The Wisdom of Twitter Crowds:

Predicting Stock Market Reactions to FOMC Meetings via Twitter Feeds

Pablo D. Azar and Andrew W. Lo

September 14, 2017[1]

[1] FIN500R: Topics in Quantitative Finance___ Presented by John Dooley

Overview

1. The wisdom of twitter crowds
   - Introduction
   - Data and empirical analysis
   - Summary
2. Comparisons and comments
   - Giving content to investor sentiment (Tetlock, 2007)
   - Comments on text analysis

Research Question

The primary focus of this paper is to consider the information useful for asset pricing.

Research Question

The primary focus of this paper is to consider the information useful for asset pricing.

- Existing measures of sentiment:

Research Question

The primary focus of this paper is to consider the information useful for asset pricing.

- Existing measures of sentiment:
    - Measured as analyst estimates, survey data, news stories, technical indicators (put/call ratios and relative strength indicators).

Research Question

The primary focus of this paper is to consider the information useful for asset pricing.

- Existing measures of sentiment:
  - Measured as analyst estimates, survey data, news stories, technical indicators (put/call ratios and relative strength indicators).
  - Generally suffer from low update frequency and represent a limited subset of the investor population

Research Question

The primary focus of this paper is to consider the information useful for asset pricing.

- Existing measures of sentiment:
  - Measured as analyst estimates, survey data, news stories, technical indicators (put/call ratios and relative strength indicators).
  - Generally suffer from low update frequency and represent a limited subset of the investor population
- Social media sources of information like Twitter offer improved timeliness and an opportunity to expand the surveyed population.

Research Question

This paper documents whether Twitter sentiment can:

1. Explain excess returns after considering traditional asset pricing factors
2. Predict asset returns and shifts in volatility

Literature

- The impact of FOMC announcements: Bernanke and Kuttner (2005), Cieslak, Morse, and Vissing-Jorgensen (2016), Lucca and Moench (2015), and Jegadeesh and Wu (2017)
- Textual analysis in finance: Tetlock (2007), Bailey and Schonhardt-Bailey (2008), Hoberg, Phillips, and Prabhala (2014), and Hoberg and Maksimovic (2015)

Data: Sentiment

TweetPolarity is a daily indicator of the sentiment of tweets mentioning the Federal Reserve.

Tweet	Polarity
@GStuedler this was caused by the worst regulation of all time, the Federal Reserve Act of 1913. Decoupled money from reality #topprog #tcot	−1.00
@SenJohnMcCain Maybe instead of partisan bickering, you should all come together and go after the real bad guys... The Federal Reserve	−1.00
Bernanke Says Biggest Worry is That Politicians Abandon Banks: (CEP News) - U.S. Federal Reserve Chairman Ben Be.. http://tinyurl.com/cosb9m	−0.75
Treasurys rise as Fed meets: Treasury prices rose Tuesday amid speculation that the Federal Reserve will begin b.. http://tinyurl.com/c42qjb	0.60
RT @jordangunderson: is proud that Jason Chaffetz is 1 of 28 Congressmen cosponsoring Ron Paul's Federal Reserve Transparency Act (HR 1207).	0.80
Very impressed w/Federal Reserve Chair Ben Bernanke!	1.00

Exhibit 1: Example tweets with polarity scores.

Data: Sentiment

The Pattern python package is used to determine document sentiment:

- Each word group is assigned a polarity based on the SentiWordnet dictionary
- Take the average polarity of all word groups as document sentiment
- Following Giannini, Irvine, and Shu (2014), Tweets are weighted by the number of followers each user has.

Data: Sentiment

The Pattern python package is used to determine document sentiment:

- Each word group is assigned a polarity based on the SentiWordnet dictionary
- Take the average polarity of all word groups as document sentiment
- Following Giannini, Irvine, and Shu (2014), Tweets are weighted by the number of followers each user has.

Example

This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can't hold up.[a]

[a]Example from Pang, Lee, et al. (2008).

