'Buy on rumor, sell on news'

the effect of news arrivals and investor sentiment on the distribution of excess returns

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13 September, 2022

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Intro

- Good news? Bad news?! News!!!
- Sentiment matters, but not for the mean: evidence in Ma, Xiao, and Ma (2018) and Al-Nasseri, Menla Ali, and Tucker (2021)
- Simple versus complex: does it pay up to use machine learning sentiment measures with high complexity?

$\rightarrow$ estimate distributional effect of news arrivals and sentiment using expectile regression.

Data

- Excess returns for 100 NASDAQ stocks, time span 201501-201909
- sentiment:
  - “the rumor”: use btm ratios as proxies of earnings expectations
  - “the news”: consider the event of new arrival and the tone of the news text separately
  - “the sentiment”: use LM and Harvard dictionaries (simple) and randomforest with FinBert (complex)
- other variables: size, alpha, turnover, nasdaq indicator.

Mean regression with random effects

- standard panel data model for the excess returns $(r_{i,t})$ of n stocks over $t = 1, \ldots, T$ and $i = 1, \ldots, n$:

$$r_{i,t} = x_{i,t}^\top \beta + u_i + v_{i,t}$$

  with
  - $r_{i,t}$ excess return of stock i at time t,
  - $x_{i,t}$ a vector of p predictors (including the constant term) known at time t,
  - u_i is unobserved random individual effect,
  - $v_{i,t}$ an error term uncorrelated with $x_{i,t}$ and $v_{i,t}$.

Expectile regression with random effects (ERRE)

- Conditional expectile regression with random effects (Diogo Barry, Charpentier, and Oualkacha (2016)) aims to estimate the τ-expectile:

$$e(\tau, r_{i,t}, x_{i,t}) = x_{i,t}^{\top}\beta_{\tau}, i = 1, \ldots, n, t = 1, \ldots T,$$

where $\tau \in (0,1)$ is the expectile level.

- The estimator minimizes the expectile loss function:

$$\arg\min_{\beta \in \mathbb{R}^p} \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} \rho_{\tau}\Big(r_{i,t} - x_{i,t}\beta(\tau)\Big)$$

with $\rho_{\tau}(y) = |\tau - \mathbf{1}(y < 0)|y^2$ is the expectile check function.

Expectile regression with random effects (ERRE)

- The resulting estimator has the form:

$$\hat{\beta}_\tau = \Big(\sum_{i=1}^{n} \sum_{t=1}^{T} \hat{w}_{i,t}(\tau) x_{i,t} x_{i,t}^\top \Big)^{-1} \Big(\sum_{i=1}^{n} \sum_{t=1}^{T} \hat{w}_{i,t}(\tau) x_{i,t} r_{i,t} \Big)$$

with $\hat{w}_{i,t}(\tau) = |\tau - \mathbf{1}(r_{i,t} \leq x_{i,t} \hat{\beta}(\tau))|$

and can be computed via *iterative weighted asymmetric least squares*.

ERRE with LM sentiment: the Model

Our first model specification is:

$$\begin{aligned} r_{i,t} =& \beta_0 + \beta_{1,\tau} \cdot \log(size_{i,t}) + \beta_{2,\tau} \cdot btm_{i,t-1} + \beta_{3,\tau} \cdot turn_{i,t-1} \\ &+ \beta_{4,\tau} \cdot alpha_{i,t} + \beta_{5,\tau} \cdot nq_{i,t} + \beta_{6,\tau} \cdot news_{i,t} + \beta_{7,\tau} \cdot lm\_tone_{i,t} \end{aligned} \tag{1}$$

- $news_{i,t}$ indicator whether a news report referred to company i has been released at t
- $lm\_tone_{i,t}$ is news sentiment computed as $\frac{\#\text{ of positive words} - \#\text{ of negative words}}{\#\text{ of positive words} + \#\text{ of negative words}}$ using the LM dictionary.

