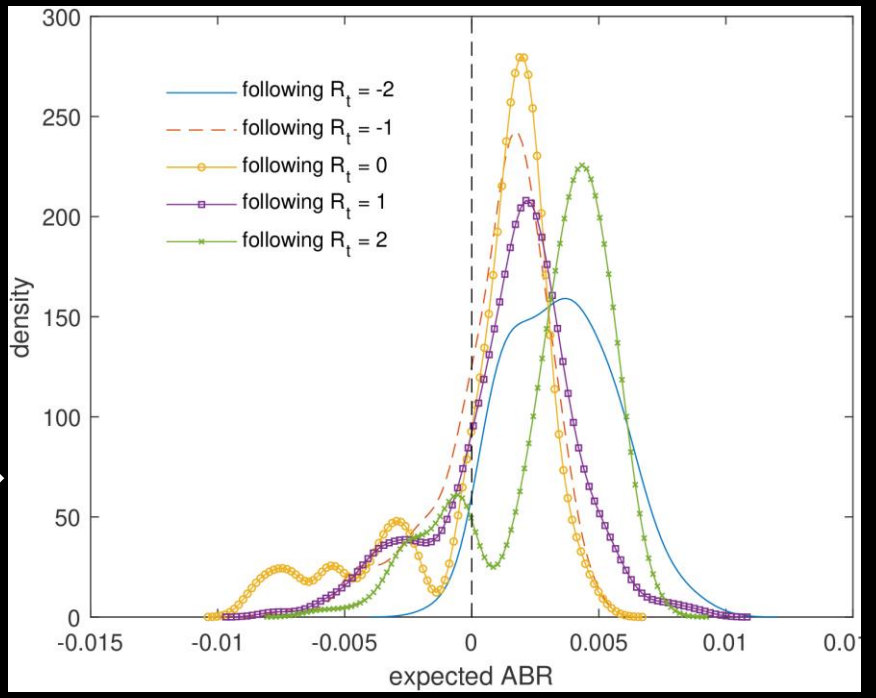
Posterior densities of the investment strategies expected abnormal returns

Note: *h = 1*.

