And Pythia said: "Buy not sell";

An analysis of analyst recommendations betting on sparsity

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Veni Arakelian
Piraeus Bank & UCL Centre for Blockchain Technologies

Mike G. Tsionas
Montpellier Business School Université de Montpellier & Lancaster University Management School
### Popular questions

<table>
<thead>
<tr>
<th><strong>Do analysts generate abnormal returns?</strong></th>
<th><strong>YES</strong></th>
<th><strong>NO</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Barber et al. (2001)</td>
<td></td>
<td>Kim and Song (2014)</td>
</tr>
<tr>
<td>Green (2006)</td>
<td></td>
<td></td>
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<tr>
<td>Crawford et al. (2017)</td>
<td></td>
<td></td>
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<tr>
<td>Crane and Crotty (2020)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Do analysts exhibit herding behavior?</strong></th>
<th><strong>YES</strong></th>
<th><strong>NO</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Clement and Tse (2005)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

$$ABR_{x,t,t+h} = \prod_{\tau=t}^{t+h}(1 + R_{x,\tau}) - \prod_{\tau=t}^{t+h}(1 + R_{m,\tau})$$

and, we assume that $ABR = X\beta + u$ is the model explaining them.

To deal with sparsity, we apply the standard shrinkage methods, LASSO and elastic net, and the

**horseshoe prior** (Carvalho et al. 2010).

We suggest use

**one-sided (or $\alpha$-stable) distribution**

instead of the horseshoe like prior.
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, these are:
  
  “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.
Variables

Analysts' recommendations usually are accompanied by a target price for the stock, which is very important for investors (Huang et al. 2019).

We model analyst’s exaggeration through the analyst's target price expected return (Huang et al. 2009), $TER$, that is

\[
\text{the return between the price of the stock at the date before the recommendation announcement and the analyst's target price,}
\]

and the analyst's target price revision (Brav and Lehavy, 2003), $DTar$, that is

\[
\text{the return between the analyst's new target price and his previous one.}
\]

Following Jegadeesh and Kim (2010), we also employ

\[
\text{the deviation of the analyst's new recommendation from the prevailing consensus, NC.}
\]
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,

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.
Jegadeesh and Kim 2010 model

\[ ABR_{x,t,t+h} = \alpha_h + b_h \times I_{multi} + c_h \times I_{single} + d_h \times NC_{x,t} + u_{t,h} \]

where \( h = \{0,1,2\} \) is the event window, and \( u_{t,h} \) the error term.

According to Jegadeesh and Kim 2010,

when analysts **herd** close to the consensus, then \( d > 0 \), and,

when analysts **exaggerate** their differences with the consensus, then \( d < 0 \).
Model

\[ ABR_{x,t,t+h} = \]

\[ X_t' \beta_1 + \left( \begin{array}{c}
TER_t, DTAR_t, NC_t, I_{R_{t-1}}, I_{R_t}, \cdots, TER_t, DTAR_t, NC_t, I_{R_{t-1}}, I_{R_t}
\end{array} \right) \beta_2 + u_{t,h} \]

where \( X_t \) contains the market conditions variables, \( I_{R_{t-1}} \equiv I(R_{t-1} = i) = 1 \), if the analyst’s recommendation is \( i = \{-2, -1, 0, 1, 2\} \). Same holds for \( I_{R_t} \equiv I(R_t = j) \).

Next, we assume a time-varying Markov switching model for \( R_t \) and \( R_{t-1} \), that is

\[ p_{ij,t} = \frac{\Phi(z_{i,t}^j \gamma_{i,j})}{\sum_{m=1}^M \Phi(z_{i,t}^j \gamma_{i,m})} \]

where \( z_t \) includes the variables \( TER, DTar, \) and \( NC \).
The table reports the sample means (with sample standard deviations in parentheses) of posterior mean estimates across the sample for the transition probabilities assuming $h = 0$. 

