

# STATISTICAL ARBITRAGE TECHNIQUES USING SOCIAL AND NEWS SENTIMENT

ARUN VERMA

QUANT RESEARCH

BLOOMBERG

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*"You know, I've been dealing with these big mathematical models for forecasting the economy...if I could figure out a way to determine whether or not people are more fearful, or changing to more euphoric, and have a third way of figuring out which of the two things are working, I don't need any of this other stuff. I could forecast the economy better than any way I know how"*

***Alan Greenspan, November 2007***

# TALK OUTLINE

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1. Extracting Sentiment from Story text
2. Sentiment Aggregation
3. Quantitative strategies
4. Topic Modeling and Sector level analysis

# SENTIMENT ANALYSIS

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News and social sentiment is captured as follows:

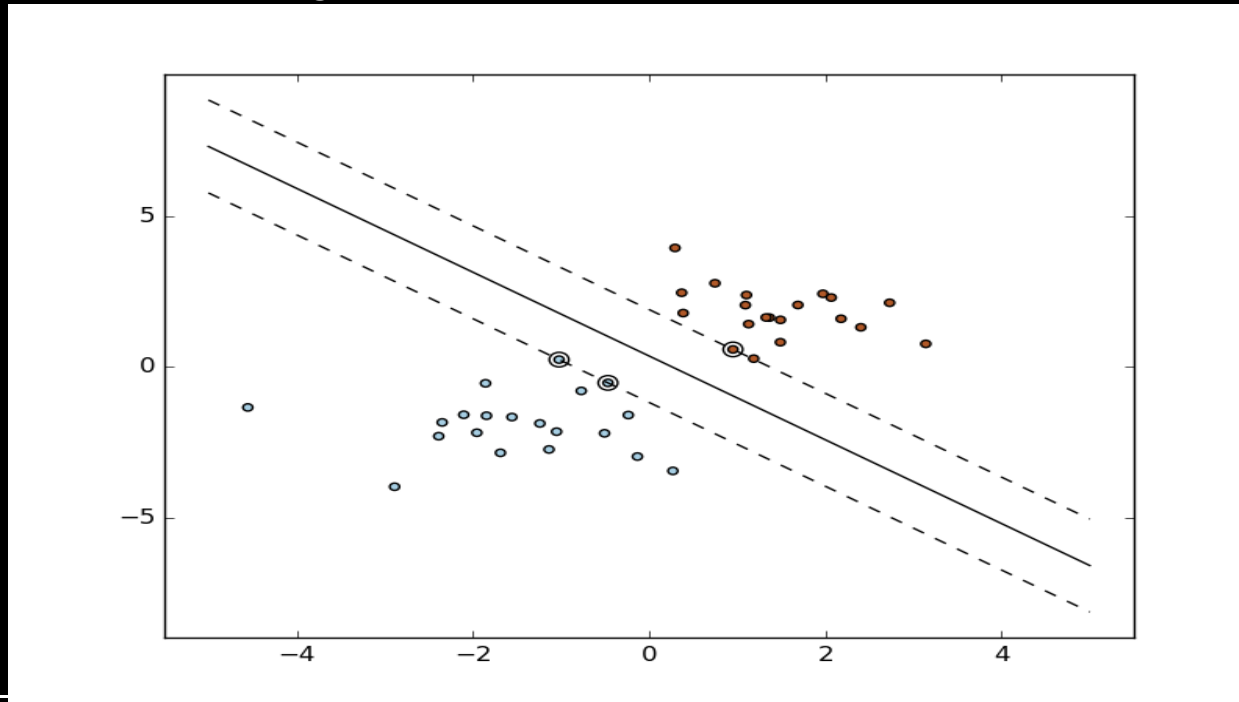
- Human experts assign positive/negative/neutral labels to stories in training set;
- The labeled data are fed into machine-learning models, such as support vector machine;
- Model assigns probability of being positive, negative and neutral to new stories Score: 1 for positive, -1 for negative, and 0 for neutral. We generate three way confidences - interpreted as probability of belonging to the label
- Company-level sentiment - weighted average of story-level sentiments – aggregated at daily and intra-day intervals.

# SENTIMENT EXTRACTION & CLASSIFICATION

Support Vector machines help assign a category to each story - unfortunately standard SVMs can only do binary classification.

Use 3 SVMs to help with pairwise classifications, one each for positive/negative, positive/neutral and neutral/negative classification

The features are multidimensional – bag of words framework is used.



# SVM FEATURES

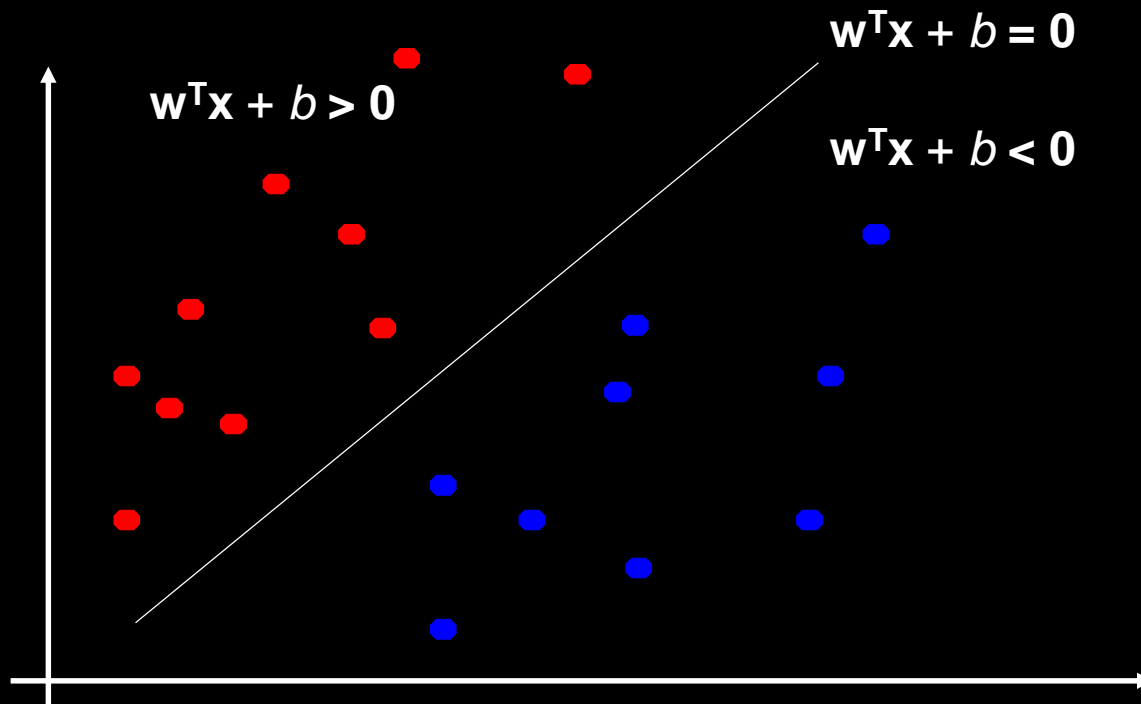
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- Keywords included in the story that are part of a (domain specific) dictionary are used as features
- This bag of words form the feature vectors in a very high dimensional space
- SVMs operate in this high dimensional space – we find a hyper plane vector which separates the two classes optimally (it's a supervised machine learning process needing a lot of training data)

# SVM BASICS

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Binary classification can be viewed as the task of separating classes in feature space:

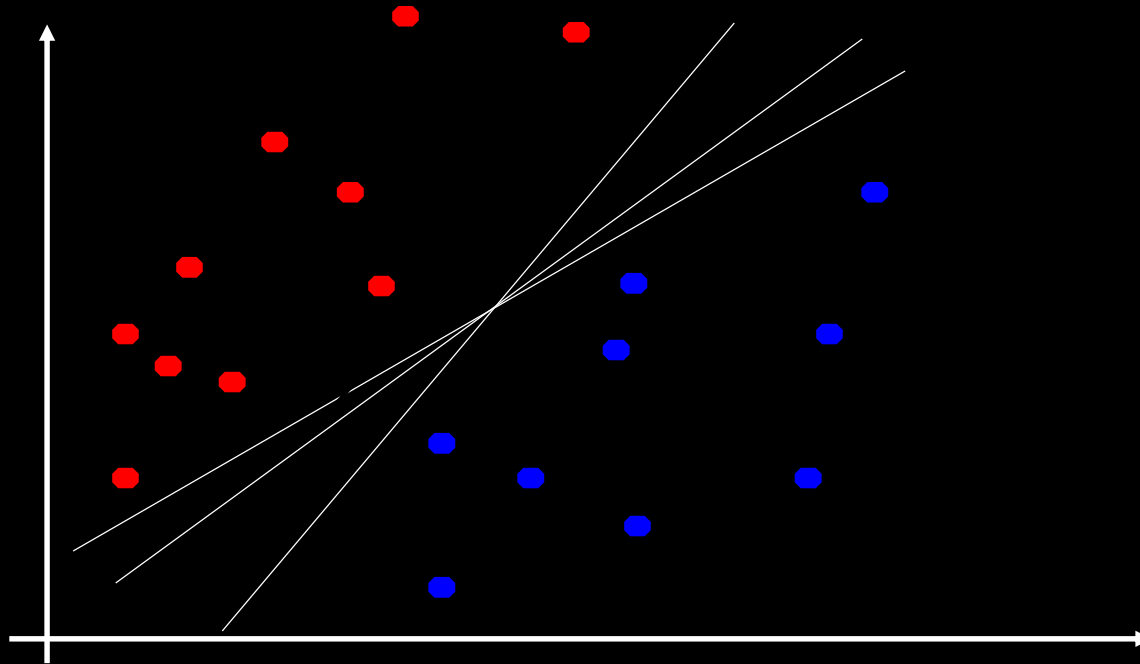


$$f(\mathbf{x}) = \text{sign}(w^T \mathbf{x} + b)$$

# SVM

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Which of the linear separators is optimal?



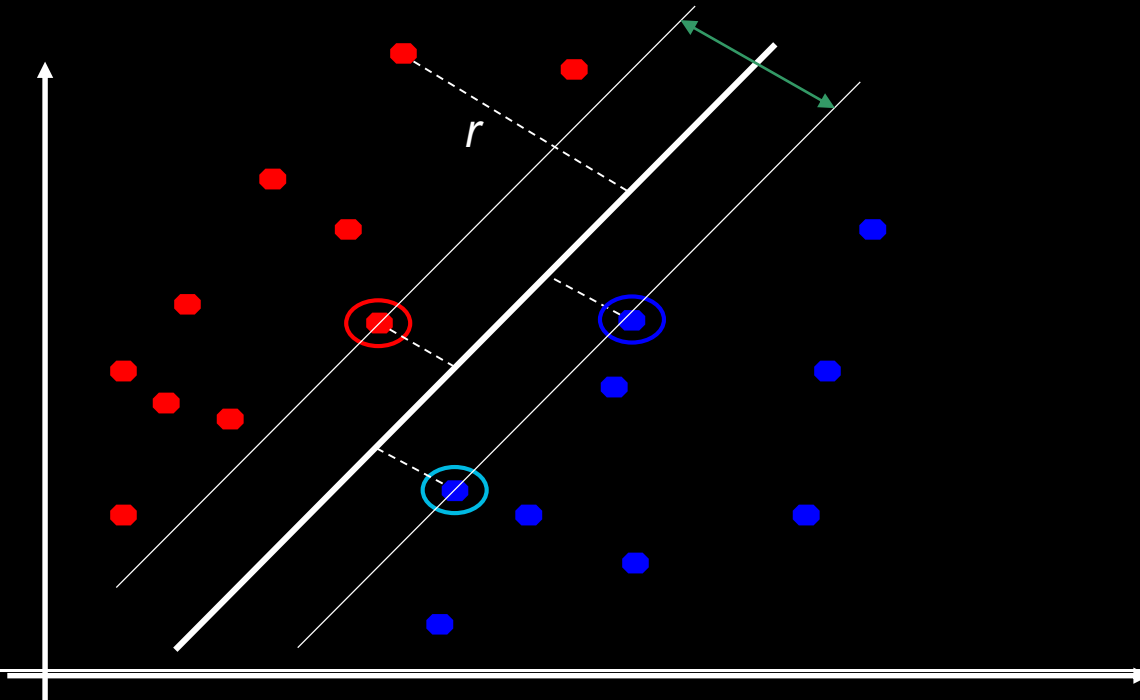


# CLASSIFICATION MARGIN

Distance from example  $\mathbf{x}_i$  to the separator is  $r = \frac{w^T \mathbf{x} + b}{\|w\|}$

Examples closest to the hyperplane are **support vectors**.

**Margin**  $\rho$  of the separator is the distance between support vectors.



# SOLVING THE OPTIMIZATION PROBLEM

Find  $\mathbf{w}$  and  $b$  such that

$\Phi(\mathbf{w}) = \frac{1}{2} \mathbf{w}^T \mathbf{w}$  is minimized and for all  $\{(\mathbf{x}_i, y_i)\}$   
 $y_i (\mathbf{w}^T \mathbf{x}_i + b) \geq 1$

Need to optimize a *quadratic* function subject to *linear* constraints.

Quadratic optimization problems are a well-known class of mathematical programming problems, and many (rather intricate) algorithms exist for solving them.

The solution involves constructing a *dual problem* where a *Lagrange multiplier*  $\alpha_i$  is associated with every constraint in the primary problem:

Find  $\alpha_1 \dots \alpha_N$  such that

$\mathbf{Q}(\boldsymbol{\alpha}) = \sum \alpha_i - \frac{1}{2} \sum \sum \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j$  is maximized and

(1)  $\sum \alpha_i y_i = 0$

(2)  $\alpha_i \geq 0$  for all  $\alpha_i$

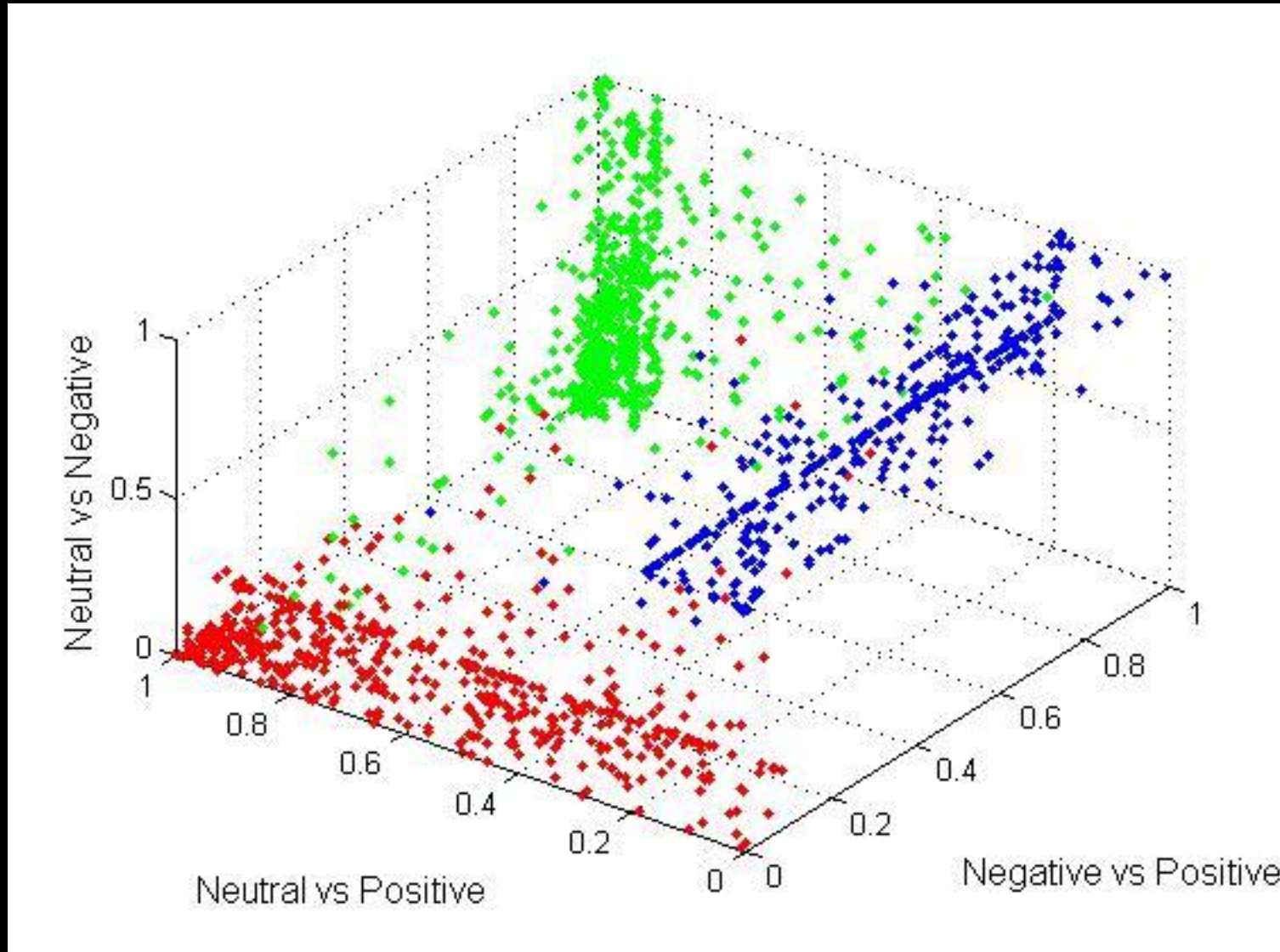
# INTERPRETING SVM RESULT AS PROBABILITY

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- Probability metric constructed based on distance from optimal hyperplane
- Logistic functional used:

$$P(y=1 \mid x) = \frac{1}{1 + e^{-\frac{w^T x + b}{\sigma}}}$$

# THREE PAIRWISE SVM RESULTS



# THREE WAY SENTIMENT METHODOLOGY

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For a target story to be classified we run the three SVM on it to find the three values.