Data

Data is collected:

- Using the Topsy API: tweets that mention: “FOMC”, “Federal Reserve”, “Bernanke”, and “Yellen”
- Value, Size, and Momentum factors
- Excess daily return R_t on the CRSP value-weighted market index

Data

Data is collected:

- Using the Topsy API: tweets that mention: "FOMC", "Federal Reserve", "Bernanke", and "Yellen"
- Value, Size, and Momentum factors
- Excess daily return R_t on the CRSP value-weighted market index

$$\begin{aligned} R_t =& \alpha + \beta_1 IndicatorFOMC_t + \beta_2 TweetPolarity_{t-1} \\ &+ \beta_3 TweetPolarity_{t-1} * IndicatorFOMC_t \\ &+ \gamma_1 HML_t + \gamma_2 SMB_t + \gamma_3 UMD_t + \gamma_4 R_{t-1} + \epsilon_t \end{aligned}$$

Empirical Analysis

VARIABLES	(1) Return	(2) Return	(3) Return	(4) Return
IndicatorFOMC	0.331*	0.338*	0.398**	0.343**
	(0.187)	(0.187)	(0.177)	(0.140)
TweetPolarity		0.0510**	0.0493*	0.0156
		(0.0249)	(0.0252)	(0.0195)
TweetPolarityFOMC			0.490	0.625**
			(0.529)	(0.296)
hml				0.843***
				(0.0757)
smb				0.857***
				(0.0640)
umd				-0.141**
				(0.0602)
L.Return	-0.0722*	-0.0715*	-0.0716*	-0.0334
	(0.0384)	(0.0384)	(0.0384)	(0.0296)
Constant	0.0630**	0.0628**	0.0628**	0.0516**
	(0.0313)	(0.0312)	(0.0313)	(0.0246)
Observations	1,506	1,506	1,506	1,506

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Exhibit 6: Regression of daily returns (in percent) on tweet polarity, FOMC meeting indicator, and Fama French factors. The interaction term is equal to TweetPolarity $\times$ IndicatorFOMC. Newey-West standard errors are computed using 4 lags.

Empirical Analysis

Would a portfolio trading on this information be profitable?

- Let us invest in a market portfolio such that $R_t \sim N(\mu_t, \sigma_t^2)$ and a risk-free asset with return R_t^f.
- Choose a fraction f_t of wealth to invest in the risky asset. The optimal investment (under a logarithmic utility function) is

$$f_t^* = \frac{\mu_t - R_{f,t}}{\sigma_t^2}$$

- Shortselling is allowed and there is an upper bound on leverage so that $|f_t^*| \leq L$.

Empirical Analysis

To determine the fraction to invest in the risky asset the authors predict $\hat{\mu}_t$ and $\hat{\sigma}_t^2$ following

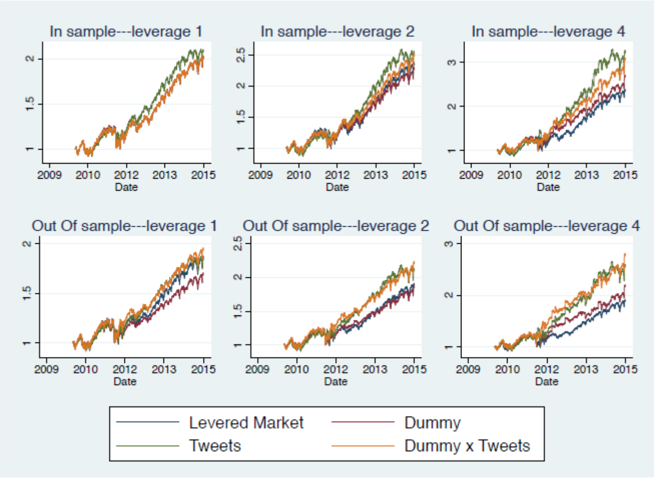
$$\hat{\mu}_t = \alpha + \beta X_t + \epsilon_t$$

$$\hat{\sigma}_t^2 = Var[\alpha + \beta X_t + \epsilon_t]$$

where X_t is one of four competing models:

1. No information
2. $X_t = (IndicatorFOMC_t)$
3. $X_t = (IndicatorFOMC_t, TweetPolarity_{t-1})$
4. $X_t = (IndicatorFOMC_t, TweetPolarity_{t-1} * IndicatorFOMC_t)$