<table>
<thead>
<tr>
<th></th>
<th>Strong sell</th>
<th>Sell</th>
<th>Hold</th>
<th>Buy</th>
<th>Strong buy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Strong sell</strong></td>
<td>0.161***</td>
<td>0.272***</td>
<td>0.252***</td>
<td>0.310***</td>
<td>0.005*</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.014)</td>
<td>(0.044)</td>
<td>(0.019)</td>
<td>(0.003)</td>
</tr>
<tr>
<td><strong>Sell</strong></td>
<td>0.108</td>
<td>0.410***</td>
<td>0.278***</td>
<td>0.189***</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.045)</td>
<td>(0.017)</td>
<td>(0.015)</td>
<td>(0.020)</td>
</tr>
<tr>
<td><strong>Hold</strong></td>
<td>0.254***</td>
<td>0.271***</td>
<td>0.214***</td>
<td>0.006</td>
<td>0.255***</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td>(0.049)</td>
<td>(0.055)</td>
<td>(0.004)</td>
<td>(0.048)</td>
</tr>
<tr>
<td><strong>Buy</strong></td>
<td>0.108*</td>
<td>0.178*</td>
<td>0.230***</td>
<td>0.302***</td>
<td>0.182**</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.098)</td>
<td>(0.047)</td>
<td>(0.092)</td>
<td>(0.081)</td>
</tr>
<tr>
<td><strong>Strong buy</strong></td>
<td>0.228*</td>
<td>0.220</td>
<td>0.244***</td>
<td>0.205***</td>
<td>0.103***</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.155)</td>
<td>(0.016)</td>
<td>(0.033)</td>
<td>(0.017)</td>
</tr>
</tbody>
</table>
### Transition probabilities drivers

**TER:** “sell” → “sell” (positively)

“buy” → “hold” (negatively)

**DTar:** “strong sell” → (positively) “hold” → “buy” (negatively)

**NC:** “hold” → “strong sell” (positively)

“buy” → “hold” (negatively)

<table>
<thead>
<tr>
<th></th>
<th>Strong sell</th>
<th>Sell</th>
<th>Hold</th>
<th>Buy</th>
<th>Strong buy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TER</td>
<td>DTar</td>
<td>NC</td>
<td>TER</td>
<td>DTar</td>
</tr>
<tr>
<td><strong>Strong sell</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strong sell</td>
<td>0.0861***</td>
<td>0.1764***</td>
<td>0.0169</td>
<td>0.0169</td>
<td>0.0376***</td>
</tr>
<tr>
<td></td>
<td>(0.0193)</td>
<td>(0.0382)</td>
<td>(0.0412)</td>
<td></td>
<td>(0.0199)</td>
</tr>
<tr>
<td><strong>Sell</strong></td>
<td>0.1401***</td>
<td>0.0714*</td>
<td>0.0628***</td>
<td>0.0350</td>
<td>0.1524***</td>
</tr>
<tr>
<td></td>
<td>(0.0383)</td>
<td>(0.0370)</td>
<td>(0.0205)</td>
<td></td>
<td>(0.0406)</td>
</tr>
<tr>
<td><strong>Hold</strong></td>
<td>-0.0449</td>
<td>-0.0162</td>
<td>0.1980***</td>
<td>0.0747</td>
<td>-0.0765***</td>
</tr>
<tr>
<td></td>
<td>(0.0346)</td>
<td>(0.0491)</td>
<td>(0.0100)</td>
<td></td>
<td>(0.0352)</td>
</tr>
<tr>
<td><strong>Buy</strong></td>
<td>0.0720***</td>
<td>0.0406</td>
<td>0.0550*</td>
<td>-0.1120***</td>
<td>-0.0399***</td>
</tr>
<tr>
<td></td>
<td>(0.0271)</td>
<td>(0.0408)</td>
<td>(0.0298)</td>
<td></td>
<td>(0.0200)</td>
</tr>
<tr>
<td><strong>Strong buy</strong></td>
<td>-0.0301</td>
<td>-0.0077</td>
<td>0.1073***</td>
<td>0.0339</td>
<td>0.0867***</td>
</tr>
<tr>
<td></td>
<td>(0.0254)</td>
<td>(0.0426)</td>
<td>(0.0052)</td>
<td></td>
<td>(0.0118)</td>
</tr>
</tbody>
</table>