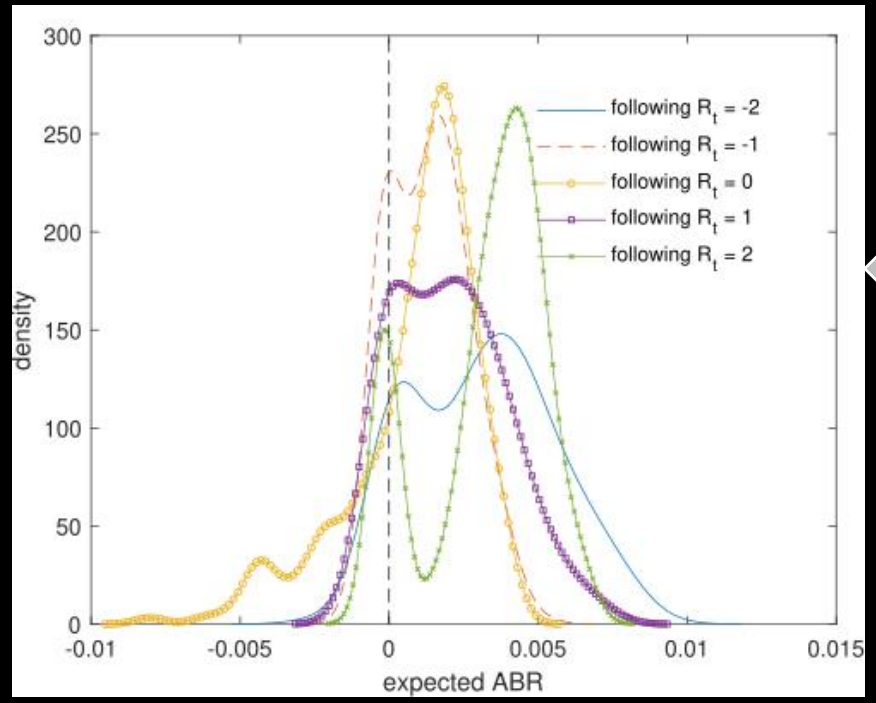
α-stable distribution prior



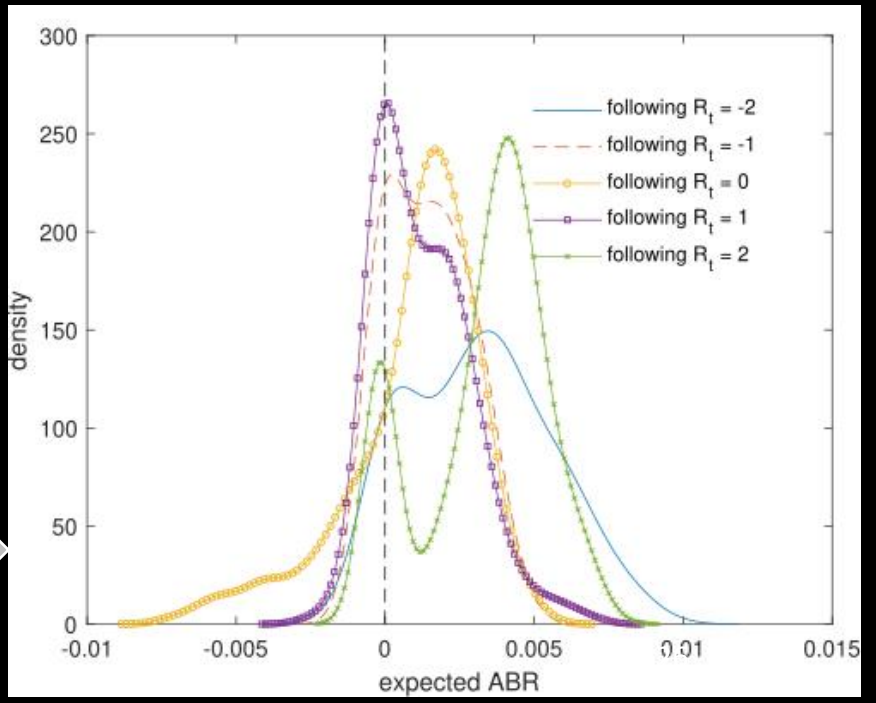
Horseshoe prior



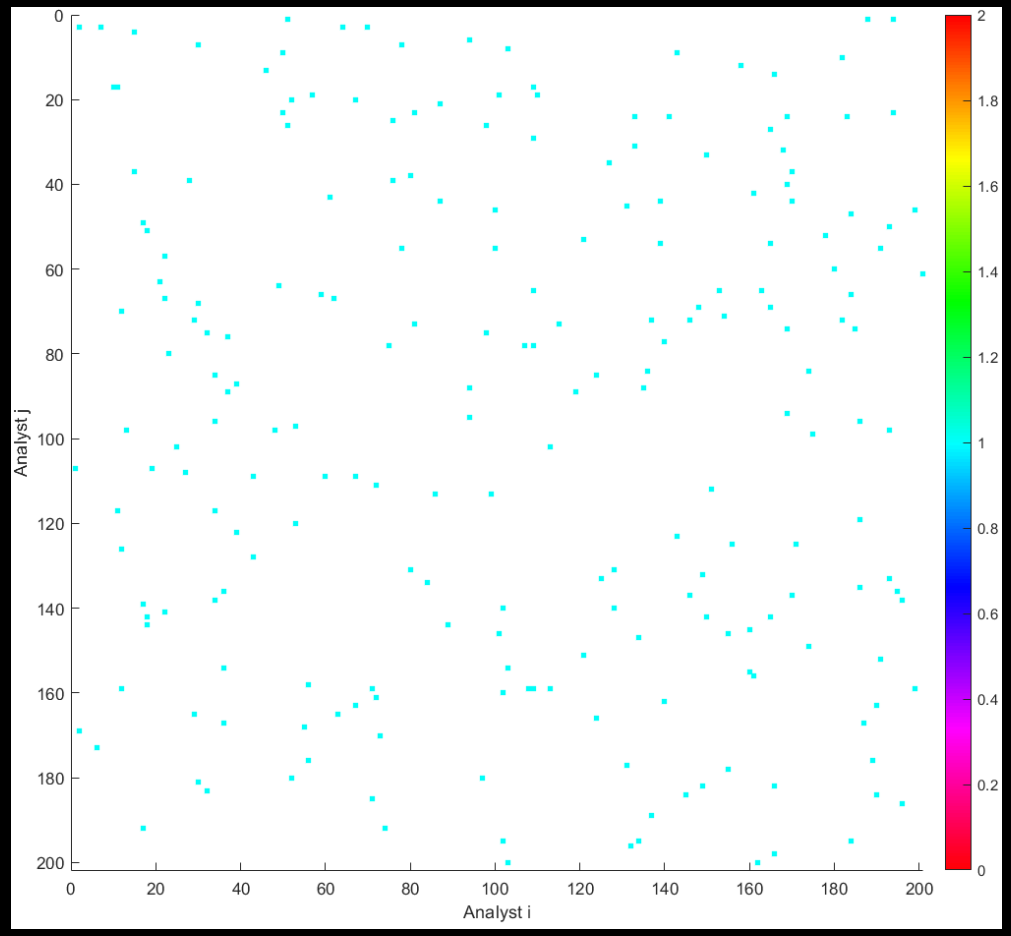