Empirical Analysis



Empirical Analysis

Strategy	L	Return	Drawdown	Sharpe	Info. Ratio	Beta	Alpha
Model 1	1.00	13.08	-7.77	0.88		0.94	-0.83
						(0.00)	(0.00)
Model 2	1.00	10.97	-4.89	0.88	-0.76	0.78	-0.67
						(0.00)	(0.00)
Model 3	1.00	12.87	-7.84	0.92	-0.11	0.85	0.18
						(0.01)	(0.00)
Model 4	1.00	14.06	-8.19	0.93	0.33	0.94	0.17
						(0.01)	(0.00)
Model 1	2.00	13.47	-7.77	0.87		0.99	-1.10
						(0.00)	(0.00)
Model 2	2.00	13.04	-3.72	0.93	-0.15	0.83	0.60
						(0.01)	(0.00)
Model 3	2.00	15.95	-9.26	0.95	0.35	0.97	1.52
						(0.01)	(0.00)
Model 4	2.00	17.11	-7.35	0.98	0.72	1.06	1.41
						(0.01)	(0.00)
Model 1	4.00	13.47	-7.77	0.87		0.99	-1.10
						(0.00)	(0.00)
Model 2	4.00	16.75	-2.71	0.91	0.28	0.93	3.16
						(0.02)	(0.00)
Model 3	4.00	20.54	-7.95	0.97	0.55	1.08	4.66
						(0.02)	(0.00)
Model 4	4.00	22.53	-5.42	1.07	0.82	1.14	5.46
						(0.02)	(0.00)

Empirical Analysis

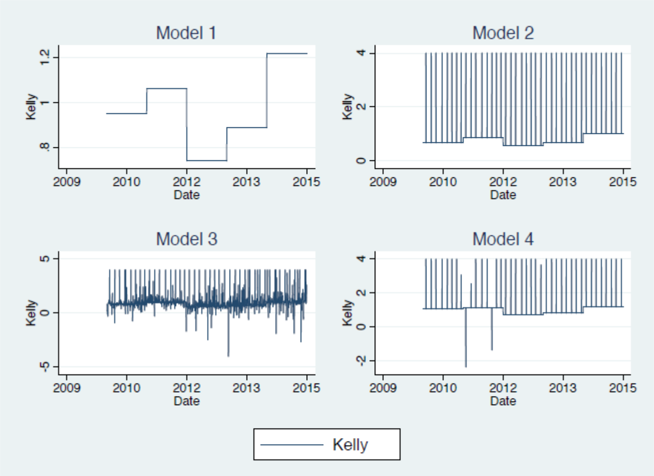


Exhibit 11: Kelly fractions over the 2010–2014 period for four strategies with the quarter-Kelly criterion and a leverage cap of 4.

Empirical Analysis

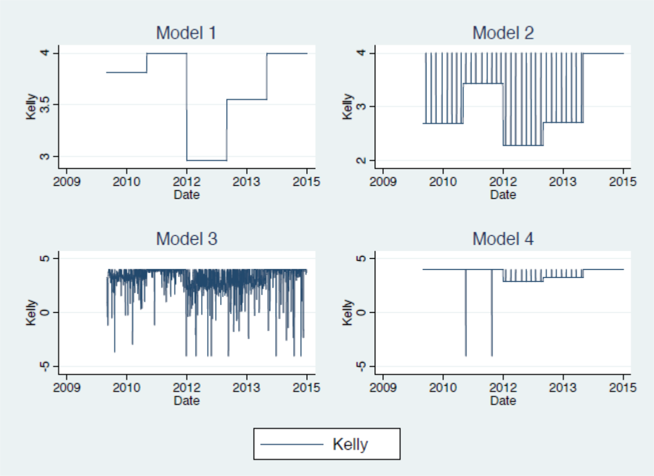


Exhibit 12: Kelly fractions over the 2010–2014 period for four strategies with the full-Kelly criterion and a leverage cap of 4.

Conclusion

So, is the information provided in Tweets useful for asset pricing?