Define the Euclidean distance between two stories  $i, j$  :

$$d(i, j)^2 = (x(i) - x(j))^2 + (y(i) - y(j))^2 + (z(i) - z(j))^2$$

Use Nearest Neighbors: We define weights for an in-sample news story  $j$  as :

$$w(j) = e^{-\frac{d(\text{target}, j)^2}{2B^2}}$$

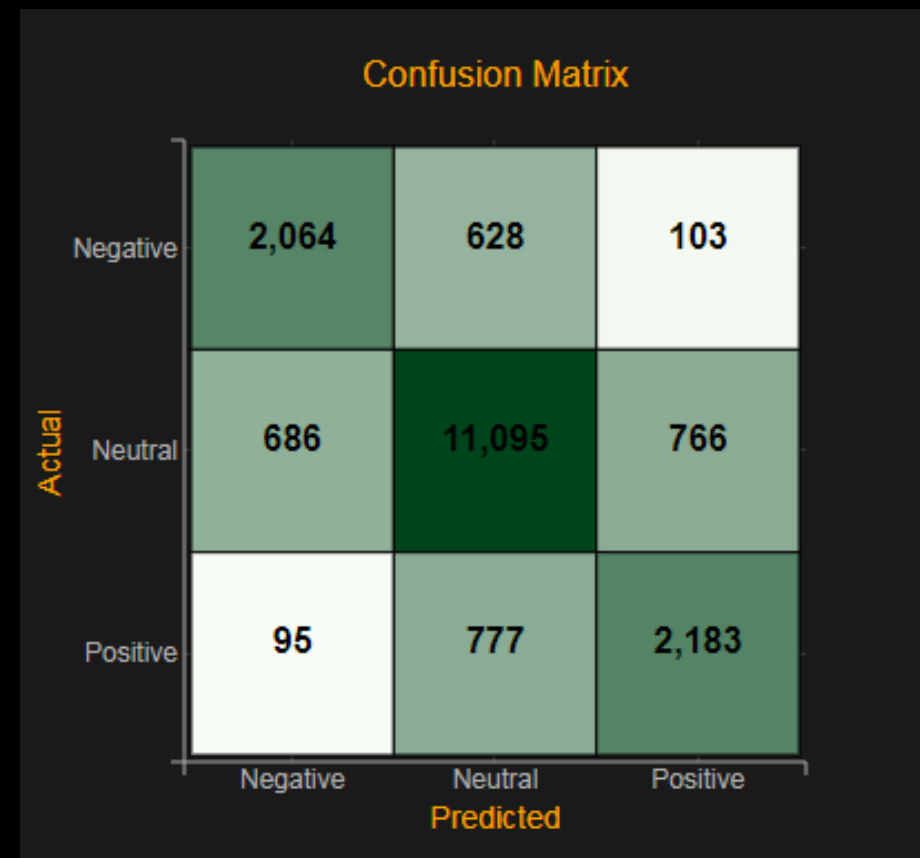
Where  $B$  is a bandwidth parameter. Normalize the weights as follows:

$$\bar{w}(j) = \frac{w(j)}{\sum w(j)}$$

Now, define the positive probability as  $\sum_{j \in Pos} \bar{w}(j)$ , negative probability as  $\sum_{j \in Neg} \bar{w}(j)$  and neutral probability as  $\sum_{j \in Neut} \bar{w}(j)$ .

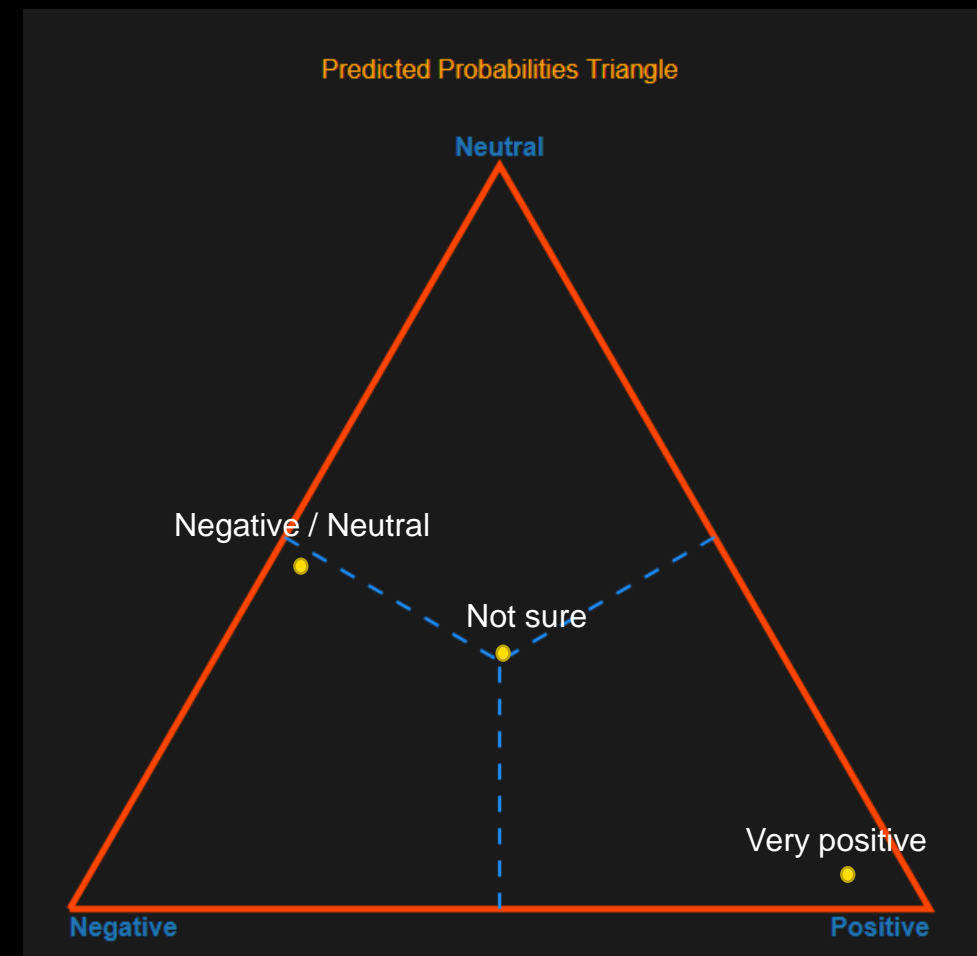
# CONFUSION MATRIX

- $K \times K$  matrix where  $K$  = number of classes
- $\text{Cell}[i, j]$  = number of samples whose:
  - Actual label =  $i$
  - Predicted label =  $j$
- Diagonal entries - correct predictions
- Off diagonal entries - misclassifications

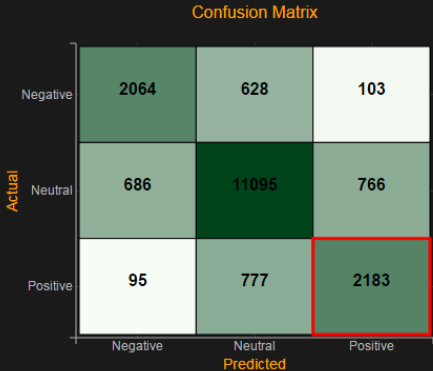


# TRIANGLE VISUALIZATION

- Model returns 3 probabilities (which sum to 1)
- How can we visualize these 3d “points”?
- Points inside an equilateral triangle



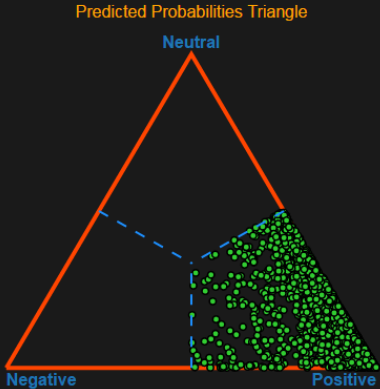
# CLASSIFICATION OF TWEETS



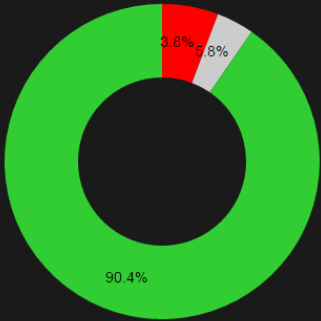
Actual: Positive, Predicted: Positive (2183 tweets)

i	Tweet
103	Hudson City Bancorp \$HCBK Posts Quarterly Earnings, Beats Estimates By \$0.01 EPS ift.tt/1uEwNa8
104	National-Oilwell Varco Sees Large Growth in Short Interest \$NOV ift.tt/1NT7M78 #acn
115	Very strong day for equities. Closing at the highs. Bulls in control for now. \$SPY
126	43.0% increased bullish conversations in \$NQ in the past 1 hour.
157	Dassault Systemes S.A. upgraded by Zacks Investment Research to buy. \$78.00 PT. ift.tt/1PnvExw \$DASTY #DAST
162	#FOREX BUSINESS Goldman Sachs profit gets big boost from bond market pickup dlvr.it/7DDZHw
167	B/E Aerospace revenue up 24 percent in Q3 syspl.at/1rv0ycz #flmfg
168	RT @Forbes: For the current quarter, Netflix expects to sign up 6.1 million new subscribers onforb.es/1nwNsA9 pic.
174	BREAKING >> PetSmart's \$8.7 Billion Buyout A Second Mega Deal For Jana Partners In 2014 forbes.com/sites/ant.
179	Microsoft Is Rising Again onforb.es/1sMZccl @forbes
192	Attento (ATTO) trades to new post-IPO highs; a play on the fast growing LatAm CRM BPO market bit.ly/1QZy789 \$
195	Greenbrier: Time To Buy, In 4 Charts seekingalpha.com/article/380795... \$GBX
205	\$ABMD ABMD Year to date has changed +26.25% percent. +46.91% in the last 30 days. \$ABMD Ablomed Full brea
219	LONG USDJPY ON 4H CLOSE ABOVE 108.24 \$USDJPY tradingview.com/v/japVm9P1/
226	RT @GlobeNewswire: B/E Aerospace Q3 Revenue Up 24% YoY, EPS Up 10% syspl.at/1rv0ycz #flmfg

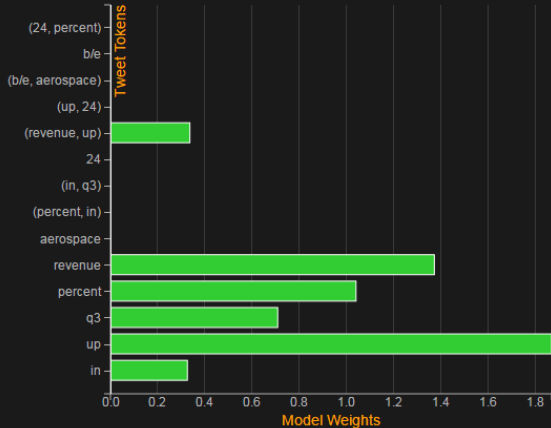
Selected Tweet: B/E Aerospace revenue up 24 percent in Q3 syspl.at/1rv0ycz #flmfg



Predicted Probabilities

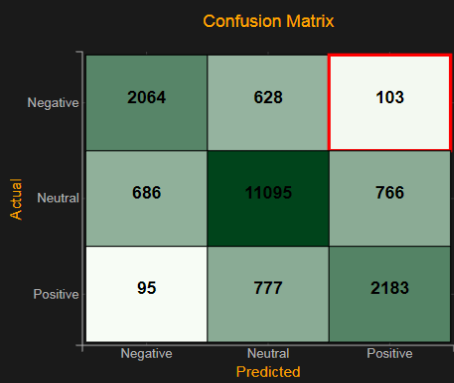


Features & Model Weights





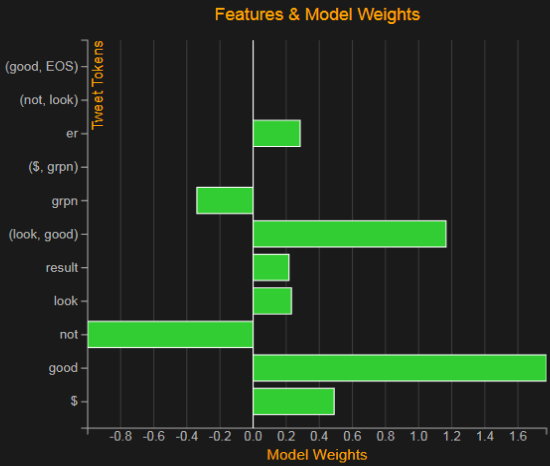
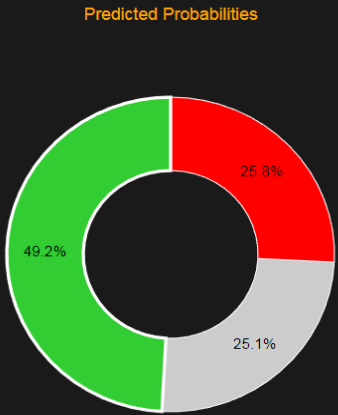
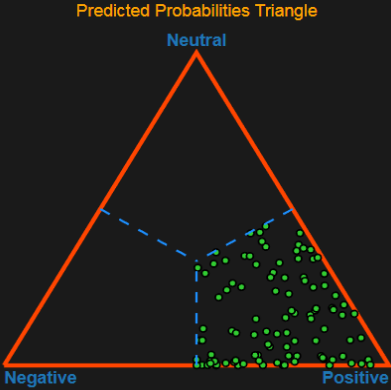
# ANALYZE MISCLASSIFICATIONS



Actual: Negative, Predicted: Positive (103 tweets)

i	Tweet
177	\$PLUG Good day, but still off \$1.20 from the last ER run very sad performance for a company with such potential.
182	\$MAR up 1.0% to 73.50 while \$HOT slips 3.0% to 72.75 in PreM on Marriott to acquire Starwood Hotels in 12.2B Dea
311	\$SMG SMG Stock year to date has changed -0.63% percent. +4.37% in the last 30 days. \$SMG Scotts Miracle-Gro C
423	The Wall Street Journal: Starbucks sales growth disappoints: Coffee giant posts 10% revenue gain, dlvr.it/7Mrkb2 MA.
699	Weight Watchers Sees Profit Slimmed 37% dlvr.it/7MGwvN
729	\$IOSP IOSP Stock year to date has changed -2.73% percent. +11.37% in the last 30 days. \$IOSP Innospec Inc Full b
757	\$XLE was looking great earlier. Emphasis on "was"...
890	\$GRPN ER results not looking good
1073	JACK DORSEY HAS DESTROYED NEARLY \$5 BILLION IN VALUE IN THE PAST 11 DAYS – Trading with The Fly \$
1141	\$SPY rate hike coming, dollar strong, not looking good for corp earnings going forward and buybacks!
1316	\$SPY A socialist win moves the market down. New job offers for marijuana bike couriers hits new high
1412	business: Siemens announces share buyback and expects no growth in 2016 profit margin bloom.bg/1SkEsqZ pic.twit
1422	\$NURO bear market but with recent highlight this tock is good
1435	Argos Christmas Sales Down Despite Digital Boost: Home Retail Group, the owner of Argos, called the results 'm... n.
1558	\$SPY ...

Selected Tweet: \$GRPN ER results not looking good



# SENTIMENT AGGREGATION METHODS

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We take all stories tagged with a particular company:

- 1) Each news story or tweet is scored with "confidences"  $C_+$ ,  $C_-$ ,  $C_n$  for positive, negative and neutral sentiment respectively.
- 2) Story specific sentiment (polarity score) :  $S^i = C_+^i - C_-^i$
- 3) Sentiment Average :

$$\mu = \frac{\sum_{i=1}^N S^i}{N} = \frac{\sum_{i=1}^N (C_+^i - C_-^i)}{N} = \overline{C_+} - \overline{C_-}$$

- 4) Sentiment dispersion = Inter-story variance + story specific dispersion

Simplifies to:  $\overline{C_+} + \overline{C_-} - \mu^2$

# DISPERSION CALCULATION

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**Sentiment Dispersion:** To calculate the overall dispersion we need to track two components.