LASSO



Elastic net

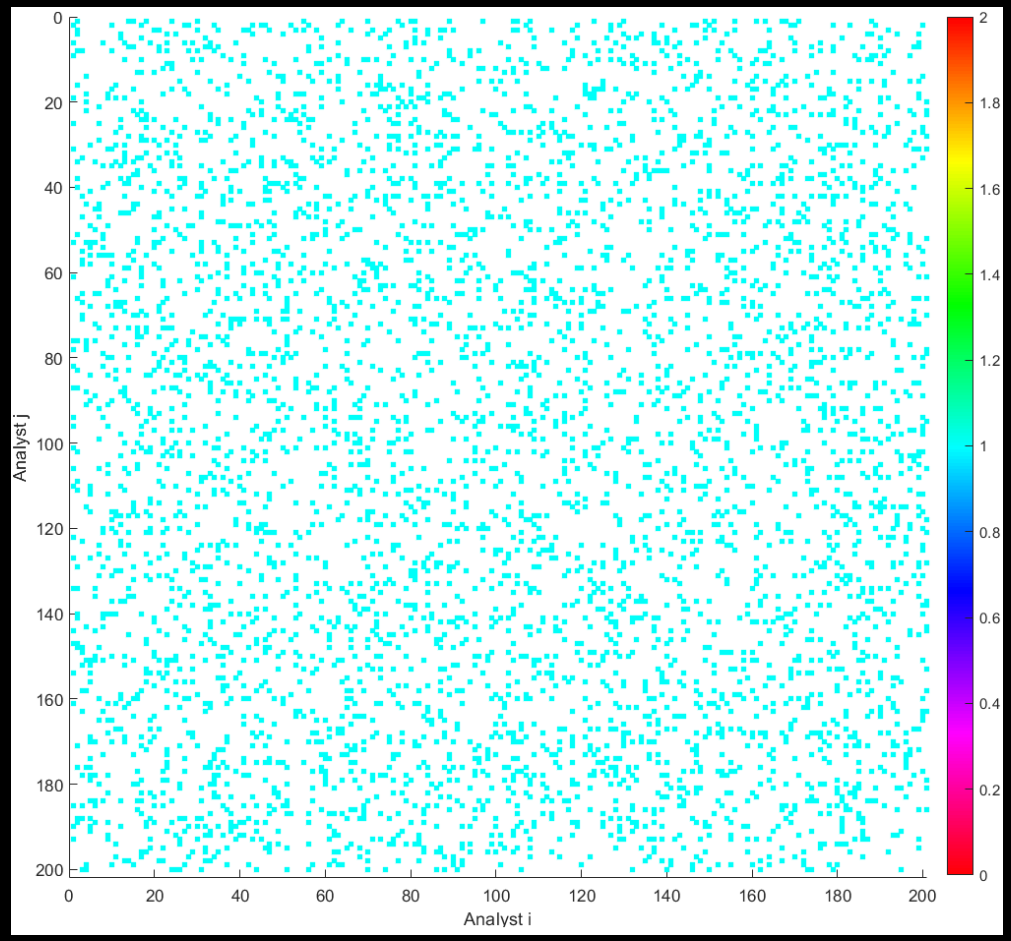


Consistency in following given analysts at the recommendation revision day (h= 0)