- Tweet based sentiment directly prior to FOMC meetings significantly explained excess returns after accounting for traditional asset pricing factors.
- Twitter sentiment may be used to adjust portfolio allocations with marginally improvements to risk and return.
- However, the low frequency of FOMC meetings, short time interval for testing, and dependence of the out-performance on a few (2-5) observations puts the claim of significant excess return in doubt.

Giving Content to Investor Sentiment (Tetlock, 2007)

- Approach: Analyze the "Abreast of the Market" column in the Wall Street Journal to the determine potential predictive content.

Giving Content to Investor Sentiment (Tetlock, 2007)

- Approach: Analyze the "Abreast of the Market" column in the Wall Street Journal to the determine potential predictive content.
- Results: Media pessimism predicts downward pressure on market prices and elevated trade volume followed by reversion to fundamentals. Results are consistent with noise and liquidity trades instead of new information about fundamental asset value.

Giving Content to Investor Sentiment (Tetlock, 2007)

- Methodology:

Giving Content to Investor Sentiment (Tetlock, 2007)

- Methodology:
  - Uses the automated program "General Inquirer" (GI) maintained by Roger Hurwitz at Harvard. The program counts the number of words in each of 77 categories of words according to the Harvard IV-4 psychosocial dictionary.

Giving Content to Investor Sentiment (Tetlock, 2007)

- Methodology:
  - Uses the automated program "General Inquirer" (GI) maintained by Roger Hurwitz at Harvard. The program counts the number of words in each of 77 categories of words according to the Harvard IV-4 psychosocial dictionary.
  - The authors complete PCA to find the primary factor in the (77 x 77) covariance matrix. The authors estimate loadings for the latent factor in year t using data from year t-1.

Giving Content to Investor Sentiment (Tetlock, 2007)

- Methodology:
  - Uses the automated program "General Inquirer" (GI) maintained by Roger Hurwitz at Harvard. The program counts the number of words in each of 77 categories of words according to the Harvard IV-4 psychosocial dictionary.
  - The authors complete PCA to find the primary factor in the (77 x 77) covariance matrix. The authors estimate loadings for the latent factor in year t using data from year t-1.
    - The factor assigns large positive weight to negative categories (Weak, Fail, Fall, Negative).

Giving Content to Investor Sentiment (Tetlock, 2007)

- Methodology:
  - Uses the automated program “General Inquirer” (GI) maintained by Roger Hurwitz at Harvard. The program counts the number of words in each of 77 categories of words according to the Harvard IV-4 psychosocial dictionary.
  - The authors complete PCA to find the primary factor in the (77 x 77) covariance matrix. The authors estimate loadings for the latent factor in year t using data from year t-1.
    - The factor assigns large positive weight to negative categories (Weak, Fail, Fall, Negative).
    - The factor assigns moderately negative weight to positive categories.

Giving Content to Investor Sentiment (Tetlock, 2007)

- Methodology:
  - Uses the automated program "General Inquirer" (GI) maintained by Roger Hurwitz at Harvard. The program counts the number of words in each of 77 categories of words according to the Harvard IV-4 psychosocial dictionary.
  - The authors complete PCA to find the primary factor in the (77 x 77) covariance matrix. The authors estimate loadings for the latent factor in year t using data from year t-1.
    - The factor assigns large positive weight to negative categories (Weak, Fail, Fall, Negative).
    - The factor assigns moderately negative weight to positive categories.
  - Test for significant explanation of return and volume by estimating a VAR model.

Comments on Text Analysis

Sample selection:

1. Availability[2]

[2] APIs (application program interfaces) can be used to download textual data into programs for analysis. Web scraping offers another means of gathering data (see selenium).

Comments on Text Analysis

Sample selection:

1. Availability[2]
2. Relevance

[2] APIs (application program interfaces) can be used to download textual data into programs for analysis. Web scraping offers another means of gathering data (see selenium).

Comments on Text Analysis

Sample selection:

1. Availability[2]
2. Relevance
3. Timeliness

[2] APIs (application program interfaces) can be used to download textual data into programs for analysis. Web scraping offers another means of gathering data (see selenium).

Comments on Text Analysis

Sample selection:

1. Availability[2]
2. Relevance
3. Timeliness
4. Quality: Standardized Format, machine readable

[2] APIs (application program interfaces) can be used to download textual data into programs for analysis. Web scraping offers another means of gathering data (see selenium).