ERRE with LM sentiment: the Results

Table 1: Coefficients and R^2 of the ERRE models with LM sentiment and different τs

	$\beta_{0.05}$	$\beta_{0.1}$	$\beta_{0.25}$	$\beta_{0.5}$	$\beta_{0.75}$	$\beta_{0.9}$	$\beta_{0.95}$
Constant	-0.09664***	-0.06397***	-0.02793***	-0.00081	0.02616***	0.06193***	0.09511***
$\log(size_{i,t})$	0.00339***	0.00223***	0.00096***	0.00003	-0.0009***	-0.00215***	-0.00335***
$\alpha_{i,t}$	0.45594*	0.38957*	0.25476*	0.10379	-0.08922	-0.30887	-0.45446
$turn_{i,t}$	-0.00181***	-0.00137***	-0.00073***	-0.00004	0.00067***	0.00143***	0.00198***
$nq_{i,t}$	0.00031	0.0003	0.0003*	0.00031*	0.00034*	0.00029	0.00026
$btm_{i,t-1}$	**0.00082*** **	**0.00057*** **	**0.00028*** **	**0.00005**	**-0.00018*** **	**-0.00045*** **	**-0.0007*** **
$news_{i,t}$	**-0.00888*** **	**-0.00535*** **	**-0.00195*** **	**0.0003**	**0.0026*** **	**0.00614*** **	**0.00987*** **
$lm\_tone_{i,t}$	**0.00238***	**0.00206** **	**0.00168*** **	**0.00171*** **	**0.00235*** **	**0.00408*** **	**0.00621*** **
R^2	**0.11256**	**0.06886**	**0.02059**	**0.0008**	**0.0193**	**0.06881**	**0.11721**

ERRE with LM sentiment: the Effects

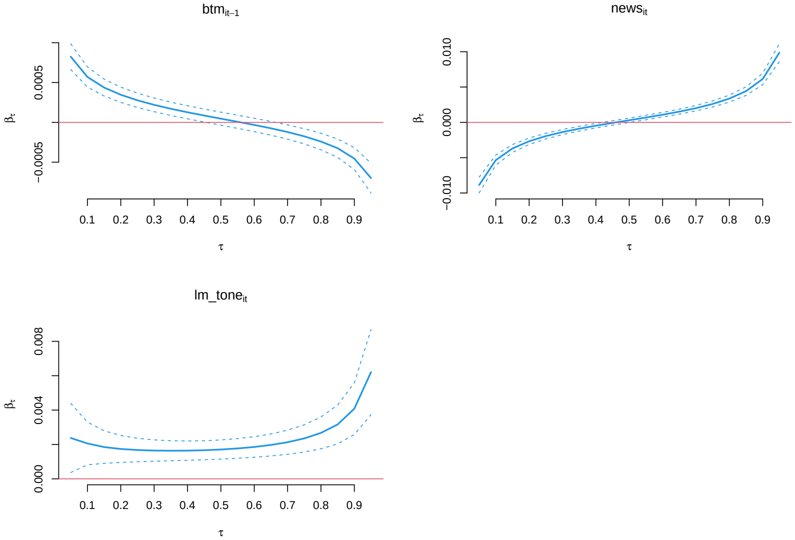

Figure 1: Coefficient profiles of sentiment related variables for different τ-levels

How do we interpret the results?

- we observe significant changes in effects across expectile levels (btm, news)
- LM dictionary seems to capture the facetts of sentiment important for the higher expectiles (for $\tau > 0.75$)
- news arrivals exhibit an effect with changing sign at aproximately $\tau = 0.5$

How do we interpret the results?

- news arrivals have a strong negative effect on low return expectiles regardless of the news tone.
- For example, given the data, the maximum of scaled *lm_tone* over all days and stocks is 1, the respective coefficient for the 5%-expectile on news arrivals is $-0.00888(-0.00892, -0.0088)$ and on net tone is $0.00238(0.00231, 0.00244)$, so the net effect of the "best" empirical tone would calculate:

$$-0.0065(-0.0066, -0.0064)$$

with an asymptotic 95%-confidence interval given in brackets.

How do we interpret the results?

- *rightarrow* in low return state also positive news can lead to a negative effect on the excess return.
- We explain this effect with the trading strategy *'Buy on rumor, sell on news'* for low return states.
- investors buy equities with low returns when they expect their growth (btm, the 'rumor' part) and sell low return stocks to ride on the hype of (positive) news arrivals.
- This effect can be also connected to the 'market sidedness' of Sarkar and Schwarz (2009): disproportionaly higher seller quote at news arrivals in case of low expectiles.
- The positive effect of btm ratio arises as a result of buyer 'sidedness' hunting the equities with low returns but promising expected performance (high btm).