Conditional herding

$||\ell||_0$ =0.54%

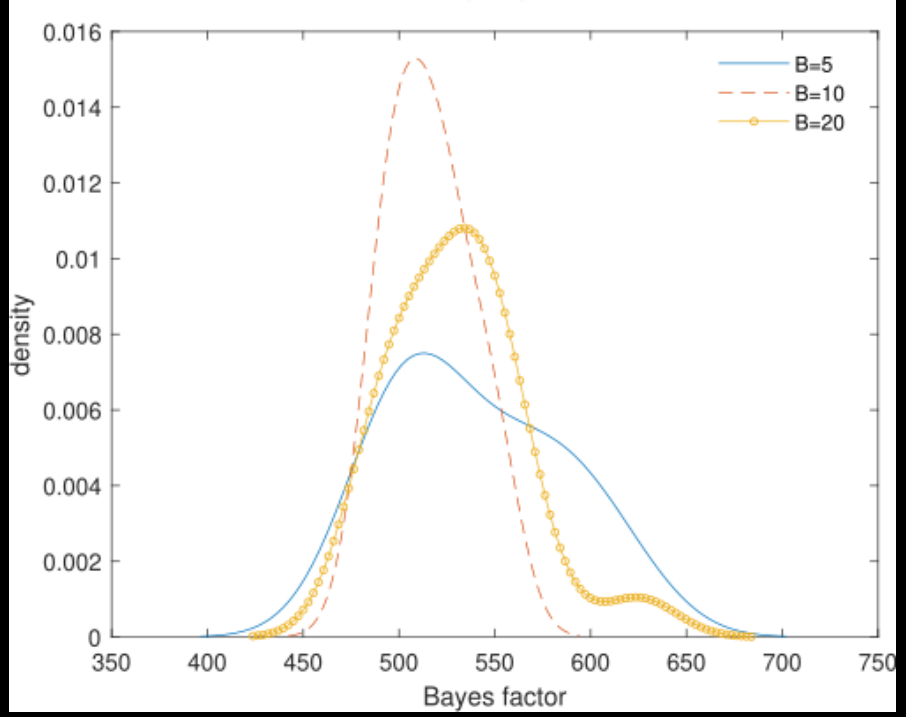


Unconditional herding

$||\ell||_0$ =11.81%

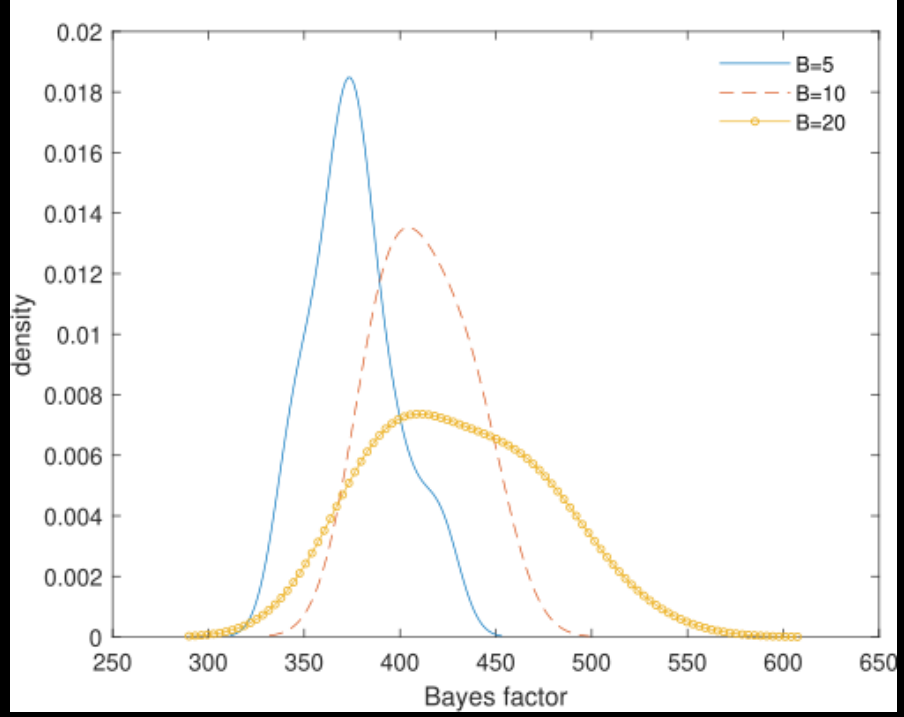
Only the statistically significant coefficients of $\boldsymbol{I}(\boldsymbol{R_t}$=1) assuming the α–stable distribution prior are plotted