- **INTRA STORY VARIANCE** – Variance within one story due to classification uncertainty

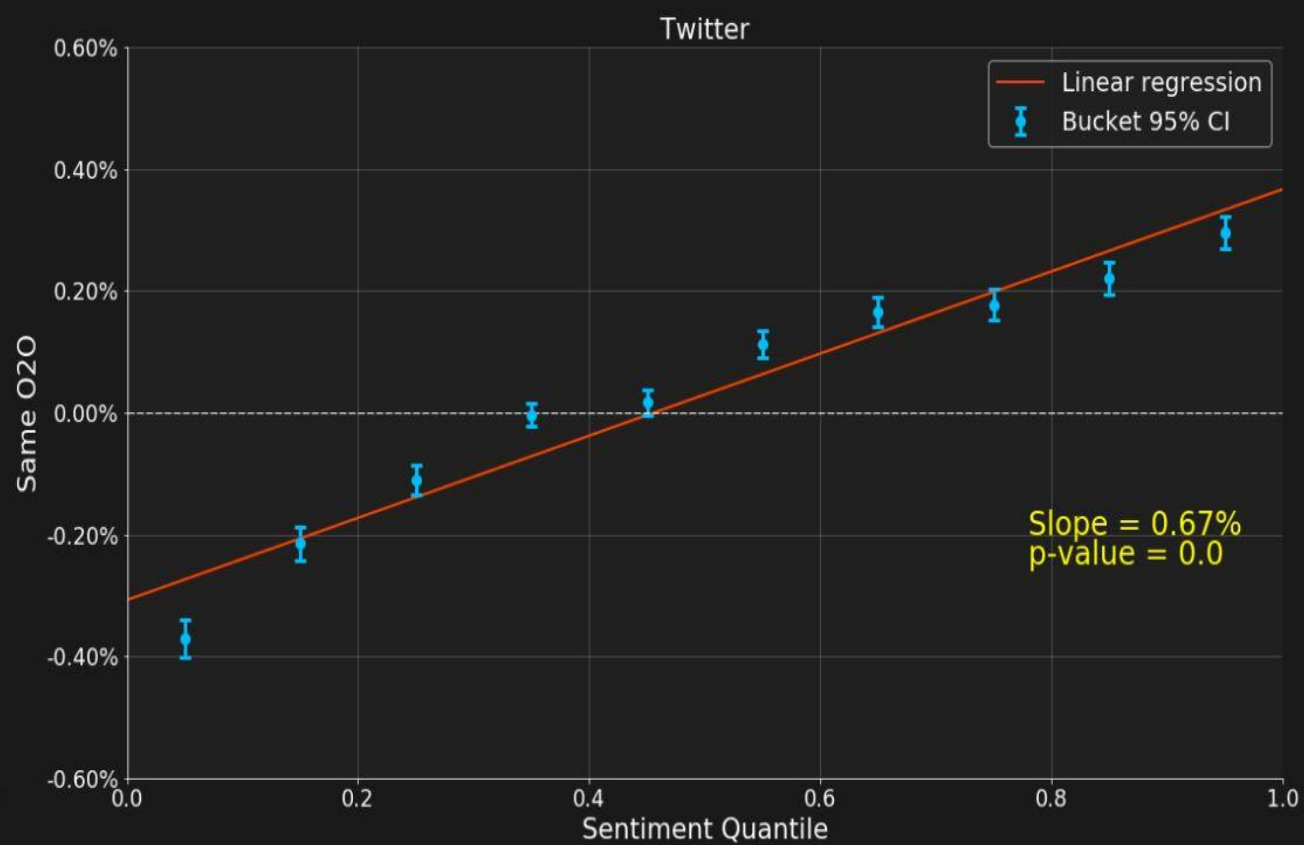
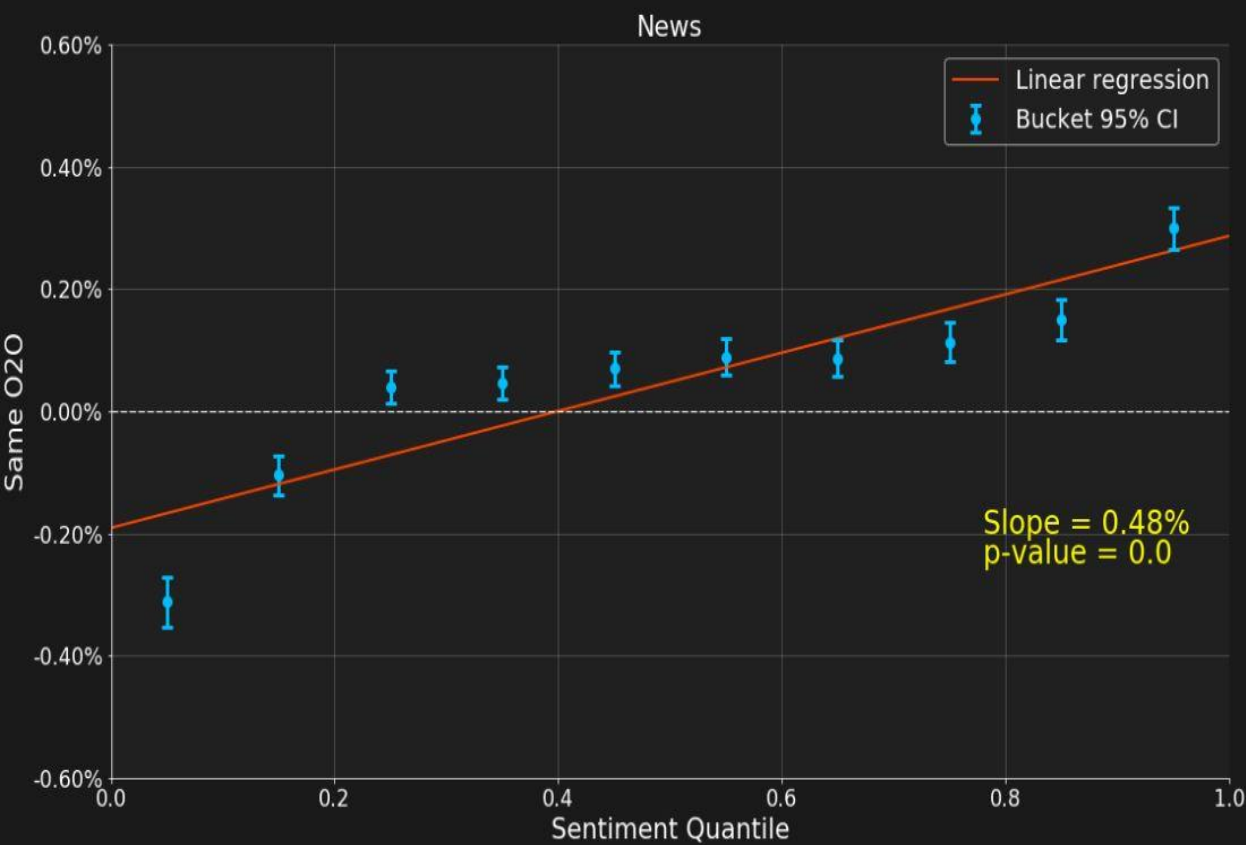
The variance of the sentiment per story is defined as the variance of the trinomial probability distribution .  $Var^i = E \left[ (X^i -$

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Romance should never begin with sentiment. It should begin with science and end with a settlement. — Oscar Wilde, An Ideal Husband

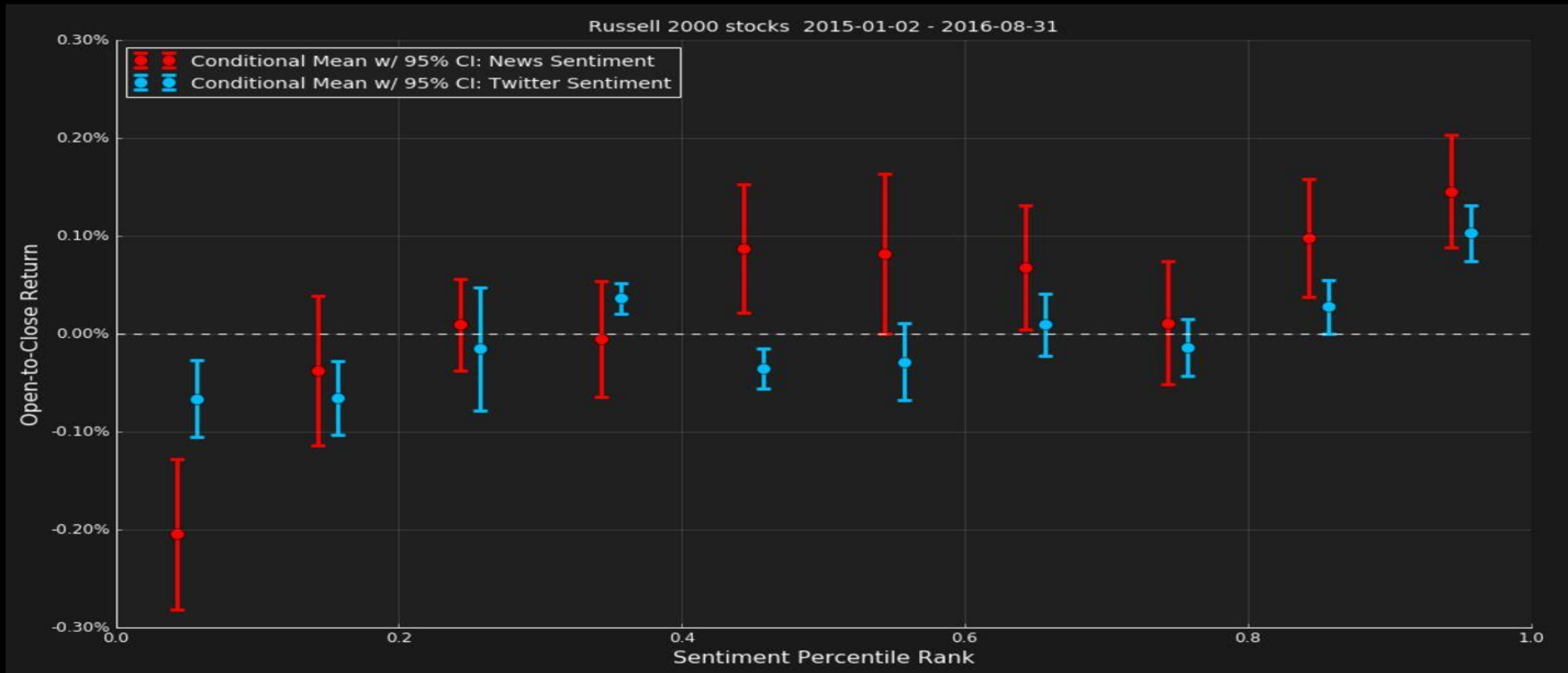
# SENTIMENT VS CONTEMPORANEOUS RETURN

- The daily sentiment score is constructed using story level sentiment data over the 24 hours period, and calculated around 9:05 am every day.



# TRADING SIGNAL (CONDITIONAL DRIFT)

Does market efficiently price in the sentiment information?



# STRATEGY I: DAILY LONG-SHORT

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Does market efficiently price in the sentiment information?

Strategy:

- Each day before market open, rank all stocks by their daily sentiment
- Three variations:
  - 1) Long top 1/3 and short bottom 1/3 stocks
  - 2) Long top 5% and short bottom 5% stocks
  - 3) Positions proportional to the difference of sentiment scores from its cross-sectional mean
- Create portfolio at market open and close out at market close

We backtest the strategy for Russell 2000 stocks from Jan-01-2015 to Jul-31-2016.

# DAILY STRATEGY

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The portfolio daily return can be computed as the following,

$$Ret_j = \sum_{i \in Long_j} w_{ij}^{Long} \left( \frac{p_{ij}^{close}}{p_{ij}^{open}} - 1 \right) - \sum_{i \in Short_j} w_{ij}^{Short} \left( \frac{p_{ij}^{close}}{p_{ij}^{open}} - 1 \right)$$

Where

$Ret_j$  is portfolio return on day  $j$ ;

$p_{ij}^{close}$  is the close price of stock  $i$  on day  $j$ ,  $p_{ij}^{open}$  is the open price of stock  $i$  on day  $j$ ;

$Long_j$  is the basket of stocks to long on day  $j$ ,  $w_{ij}^{Long}$  is the weight of stock  $i$  in  $Long_j$ ;

$Short_j$  is the basket of stocks to short on day  $j$ ,  $w_{ij}^{Short}$  is the weight of stock  $i$  in  $Short_j$ ;

For HML portfolio,  $w_{ij}^{Long} = \frac{1}{\# \text{ of Stocks in } Long_j}$ ,  $w_{ij}^{Short} = \frac{1}{\# \text{ of Stocks in } Short_j}$

For proportional portfolio,  $w_{ij}^{Long} = \frac{SS_{ij}^{Long} - \mu_j}{\sum_{i \in Long_j} (SS_{ij}^{Long} - \mu_j)}$ ,  $w_{ij}^{Short} = \frac{SS_{ij}^{Short} - \mu_j}{\sum_{i \in Short_j} (SS_{ij}^{Short} - \mu_j)}$

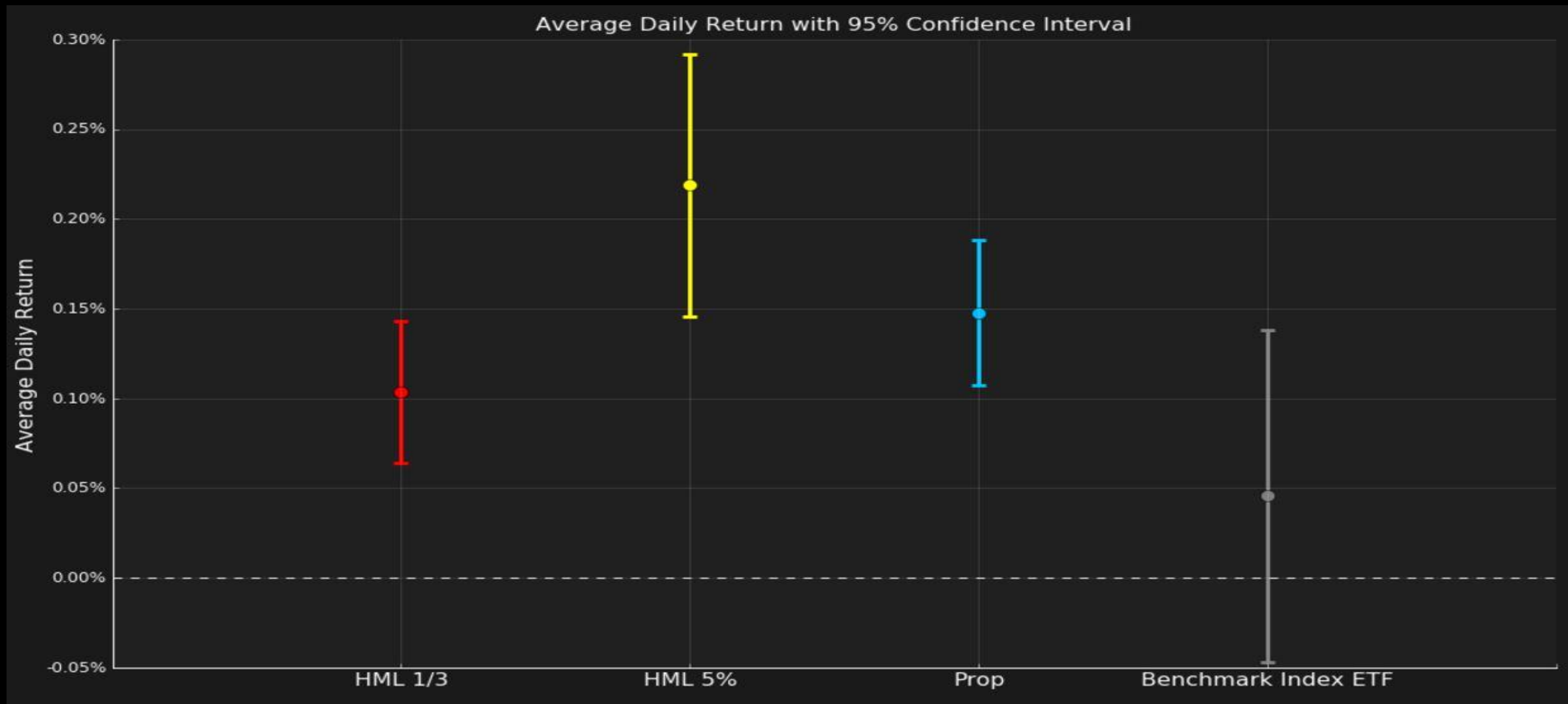
$\mu_j$  is the cross-sectional mean of the company-level sentiment on day  $j$ ;