ERRE with HV sentiment: the Model

Our second model specification is:

$$\begin{aligned} r_{i,t} =& \beta_0 + \beta_{1,\tau} \cdot \log(size_{i,t}) + \beta_{2,\tau} \cdot btm_{i,t-1} + \beta_{3,\tau} \cdot turn_{i,t-1} \\ &+ \beta_{4,\tau} \cdot alpha_{i,t} + \beta_{5,\tau} \cdot nq_{i,t} + \beta_{6,\tau} \cdot news_{i,t} + \beta_{7,\tau} \cdot lm\_tone_{i,t} \end{aligned} \tag{2}$$

- $news_{i,t}$ indicator whether a news report referred to company i has been released at t
- $hv\_tone_{i,t}$ is news sentiment computed as $\frac{\text{\# of positive words} - \text{\# of negative words}}{\text{\# of positive words} + \text{\# of negative words}}$ using the Harvard dictionary.

ERRE with HV sentiment: the Results

Table 2: Coefficients and R^2 of the ERRE models with LM sentiment and different τs

	$\beta_{0.05}$	$\beta_{0.1}$	$\beta_{0.25}$	$\beta_{0.5}$	$\beta_{0.75}$	$\beta_{0.9}$	$\beta_{0.95}$
Constant	-0.09644***	-0.06377***	-0.0278***	-0.00071	0.02627***	0.06216***	0.09583***
$\log(size_{i,t})$	0.00339***	0.00222***	0.00096***	0.00003	-0.0009***	-0.00216***	-0.00338***
$\alpha_{i,t}$	0.45381*	0.39254*	0.26276*	0.11706	-0.06638	-0.26797	-0.39089
$turn_{i,t}$	-0.00179***	-0.00136***	-0.00073***	-0.00004	0.00067***	0.00143***	0.00197***
$nq_{i,t}$	0.00033	0.00033	0.00032*	0.00033**	0.00036*	0.00033	0.0003
$btm_{i,t-1}$	**0.00083*** **	**0.00057*** **	**0.00028*** **	**0.00004**	**-0.00018*** **	**-0.00046*** **	**-0.00071*** **
$news_{i,t}$	**-0.01325*** **	**-0.00839*** **	**-0.00357*** **	**-0.00062* **	**0.00203*** **	**0.00574*** **	**0.0096*** **
$lm\_tone_{i,t}$	**0.01153*** **	**0.00788*** **	**0.0041*** **	**0.0022*** **	**0.00118**	**0.00045**	**-0.00017**
R^2	**0.11368**	**0.06974**	**0.02072**	**0.00046**	**0.01852**	**0.06709**	**0.11499**

ERRE with HV sentiment: the Effects

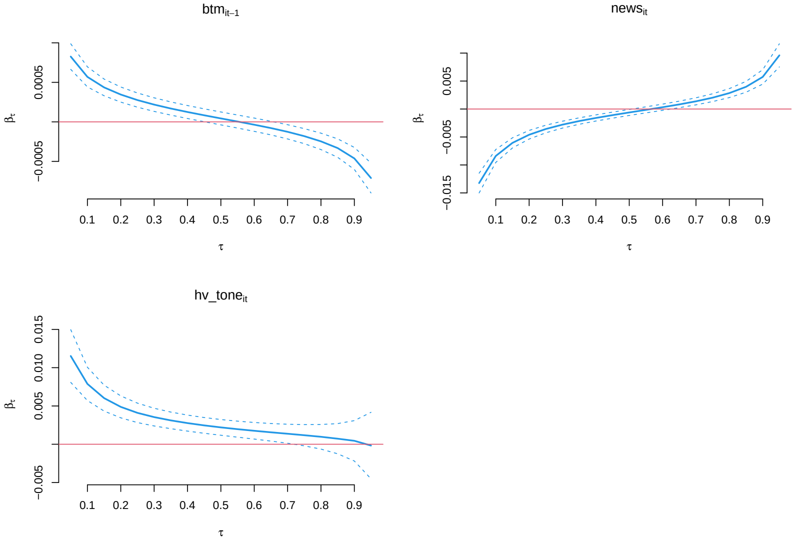

Figure 2: Coefficient profiles of sentiment related variables for different τ-levels

How do we interpret the results?

- the effects of news arrivals and btm ratio are similar to the previous model.
- explanatory power of HV dictionary is lower than that of LM dictionary (as mesured by R^2)
- HV dictionary seems to capture the facetts of sentiment important for the lower expectiles (for $\tau < 0.5$)

ERRE with ML sentiment: the Model

Our next model specification is:

$$\begin{aligned} r_{i,t} =& \beta_0 + \beta_{1,\tau} \cdot \log(size_{i,t}) + \beta_{2,\tau} \cdot btm_{i,t-1} + \beta_{3,\tau} \cdot turn_{i,t-1} \\ &+ \beta_{4,\tau} \cdot alpha_{i,t} + \beta_{5,\tau} \cdot nq_{i,t} + \beta_{6,\tau} \cdot news_{i,t} + \beta_{7,\tau} \cdot ml\_tone_{i,t} \end{aligned} \tag{3}$$

- $ml\_tone_{i,t}$ is news sentiment defined as an out-of-sample return forecast for stock i and time t produced by a random forest model based on the FinBert embeddings.