Model comparison

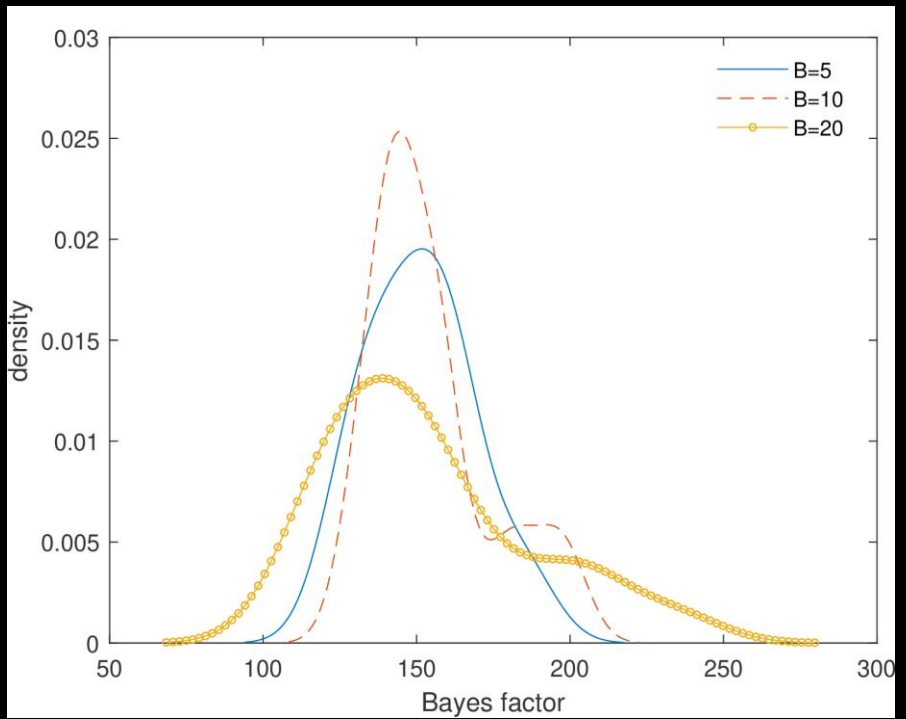


against LASSO

against elastic net

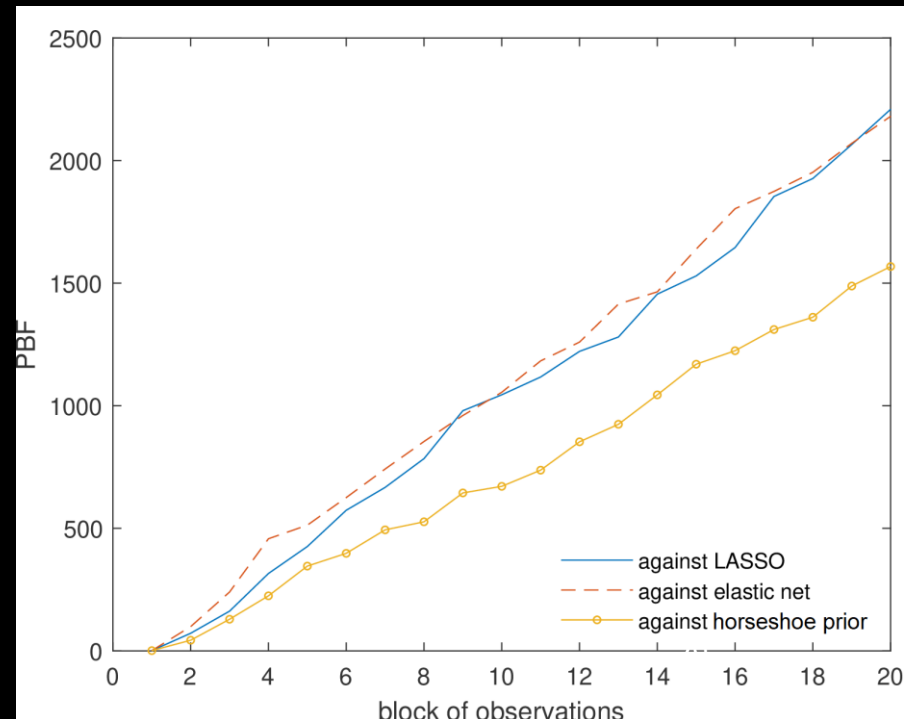


Bayes factor and predictive Bayes factor



against horseshoe prior