$SS_{ij}^{Long}$  is the sentiment score of stock  $i$  in  $Long_j$  on day  $j$

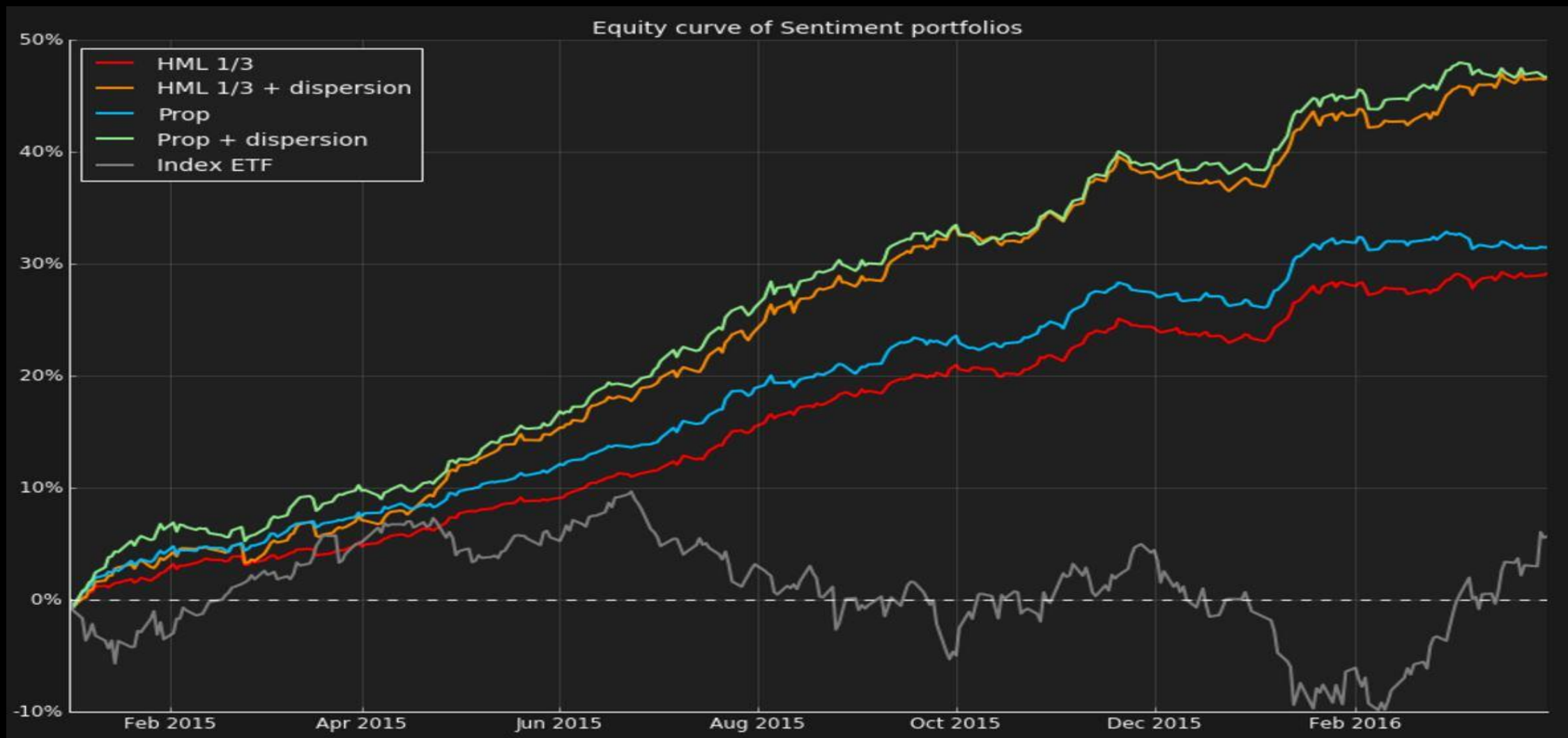
$SS_{ij}^{Short}$  is the sentiment score of stock  $i$  in  $Short_j$  on day  $j$



# RUSSELL 2000 STOCKS



# RUSSELL 2000 STOCKS

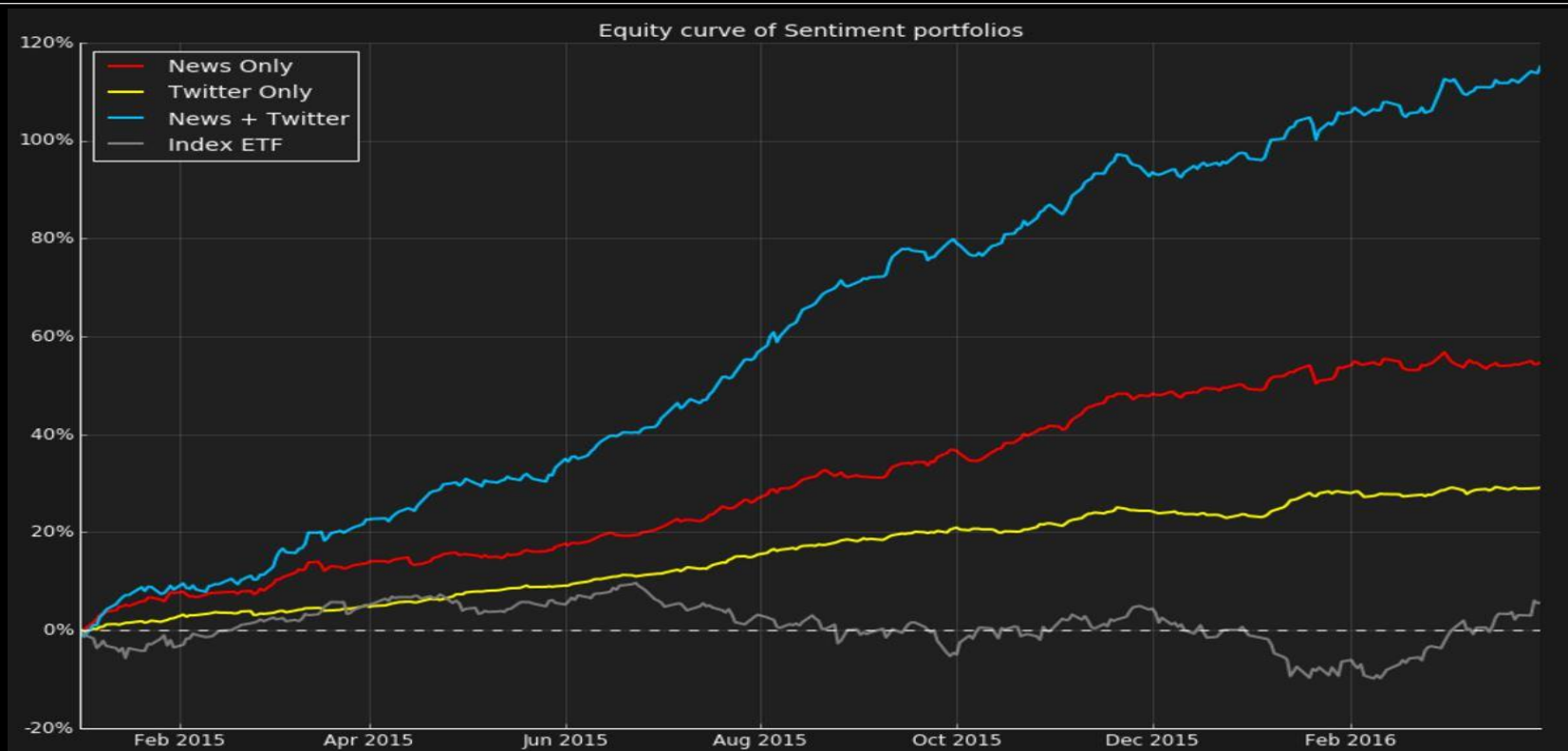


# RUSSELL 2000 STOCKS

## Performance Statistics:

	Beta	Annualized Ret	Annualized Vol	Sharpe
HML 1/3	-0.04	23%	4%	5.37
HML 1/3 + dispersion	-0.08	38%	7%	5.48
Prop	-0.06	25%	5%	5.06
Prop + dispersion	-0.06	38%	7%	5.39
Index ETF (IWM)	1.00	5%	15%	0.30

# RUSSELL 2000 –COMBINING NEWS & TWITTER



	Beta	Annualized Ret	Annualized Vol	Sharpe
News Only	-0.15	44%	9%	5.08
Twitter Only	-0.04	23%	4%	5.35
News + Twitter	-0.12	92%	15%	6.25
Index ETF (IWM)	1.00	5%	15%	0.30

# RUSSELL 2000 – WITH TRANSACTION COST



## STRATEGY II: EARNINGS EVENT DRIVEN

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Does sentiment before earnings have predicting power for earning day return?

Strategy:

Each day, if there are companies to release earnings,

- Long positive sentiment and short negative sentiment;  
If portfolio has only long positions, short market ETF;  
If portfolio has only short positions, long market ETF;
- Create at market open and close out at the next market open.

Sentiment sources: News only, Twitter only, News/Twitter combined

We backtest the strategy for S&P 500 stocks from Jan-01-2015 to Jul-31-2016.

# EVENTS DRIVEN STRATEGY

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The portfolio daily return can be computed as the following,

$$Ret_j = \sum_{i \in Long_j} \frac{1}{N_j^{Long}} \left( \frac{P_{i(j+1)}^{open}}{P_{ij}^{open}} - 1 \right) \mathbb{I}(N_j^{Long} > 0) - \sum_{i \in Short_j} \frac{1}{N_j^{Short}} \left( \frac{P_{i(j+1)}^{open}}{P_{ij}^{open}} - 1 \right) \mathbb{I}(N_j^{Short} > 0)$$

Where

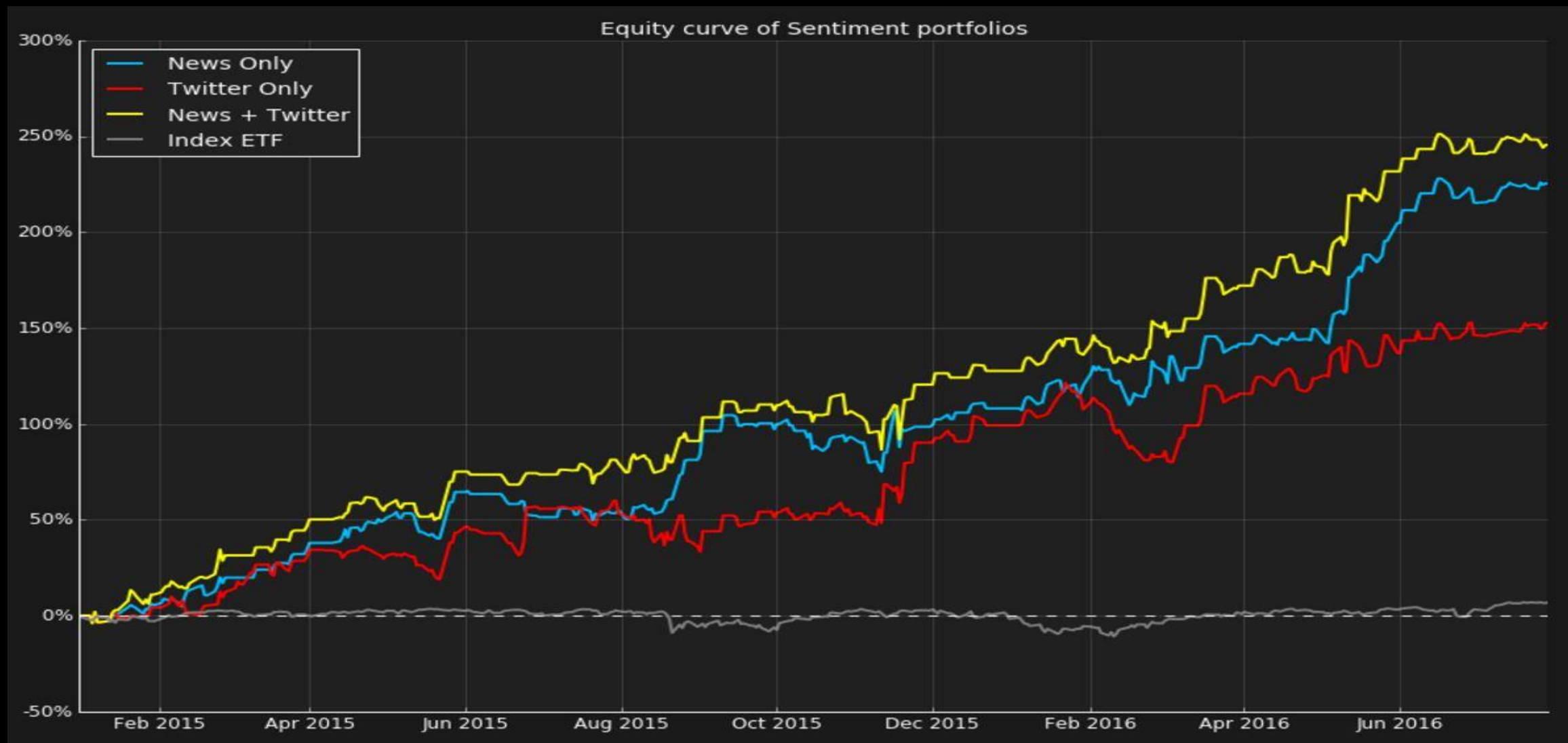
$Ret_j$  is portfolio return on day  $j$ ;

$P_{ij}^{open}$  is the open price of stock  $i$  on day  $j$ ,  $P_{i(j+1)}^{open}$  is the open price of stock  $i$  on day  $j+1$ ;

$Long_j$  is the basket of stocks to long on day  $j$ ,  $N_j^{Long}$  is the number of stocks in  $Long_j$ ;

$Short_j$  is the basket of stocks to short on day  $j$ ,  $N_j^{Short}$  is the number of stocks in  $Short_j$ ;

# S&P 500 STOCKS





# S&P 500 STOCKS

## Performance Statistics:

	Beta	Annualized Ret	Annualized Vol	Sharpe	Average # of Short	Average # of Long
News Only	0.08	140%	59%	2.37	2	7
Twitter Only	-0.14	108%	61%	1.77	4	7
News + Twitter	0.12	156%	58%	2.68	2	5
Index ETF (SPY)	1.00	4%	15%	0.29	NaN	NaN

# SHARPENING THE SENTIMENT SIGNAL – USING MEAN VARIANCE OPTIMIZATION

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Instead of using sentiment directly to determine weights, we could use sentiment as an expected return for next day and optimize the portfolio