ERRE with ML sentiment: the Results

Table 3: Coefficients and R^2 of the ERRE models with LM sentiment and different τs

	$\beta_{0.05}$	$\beta_{0.1}$	$\beta_{0.25}$	$\beta_{0.5}$	$\beta_{0.75}$	$\beta_{0.9}$	$\beta_{0.95}$
Constant	-0.09655***	-0.06393***	-0.02792***	-0.00082	0.0262***	0.06203***	0.09573***
$\log(size_{i,t})$	0.00339***	0.00223***	0.00096***	0.00003	-0.0009***	-0.00216***	-0.00337***
$\alpha_{i,t}$	0.44256	0.38281*	0.25271*	0.10388	-0.0865	-0.30388	-0.43534
$turn_{i,t}$	-0.00179***	-0.00136***	-0.00073***	-0.00003	0.00068***	0.00144***	0.00198***
$nq_{i,t}$	0.00028	0.00029	0.00029*	0.00031*	0.00034*	0.00028	0.00023
$btm_{i,t-1}$	**0.00082*** **	**0.00056*** **	**0.00027*** **	**0.00004**	**-0.00018*** **	**-0.00046*** **	**-0.00071*** **
$news_{i,t}$	**-0.00908*** **	**-0.00556*** **	**-0.00213*** **	**0.00013**	**0.00238*** **	**0.00577*** **	**0.00933*** **
$lm\_tone_{i,t}$	**0.0502*** **	**0.04283*** **	**0.03422*** **	**0.03156*** **	**0.0364*** **	**0.04943*** **	**0.0612*** **
R^2	**0.11473**	**0.07134**	**0.02214**	**0.00202**	**0.0205**	**0.07009**	**0.11844**

ERRE with ML sentiment: the Effects

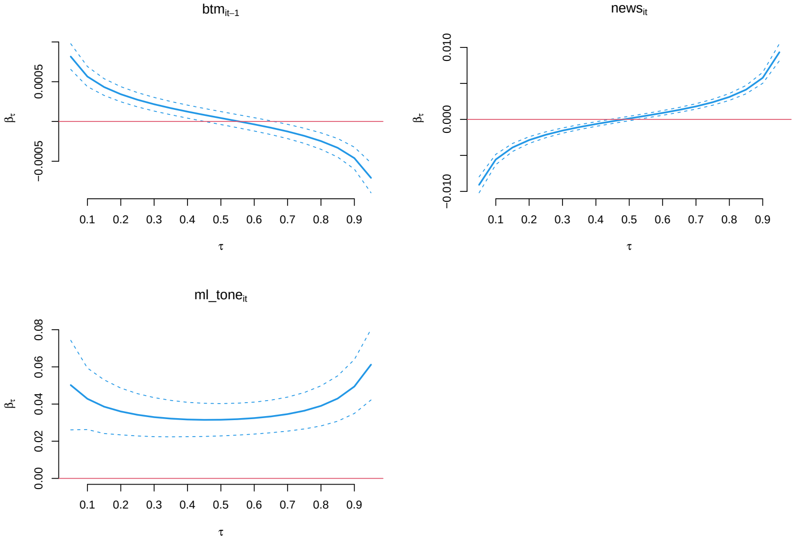

Figure 3: Coefficient profiles of sentiment related variables for different τ-levels

How do we interpret the results?

- the effects of news arrivals and btm ratio are similar to the previous models.
- explanatory power of ML approach is higher than that of LM/HV dictionary (as mesured by R^2)
- ML tone seems to capture the facetts of sentiment important for both lower and higher expectiles (U-shape).
- *rightarrow* can we achieve better performance of dictionary methods by mimicing the ML approach, i.e.by combining both sentiment tones, so that important features for lower and higher expectiles are captured?