Predictive Bayes factor



Call to Action

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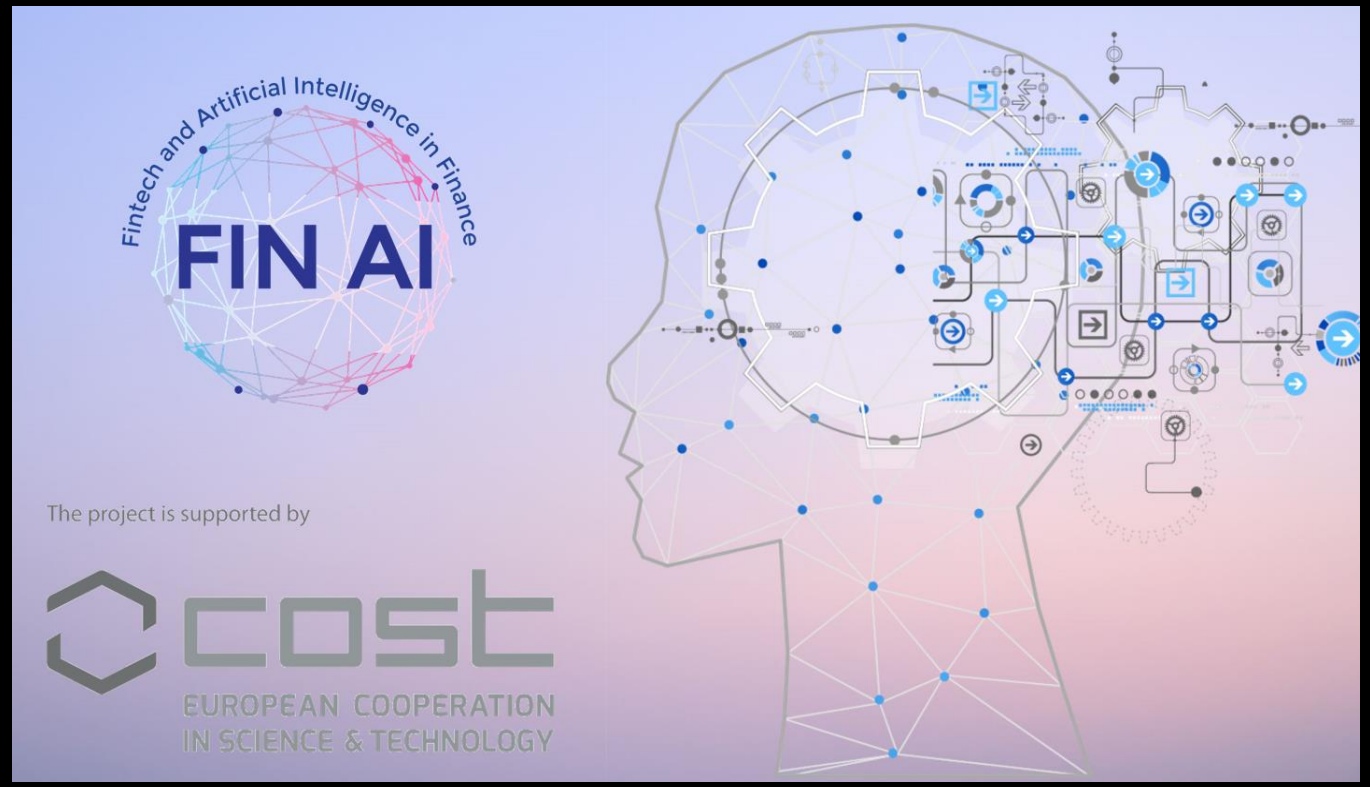

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