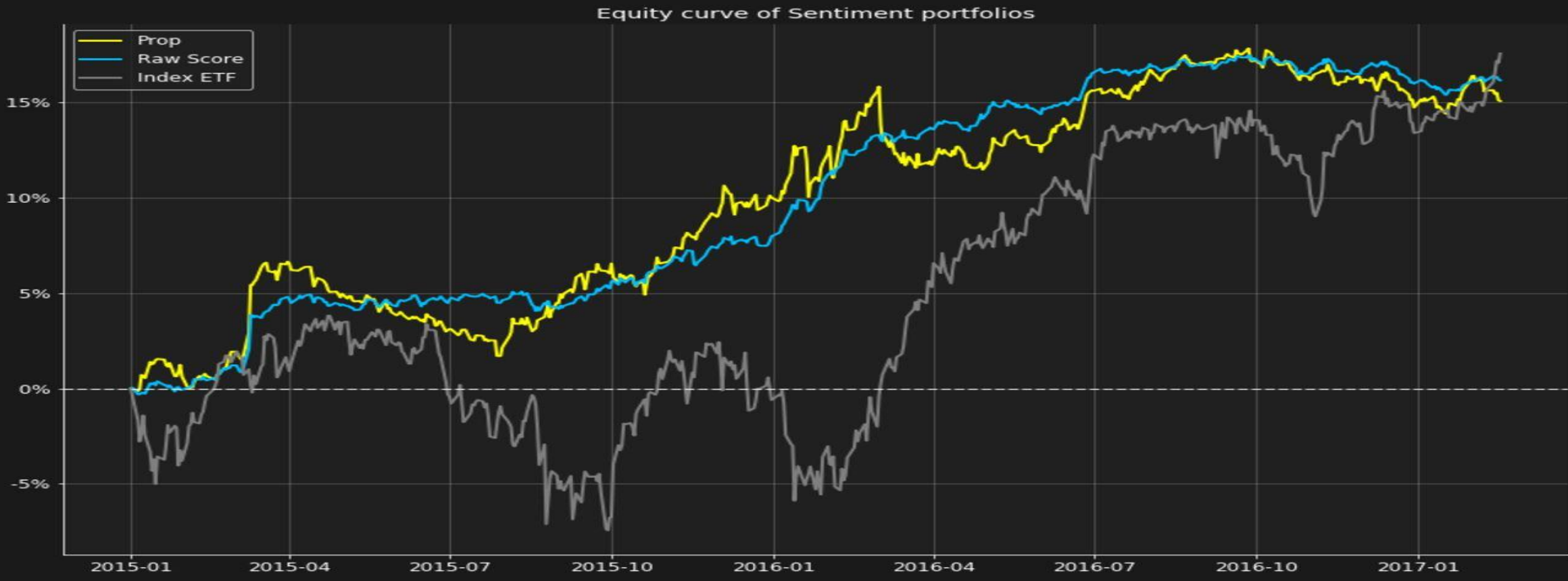
$$\text{minimize } w^T C w$$

$$\text{s.t. } w^T r \geq \mu$$

$$w^T \mathbf{1} = 0$$

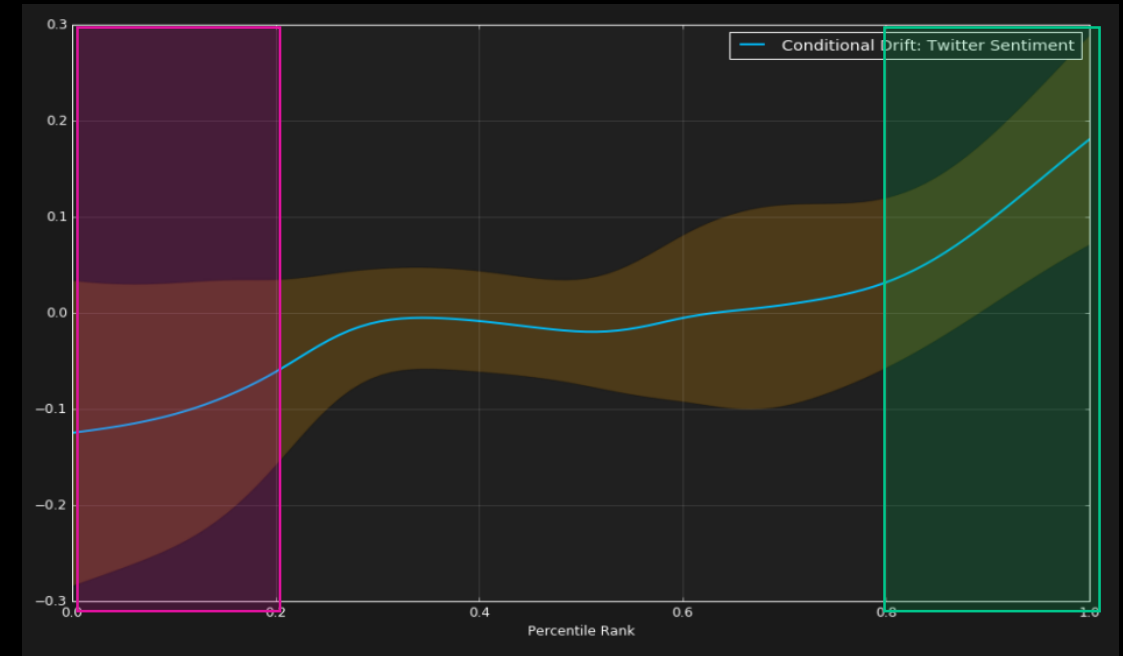
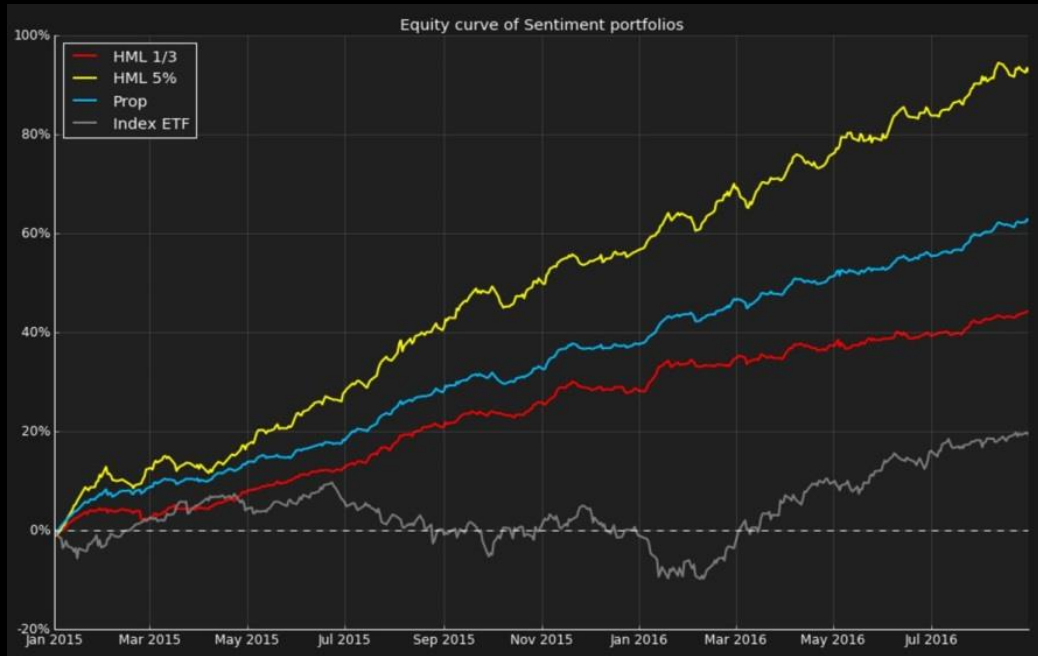
$$r = S - E[S]$$

# MEAN VARIANCE OPTIMIZATION



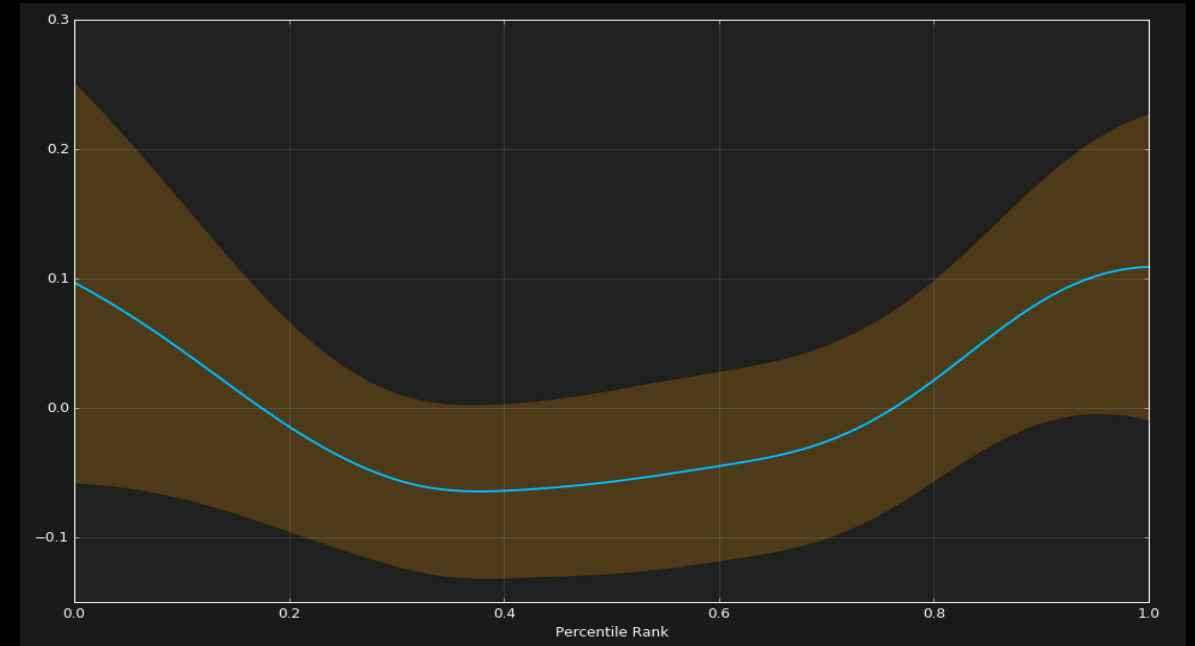
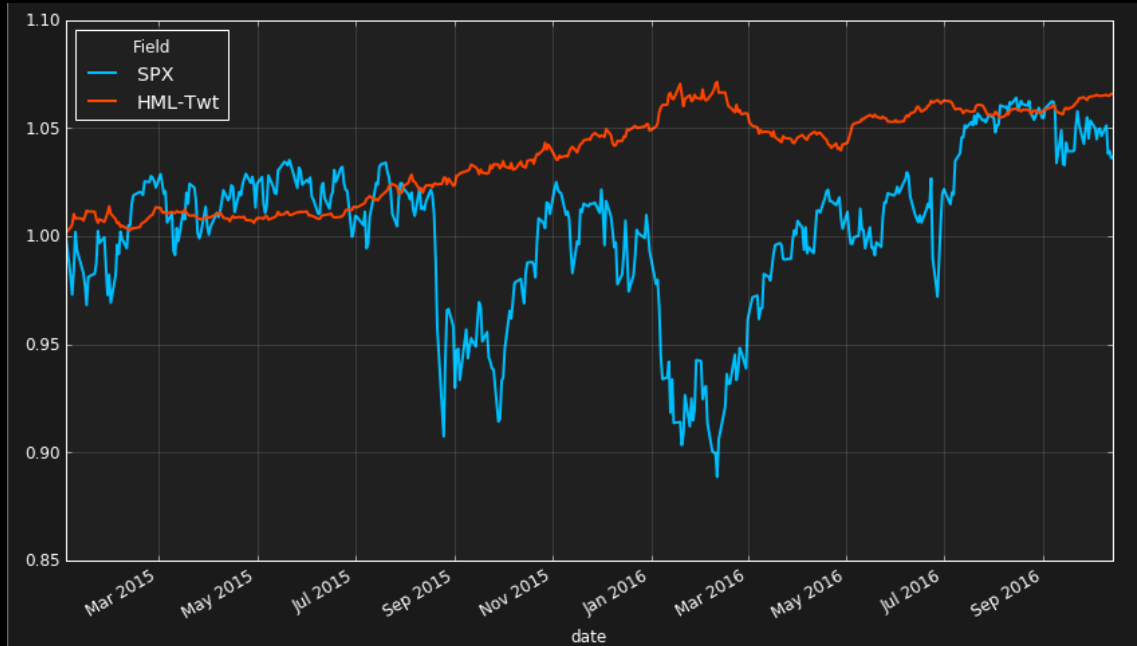
# STRATEGY WORKS FOR SMALL CAPS

## Russel 2000



# BUT NOT FOR SPX STOCKS

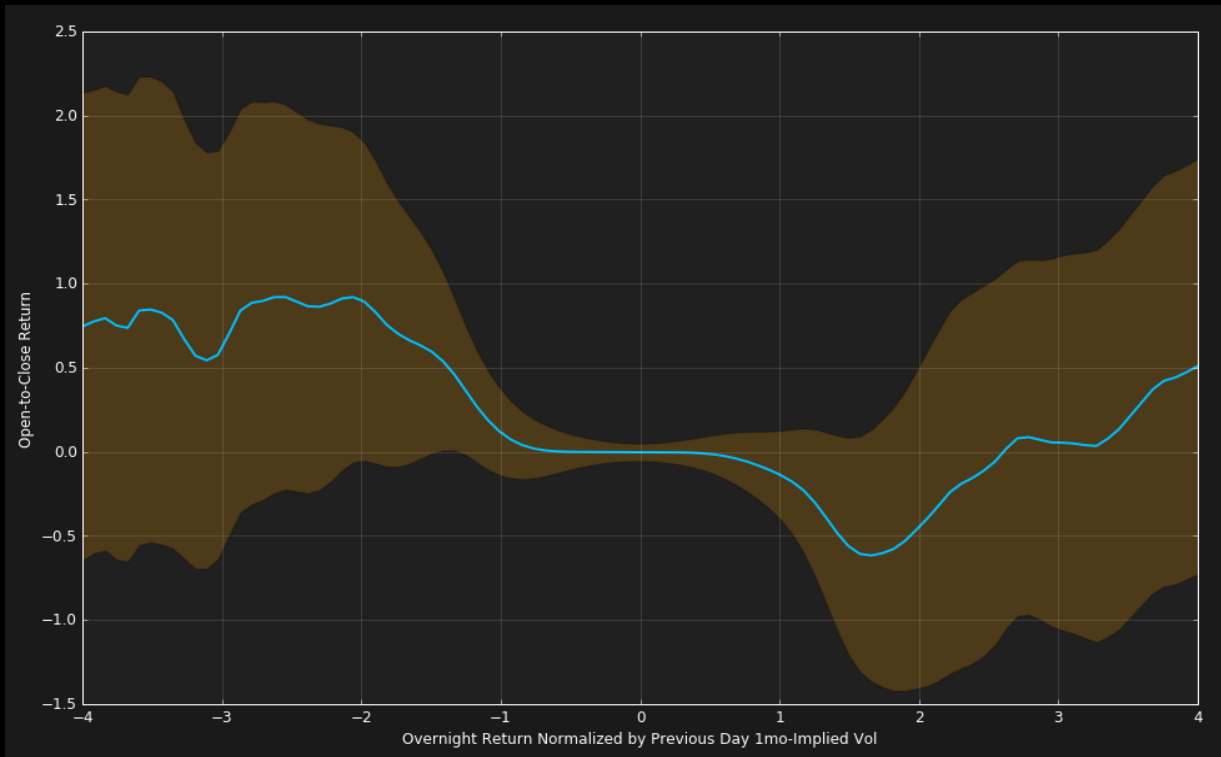
## S&P 500



# SENTIMENT USEFUL ONLY FOR SMALL CAP?

Here is a mean-reversion “signal” that works for S&P 500 stocks

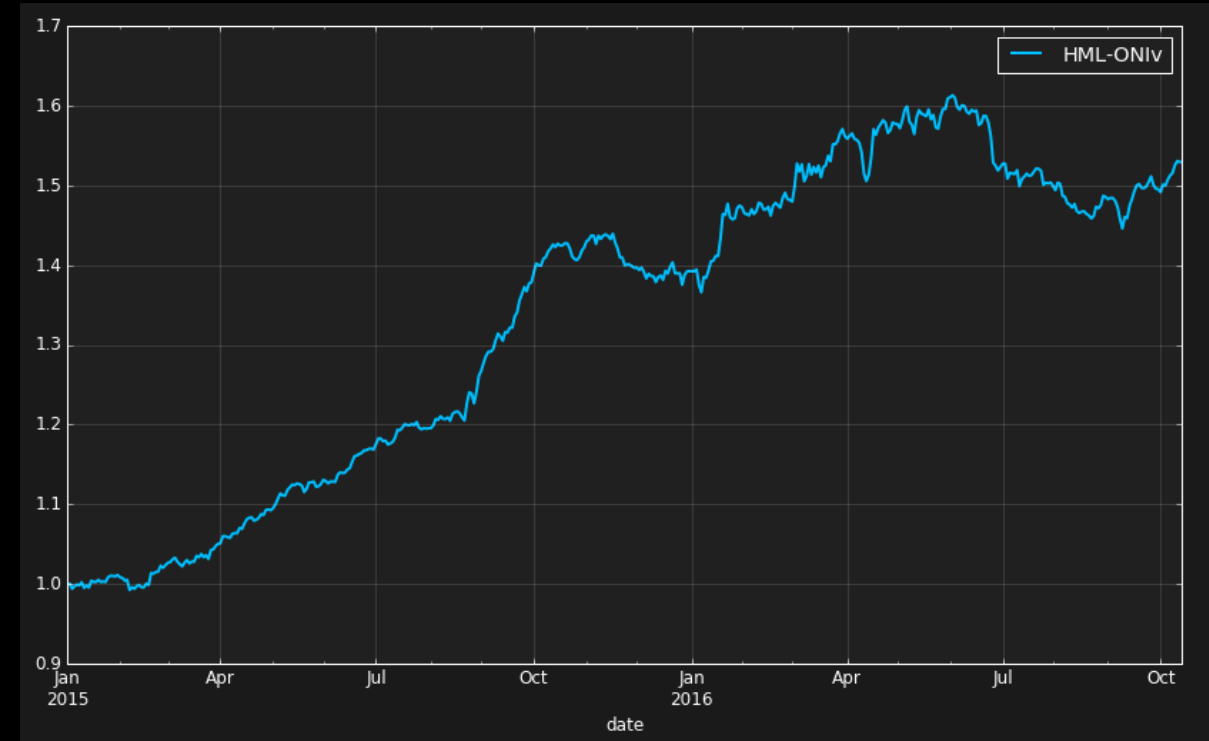
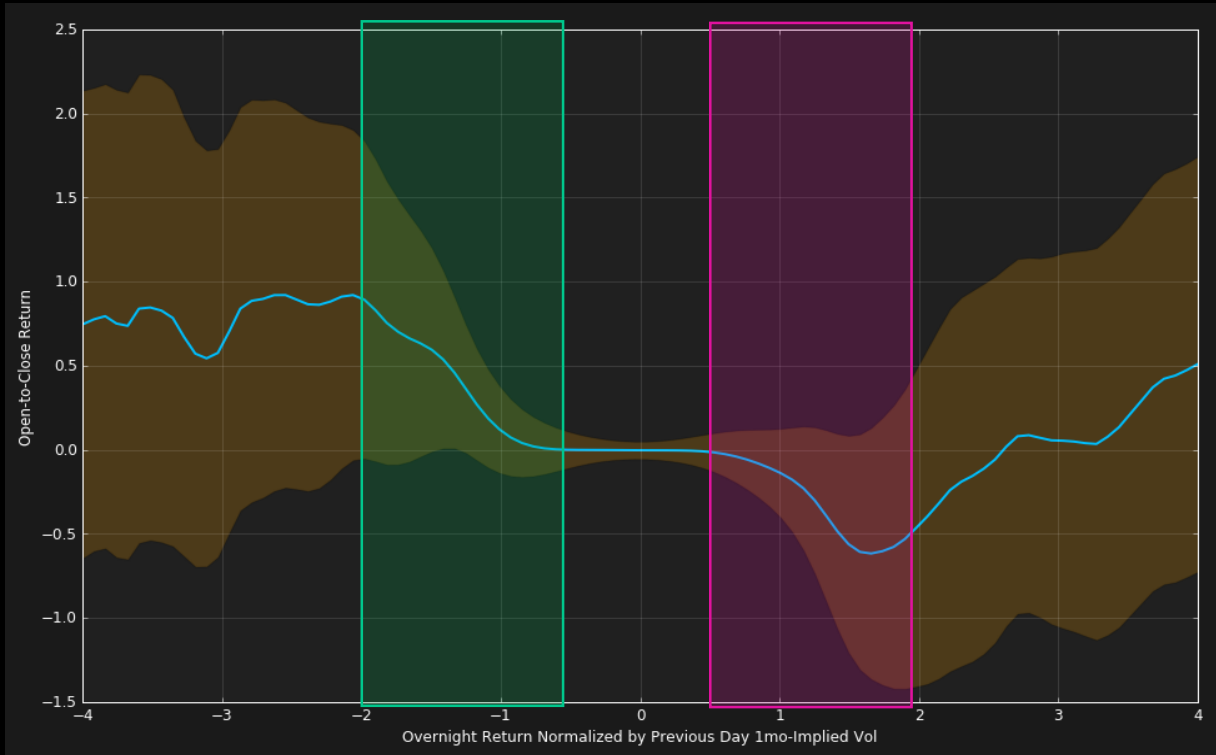
Return(Open\_t, Close\_t) vs Return(Close\_(t-1), Open\_t)/30d\_impvol\_(t-1)