### Notes

- *****:** Statistical significance at the 0.01 level.
- **:** Statistical significance at the 0.05 level.
- **:** Statistical significance at the 0.10 level.
Cross-sectional regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>TER</td>
<td>0.038***</td>
<td></td>
</tr>
<tr>
<td>DTar</td>
<td>0.012***</td>
<td></td>
</tr>
<tr>
<td>NC</td>
<td>0.010***</td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500 P/E Index</td>
<td>0.017***</td>
<td></td>
</tr>
<tr>
<td>2/10 U.S. Government bond yield spread</td>
<td>-0.008***</td>
<td></td>
</tr>
<tr>
<td>U.S. inflation</td>
<td>-0.004***</td>
<td></td>
</tr>
<tr>
<td>U.S. ISM Manufacturing Purchasing Managers Index</td>
<td>-0.015***</td>
<td></td>
</tr>
<tr>
<td>$I(R_{t-1}=-2)$</td>
<td>-0.004**</td>
<td></td>
</tr>
<tr>
<td>$I(R_{t-1}=-1)$</td>
<td>-0.004***</td>
<td></td>
</tr>
<tr>
<td>$I(R_{t-1}=0)$</td>
<td>0.003**</td>
<td></td>
</tr>
<tr>
<td>$I(R_{t-1}=1)$</td>
<td>0.002**</td>
<td></td>
</tr>
<tr>
<td>$I(R_{t-1}=2)$</td>
<td>0.004**</td>
<td></td>
</tr>
<tr>
<td>$I(R_t=-2)$</td>
<td>-0.015***</td>
<td></td>
</tr>
<tr>
<td>$I(R_t=-1)$</td>
<td>-0.0073***</td>
<td></td>
</tr>
<tr>
<td>$I(R_t=0)$</td>
<td>0.020***</td>
<td></td>
</tr>
<tr>
<td>$I(R_t=1)$</td>
<td>0.015***</td>
<td></td>
</tr>
<tr>
<td>$I(R_t=2)$</td>
<td>0.018***</td>
<td></td>
</tr>
</tbody>
</table>
Posterior mean estimates of the coefficients of the market conditions variables

\[ \alpha \text{-stable distribution prior} \]

\[ \text{Horseshoe prior} \]

\text{\textbf{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

\text{\textbf{y-axis:}} 200 randomly chosen analyst

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
Posterior mean estimates of the coefficients of the market conditions variables
Marginal posterior densities of coefficients of $I(R_t=1)$

Note: The $\alpha$–stable distribution prior is used. Only the not zero mass marginal posterior densities are plotted.
Average posterior predictive densities and cumulative distribution functions of abnormal returns

Note: The densities are obtained using the $\alpha$–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
Relations between the coefficients of $I(R_t=1)$ at the recommendation revision day ($h=0$).

- α-stable distribution prior
- Horseshoe prior
Consistency in following given analysts at the recommendation revision day (\(h=0\))

Note: Only the statistically significant coefficients of \(I(R_t=1)\) assuming the \(\alpha\)-stable distribution prior are plotted.

Conditional herding

Unconditional herding
Model comparison
against horseshoe prior

against LASSO

against elastic net

Bayes factor and predictive Bayes factor

against horseshoe prior

Predictive Bayes factor
Conclusions

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

• Conditional herding (inferred by the relationships among the analysts' recommendations coefficients obtained from the estimation of the abnormal returns model when we account for the effect of the deviation of the analyst's new recommendation from the prevailing consensus) is not pervasive.

• On the contrary, the structure is very dense when unconditional herding is assumed.

• \( \alpha \)-stable distribution performs better than LASSO, elastic net, and the horseshoe prior, both in-sample and out-of-sample.
References