ERRE with combined LM/HV sentiment: the Model

In this model specification we use $comb\_tone_{i,t}$ set to $(1-\tau) \cdot hv\_tone_{i,t} + \tau \cdot lm\_tone_{i,t}$ in order to overweight $hv\_tone_{i,t}$ for low and to overweight $lm\_tone_{i,t}$ for high τ-values:

$$\begin{aligned} r_{i,t} =& \beta_0 + \beta_{1,\tau} \cdot \log(size_{i,t}) + \beta_{2,\tau} \cdot btm_{i,t-1} + \beta_{3,\tau} \cdot turn_{i,t-1} \\ &+ \beta_{4,\tau} \cdot alpha_{i,t} + \beta_{5,\tau} \cdot nq_{i,t} + \beta_{6,\tau} \cdot news_{i,t} + \beta_{7,\tau} \cdot comb\_tone_{i,t} \end{aligned} \tag{4}$$

ERRE with ML sentiment: the Results

Table 4: Coefficients and R^2 of the ERRE models with LM sentiment and different τs

	$\beta_{0.05}$	$\beta_{0.1}$	$\beta_{0.25}$	$\beta_{0.5}$	$\beta_{0.75}$	$\beta_{0.9}$	$\beta_{0.95}$
Constant	-0.09649***	-0.06383***	-0.02786***	-0.00077	0.02619***	0.06195***	0.09513***
$\log(size_{i,t})$	0.00339***	0.00222***	0.00096***	0.00003	-0.0009***	-0.00216***	-0.00335***
$\alpha_{i,t}$	0.44961*	0.38623*	0.25338*	0.10395	-0.08842	-0.3082	-0.45395
$turn_{i,t}$	-0.00179***	-0.00136***	-0.00073***	-0.00004	0.00067***	0.00143***	0.00198***
$nq_{i,t}$	0.00033	0.00032	0.00031*	0.00031**	0.00034*	0.00029	0.00026
$btm_{i,t-1}$	**0.00083***	**0.00057***	**0.00028***	**0.00005**	**-0.00018***	**-0.00045***	**-0.0007***
$news_{i,t}$	**-0.01296***	**-0.00802***	**-0.00315***	**-0.00022**	**0.00233***	**0.00597***	**0.00974***
$lm\_tone_{i,t}$	**0.01141***	**0.00779***	**0.00416***	**0.00269***	**0.00279***	**0.00434***	**0.0064***
R^2	**0.11358**	**0.0698**	**0.02087**	**0.00081**	**0.01925**	**0.06871**	**0.11712**

ERRE with ML sentiment: the Effects

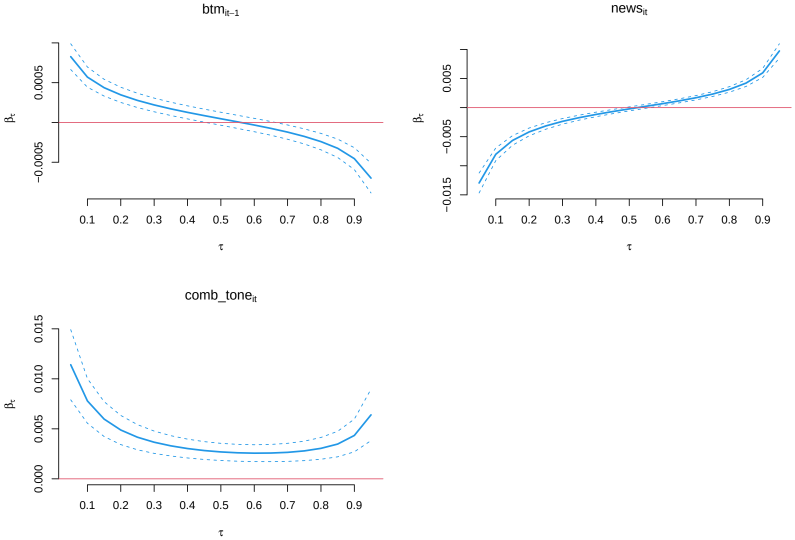

Figure 4: Coefficient profiles of sentiment related variables for different τ-levels

How do we interpret the results?

- The model fit is improved in terms of R^2.
- the combined dictionary model still can not "beat" the machine learning approach to the sentiment tone extraction.
- it clearly replicates the U-shape coefficient profile and is to prefer in terms of complexity and transparency/ interpretability of the results to the ML approach.

Conclusions

- sign change in the coefficient profiles of btm ratios and new arrivals
- also good news can lead to over-all negative effect on return for low return states.
- $\rightarrow$ "buy on rumor sell on news" strategy for low expectiles?
- the news tone is best captured by the machine learning approach.
- sentiment assement via dictionaries can be improved using a combined expectile weighted tone based on both LM and HV dictionaries.

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