# MOMENTUM STRATEGY

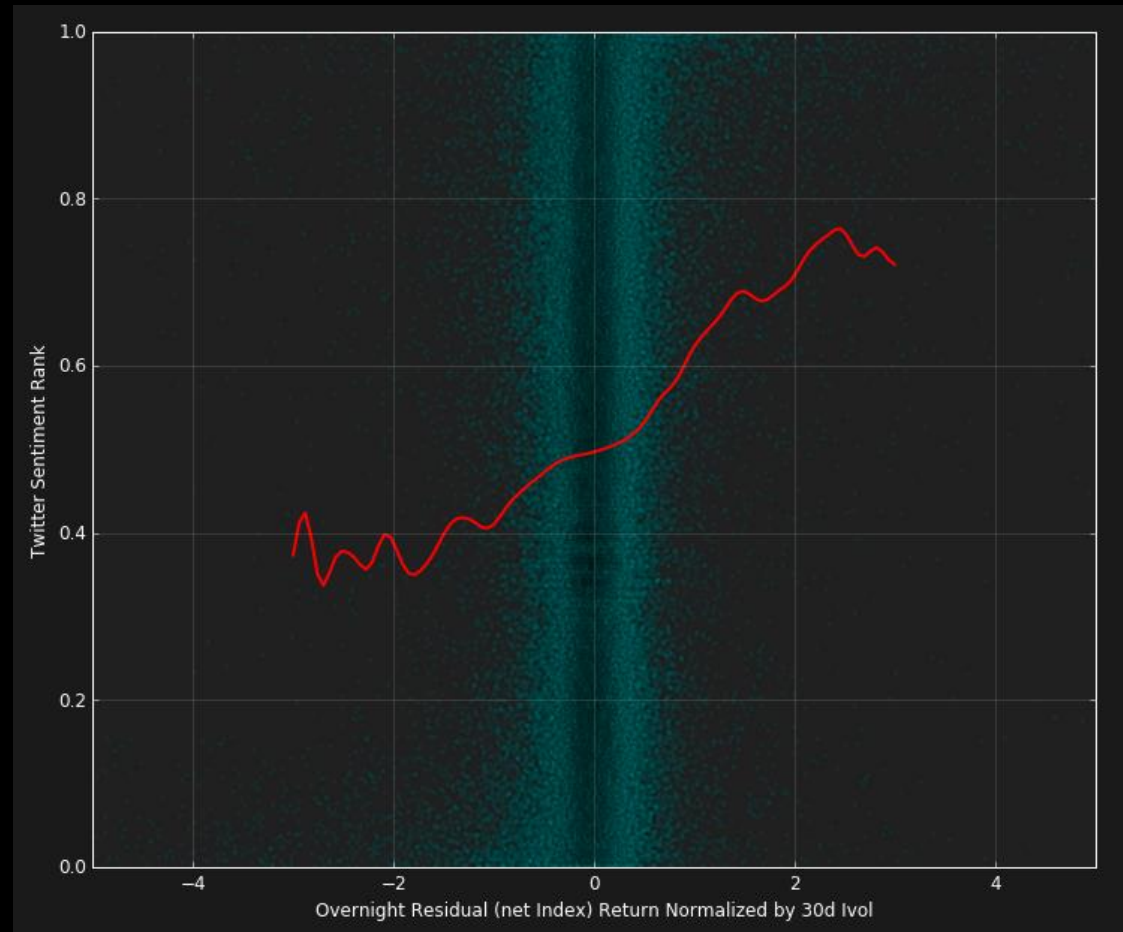
Unless one can observe and trade immediately at open

Return(Open\_t, Close\_t) vs Return(Close\_(t-1), Open\_t)/30d\_impvol\_(t-1)



# YET CORRELATED TO SENTIMENT

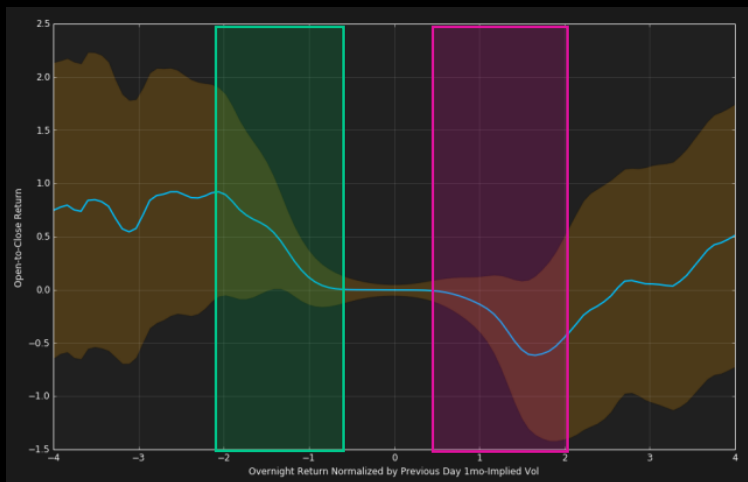
## Twitter Sentiment Rank vs Vol-Normalized OV Return



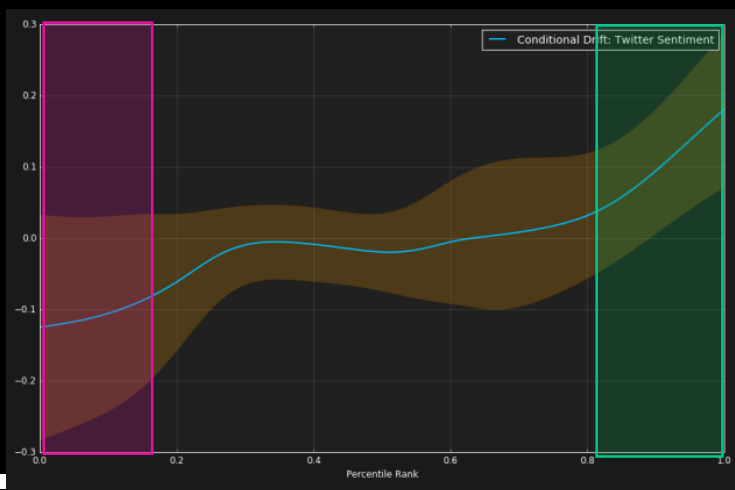


# BUT WAIT A MINUTE...

Sentiment is Momentum while OV return is Mean Reversion signal!



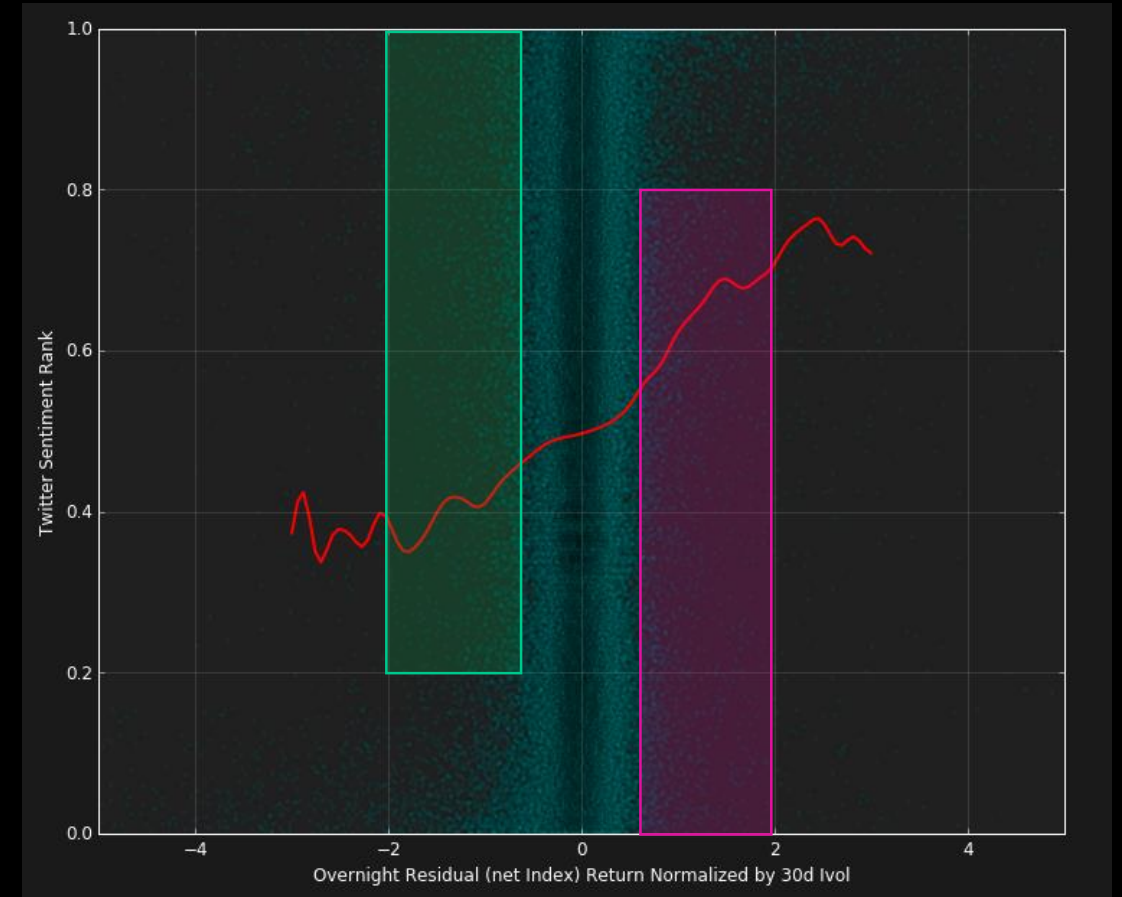
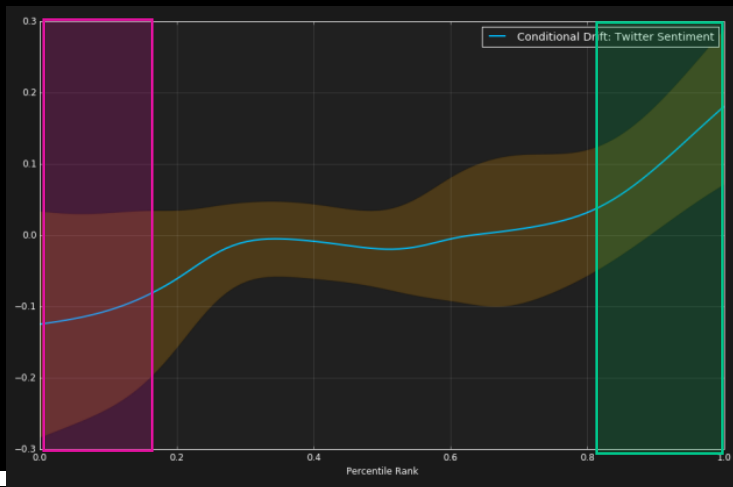
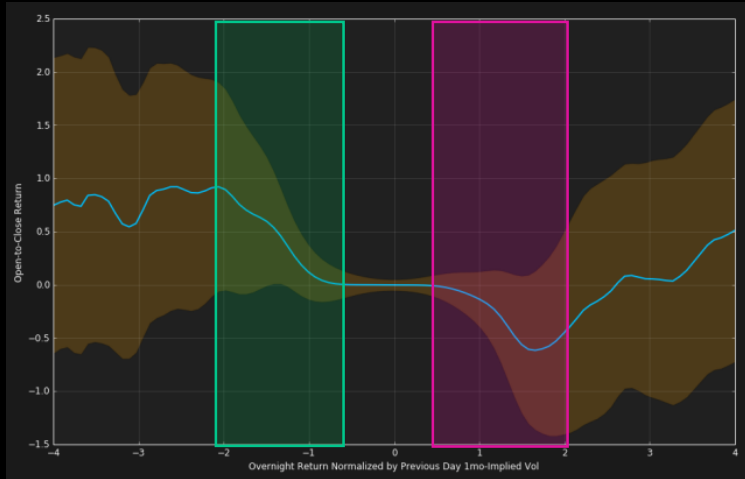
Normalized OV returns  
In S&P 500



Sentiment in Russel 2000

# HOW ABOUT WE TRY....

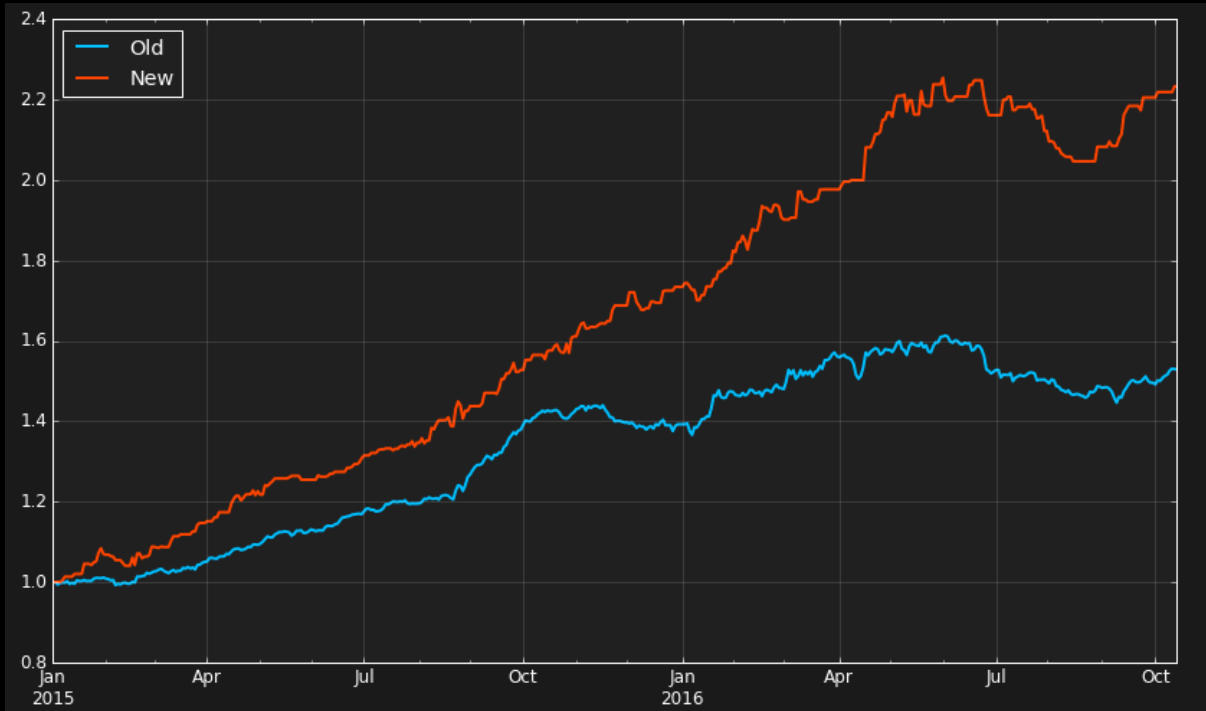
S&P 500 2sig Overnight movers with **neutral-to-opposite** sentiment



Up to 2sig OV moves, **neutral-to-opposite** sentiment

# SENTIMENT SEEMS TO ADD VALUE

## S&P 500 2sig Overnight movers with **neutral-to-opposite** sentiment



- Even if the original overnight vs open-close strategy is a losing proposition if one were to take transaction costs into account, adding sentiment should make it less so

# NEWS TOPIC CODES

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One year (2016) of story-level data with topic codes

Use only stories that have a non-empty headline. This excludes tweets.

Look at one stock at a time. We looked at all current member of the S&P 500 for which data is available.

For each calendar day, compute the average Sentiment Score weighted by Sentiment Confidence, possibly including and excluding stories based on their topic codes.

Regress the daily excess return of the stock over the market on the same-calendar-day average sentiment score to obtain a measure of “sentiment impact”.

# THE TEN “CONTROVERSIAL” TOPICS

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ESGCONTROV: ESG Controversy Screening

LAW: Law

ESGRES: ESG Research

LITIGATE: Litigation

LAWPRAC: Legal Practice Areas

LAWSUITS: Lawsuits

IP: Intellectual Property

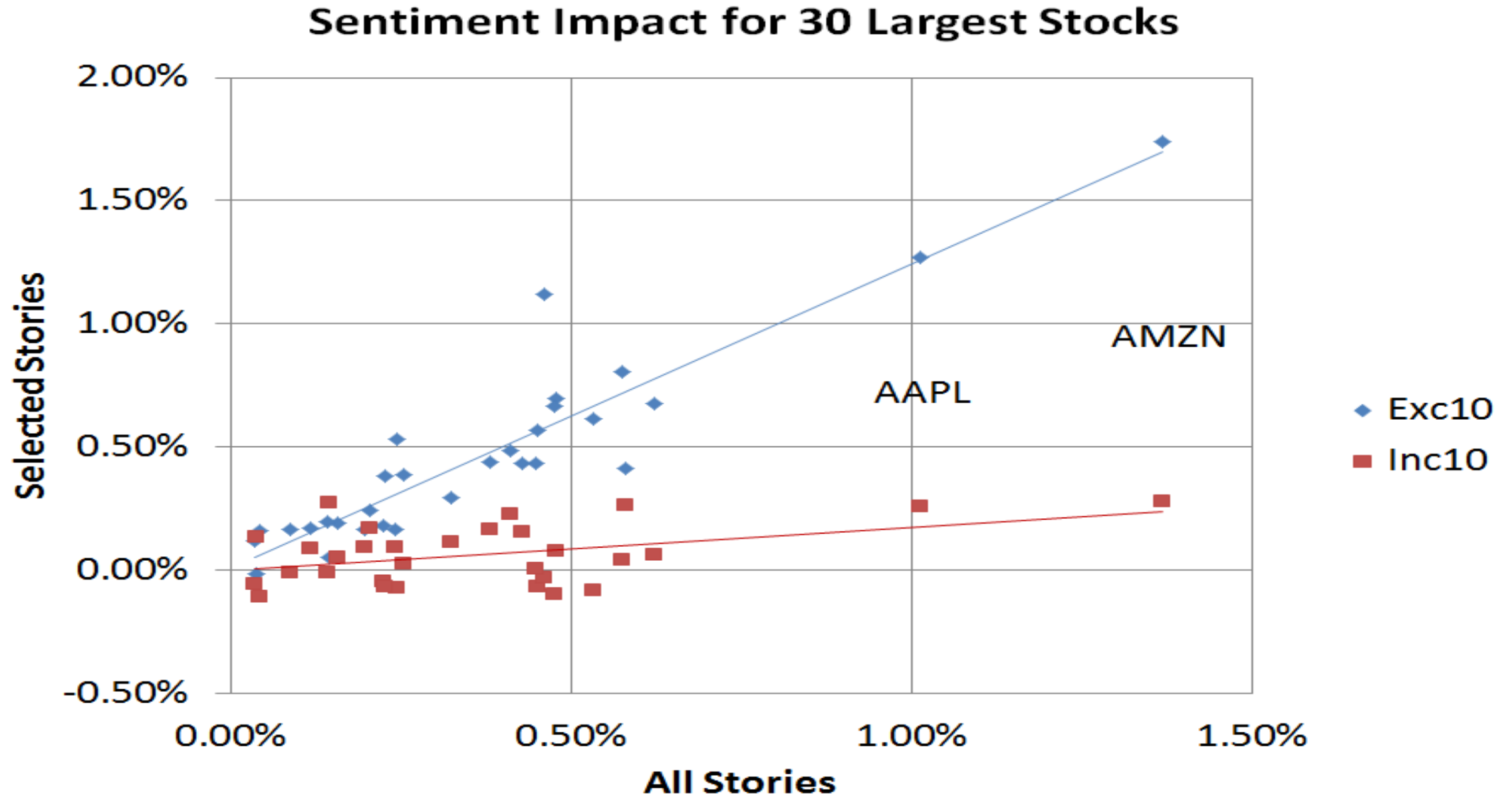
PATENT: Patents

CLASS: Class Action Lawsuits

CALVPOSS: Possible ESG Ledes

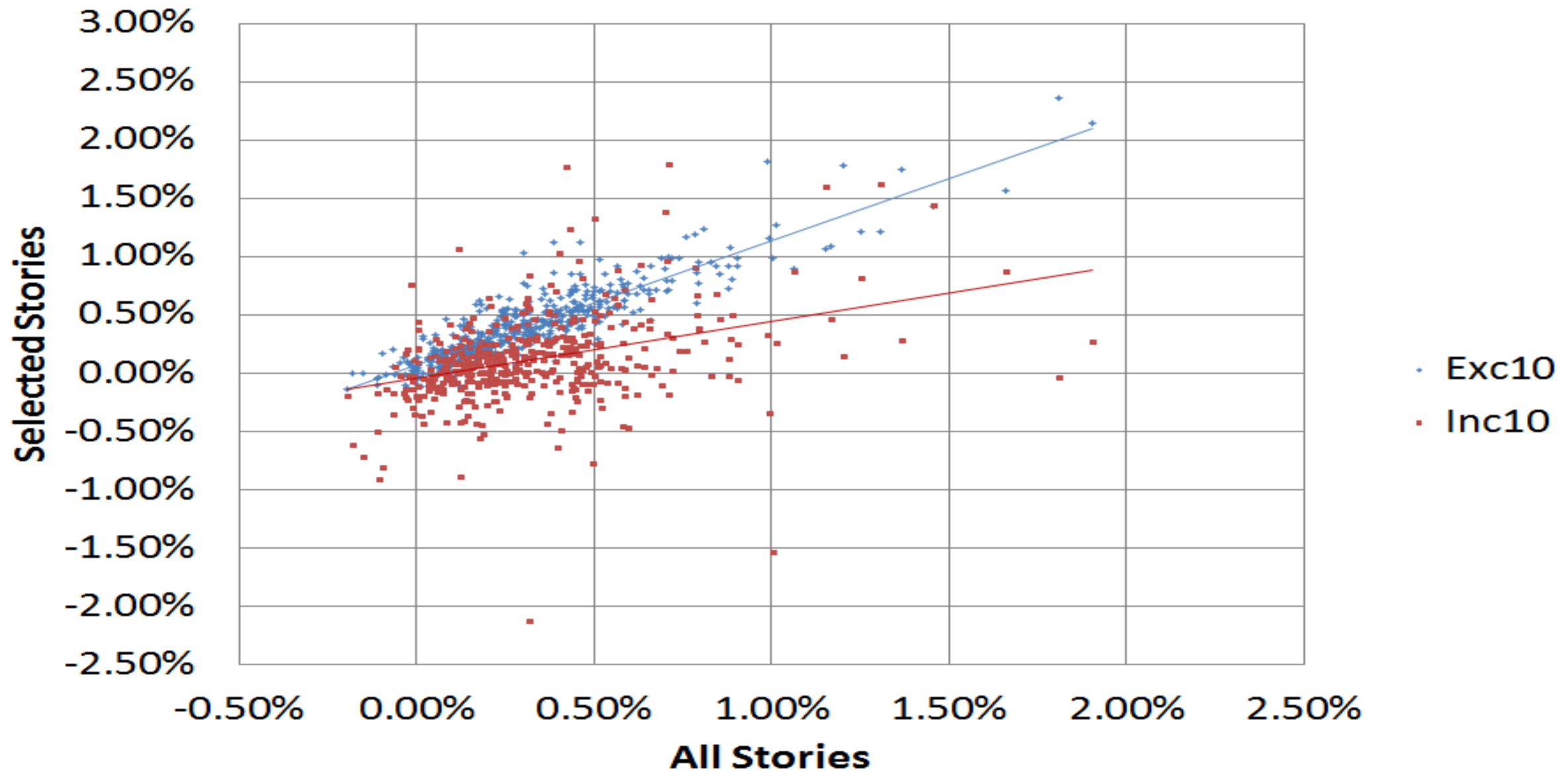
These ten codes were identified after staring at results from the 30 biggest (as of today) stocks, so the results for other stocks are kind of (OK not really) “out-of-sample”.

# 30 BIGGEST STOCKS

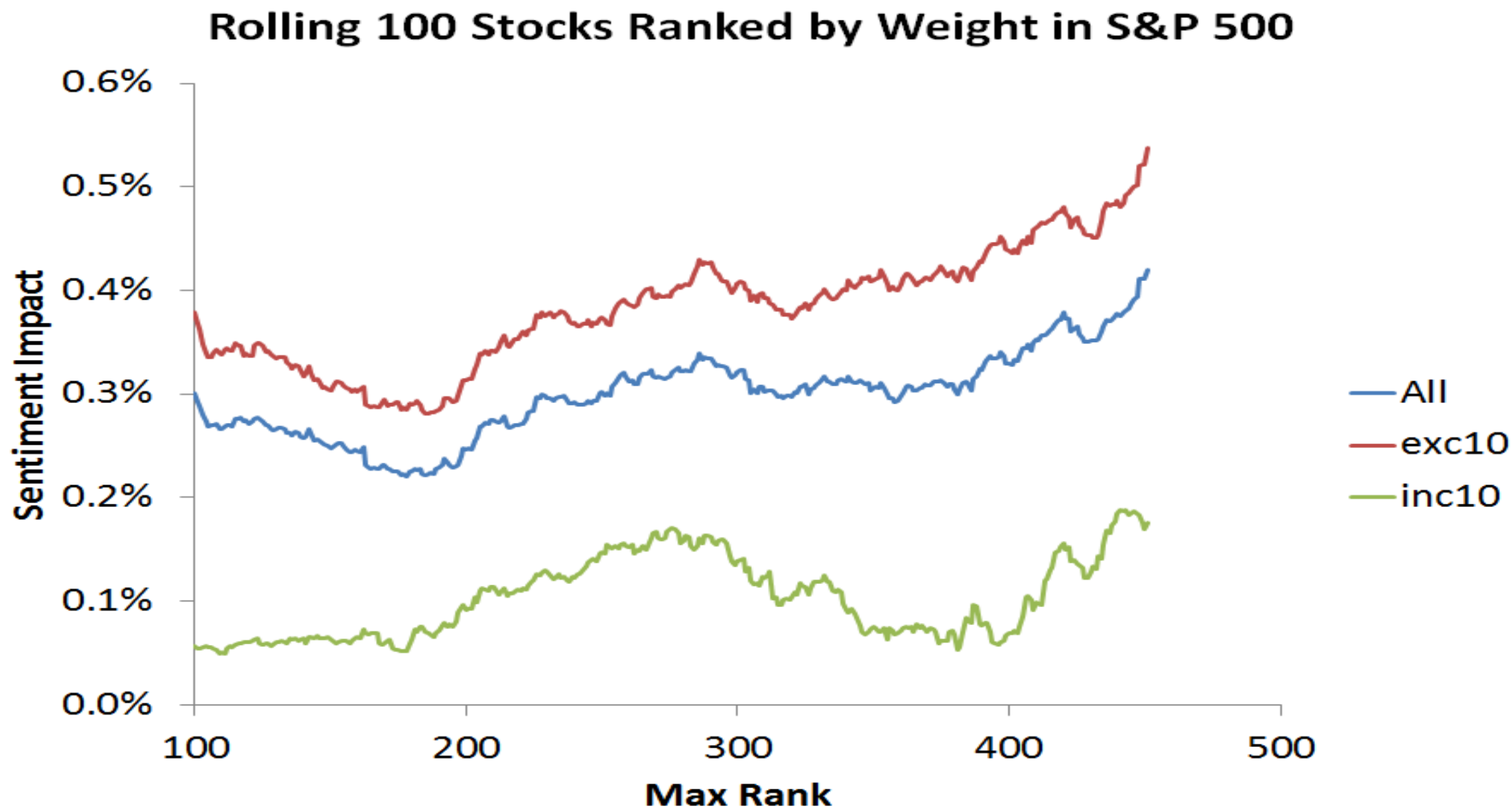


# S&P 500 STOCKS

Sentiment Impact



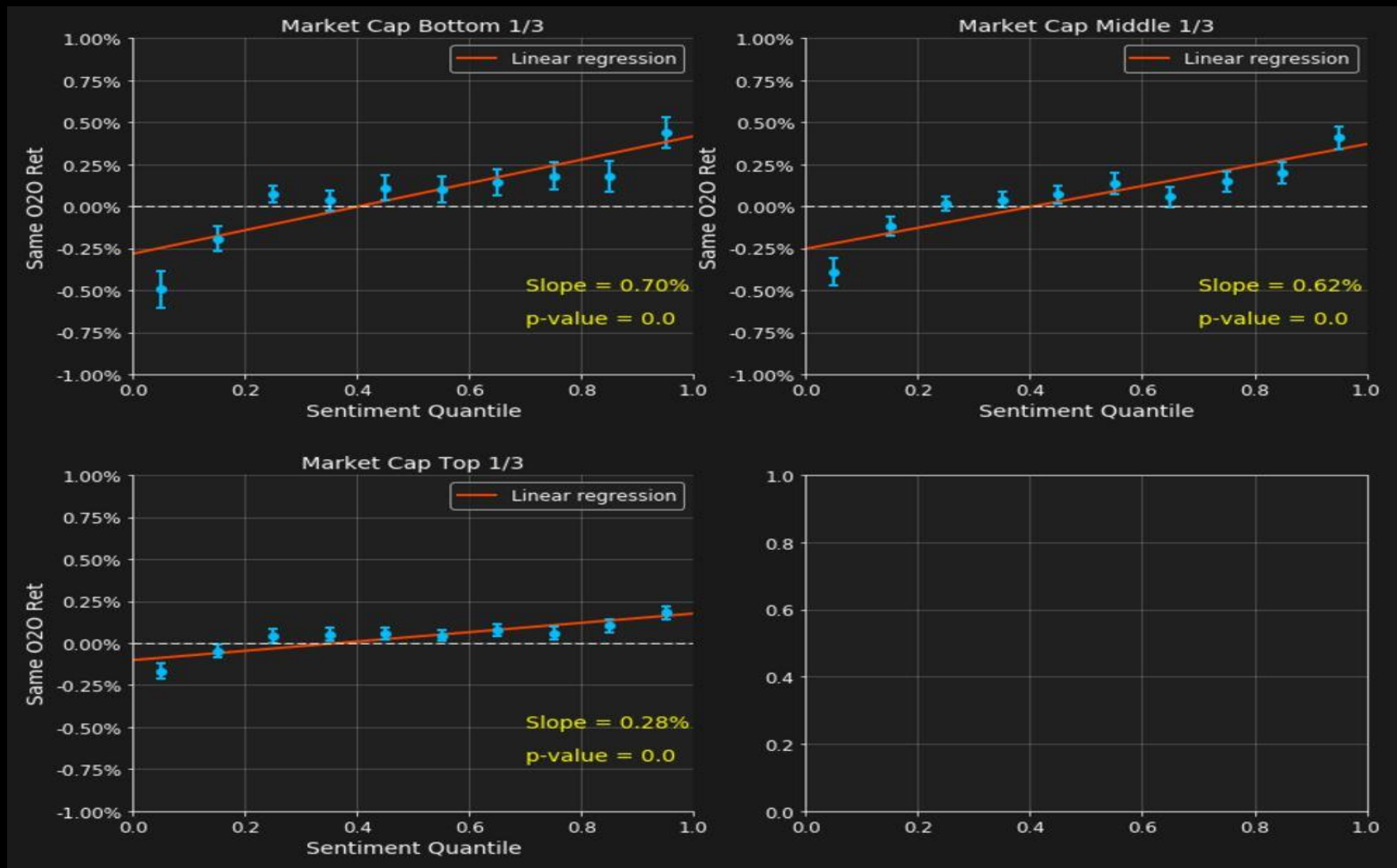
# PATTERN IS CONSISTENT ACROSS LARGER AND SMALLER STOCKS IN S&P 500





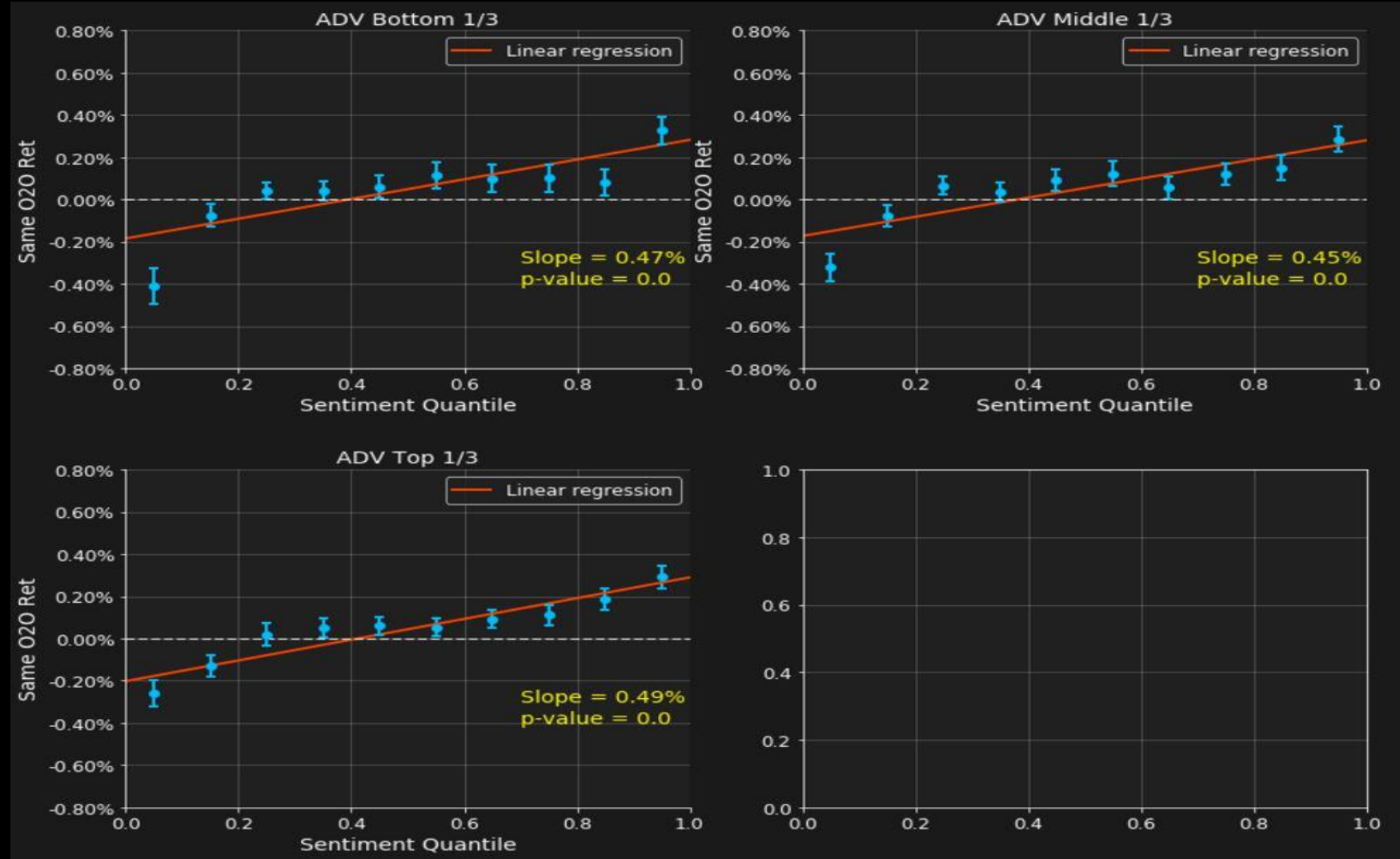
# MARKET CAP (NEWS)

- Small cap stocks are more sensitive to news



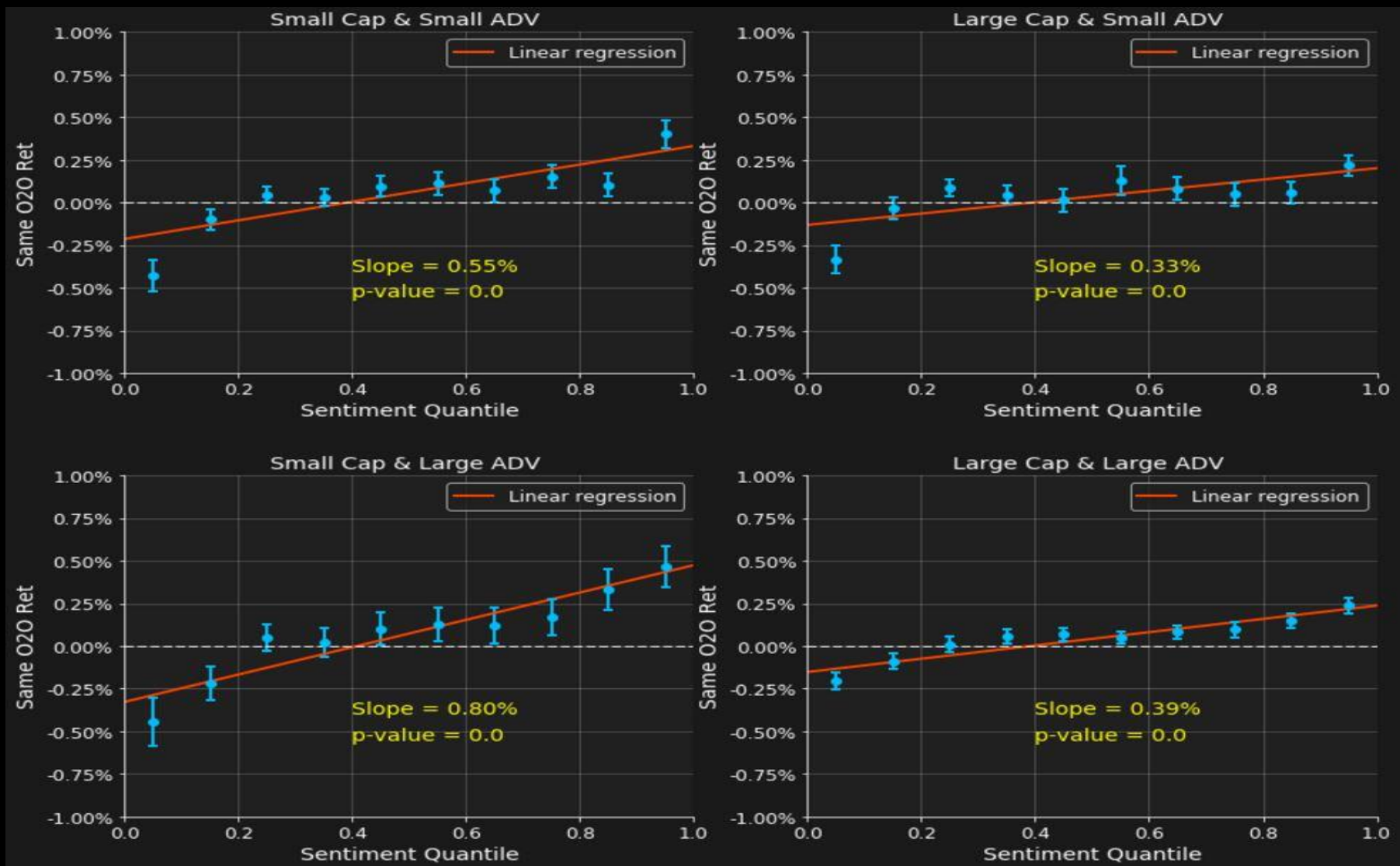
# ADV (NEWS)

- 30-day average daily volume is estimated at the beginning of the testing period.
- Average daily trading volume doesn't impact the sensitivity



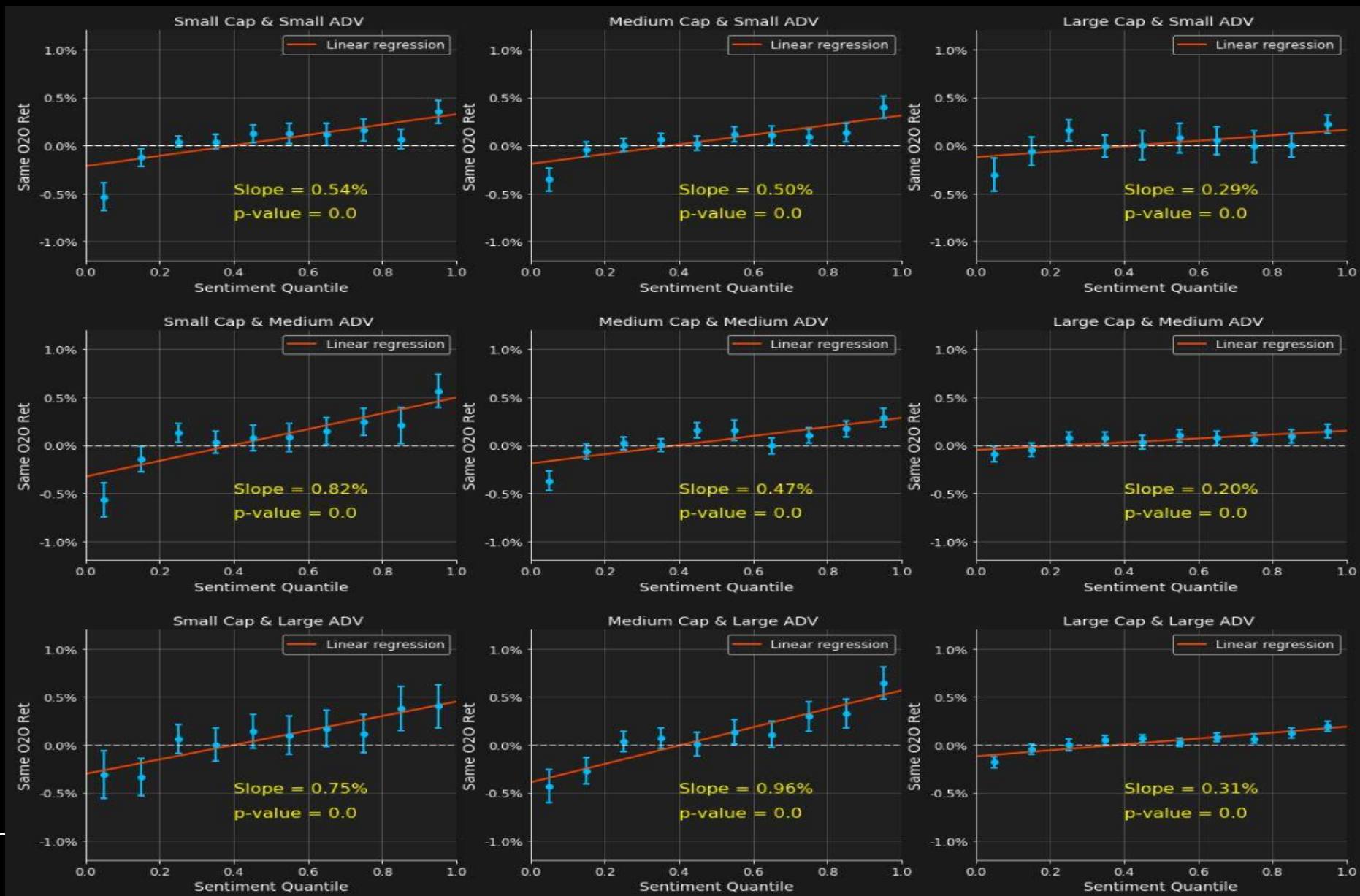
# MARKET CAP & ADV (NEWS)

- Stocks are bucketed by median of their market cap and ADV, resp.
- Small cap stocks with larger trading volume are most sensitive to news



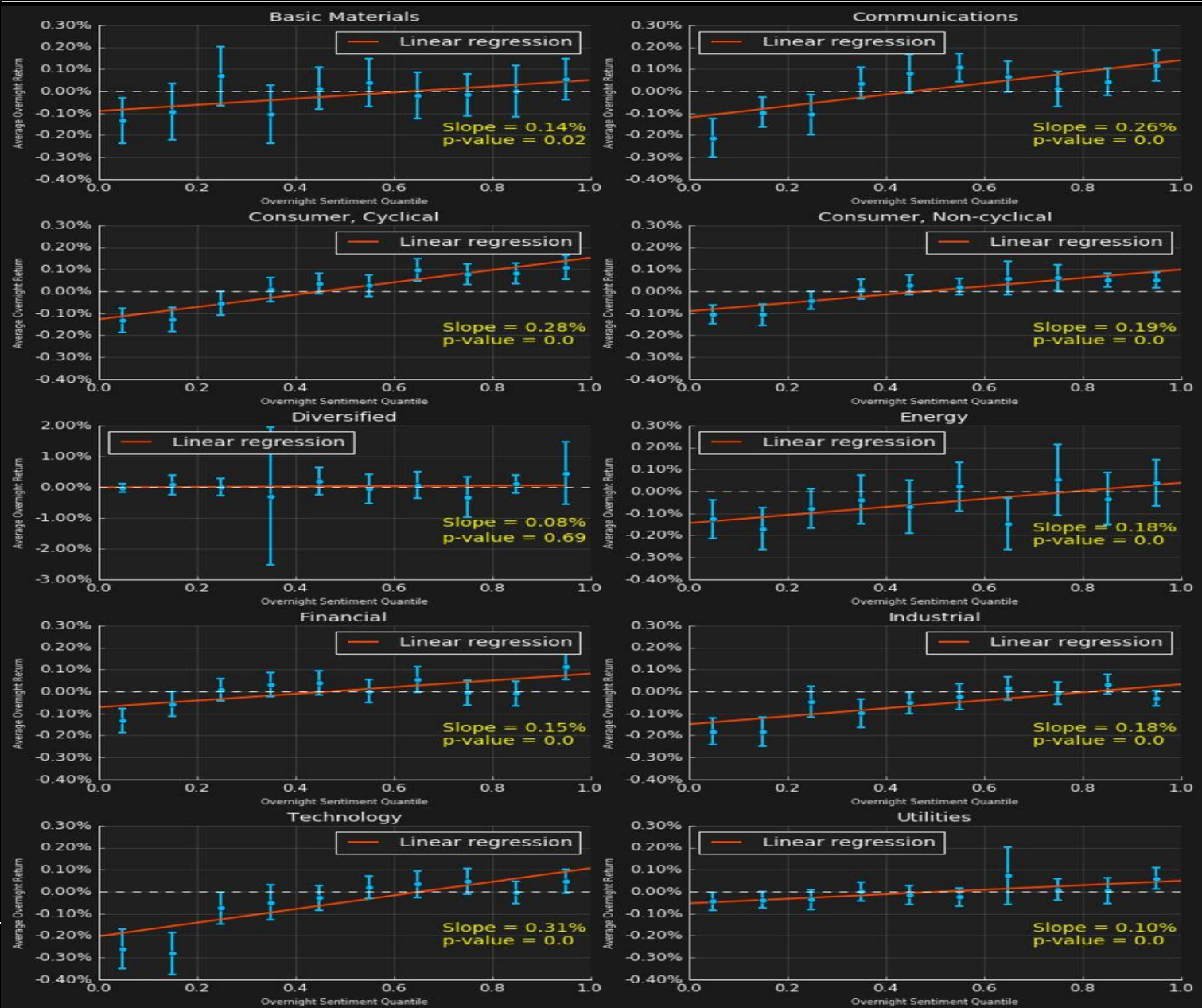
# MARKET CAP & ADV (NEWS)

- Stocks are bucketed by quantiles [1/3, 2/3] of their market cap and ADV, resp.
- Small cap stocks with larger trading volume are most sensitive to news





# SECTOR (NEWS SENTIMENT)



- Communications, Consumer Cyclical, Technology have the strongest dispersion relationships.

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Sentiment without action is the ruin of the soul. —

Edward Abbey

**THANK YOU!**