Comments on Text Analysis

Methodology:

1. Dictionary:

Comments on Text Analysis

Methodology:

1. Dictionary:
   1. Nardo, Petracco, and Naltsidis (2016) discuss dictionaries used for financial text analysis.

Comments on Text Analysis

Methodology:

1. Dictionary:
    1. Nardo, Petracco, and Naltsidis (2016) discuss dictionaries used for financial text analysis.
    2. Azar and Lo (2016) use the Pattern package in python which uses the SentiWordnet dictionary. Li et al. (2014), Tetlock (2007), and Pang, Lee, et al. (2008) use other dictionaries.

Comments on Text Analysis

Methodology:

1. Dictionary:
   1. Nardo, Petracco, and Naltsidis (2016) discuss dictionaries used for financial text analysis.
   2. Azar and Lo (2016) use the Pattern package in python which uses the SentiWordnet dictionary. Li et al. (2014), Tetlock (2007), and Pang, Lee, et al. (2008) use other dictionaries.
2. Bag of Words vs Natural Language Processing (NLP)

Comments on Text Analysis

Methodology:

1. Dictionary:
   1. Nardo, Petracco, and Naltsidis (2016) discuss dictionaries used for financial text analysis.
   2. Azar and Lo (2016) use the Pattern package in python which uses the SentiWordnet dictionary. Li et al. (2014), Tetlock (2007), and Pang, Lee, et al. (2008) use other dictionaries.
2. Bag of Words vs Natural Language Processing (NLP)
3. Topic Categorization

Comments on Text Analysis

Methodology:

1. Dictionary:
    1. Nardo, Petracco, and Naltsidis (2016) discuss dictionaries used for financial text analysis.
    2. Azar and Lo (2016) use the Pattern package in python which uses the SentiWordnet dictionary. Li et al. (2014), Tetlock (2007), and Pang, Lee, et al. (2008) use other dictionaries.
2. Bag of Words vs Natural Language Processing (NLP)
3. Topic Categorization
4. Supervised vs. Unsupervised

Comments on Text Analysis

Methodology:

1. Dictionary:
    1. Nardo, Petracco, and Naltsidis (2016) discuss dictionaries used for financial text analysis.
    2. Azar and Lo (2016) use the Pattern package in python which uses the SentiWordnet dictionary. Li et al. (2014), Tetlock (2007), and Pang, Lee, et al. (2008) use other dictionaries.
2. Bag of Words vs Natural Language Processing (NLP)
3. Topic Categorization
4. Supervised vs. Unsupervised
5. Robustness to user defined methods and settings

Additional References

- Other references to consider include Aggarwal and Zhai (2012), Bird, Klein, and Loper (2009), Wilkerson and Casas (2017), and Pang, Lee, et al. (2008).
- Although Plakandaras et al. (2015) don't use text analysis, they provide references to several papers that do use text analysis to predict commodity and equity market movements.

Bibliography I

Aggarwal, Charu C and ChengXiang Zhai (2012). *Mining text data*. Springer Science & Business Media (cit. on p. 42).

Azar, Pablo D and Andrew W Lo (2016). "The wisdom of twitter crowds: Predicting stock market reactions to fomc meetings via twitter feeds". In: *The Journal of Portfolio Management* 42.5, pp. 123–134 (cit. on pp. 35–41).

Bailey, Andrew and Cheryl Schonhardt-Bailey (2008). "Does deliberation matter in FOMC monetary policymaking? The Volcker Revolution of 1979". In: *Political Analysis*, pp. 404–427 (cit. on p. 9).

Bernanke, Ben S and Kenneth N Kuttner (2005). "What explains the stock market's reaction to Federal Reserve policy?". In: *The Journal of finance* 60.3, pp. 1221–1257 (cit. on p. 9).

Bibliography II

Bird, Steven, Ewan Klein, and Edward Loper (2009). *Natural language processing with Python: analyzing text with the natural language toolkit.* " O'Reilly Media, Inc." (cit. on p. 42).

Cieslak, Anna, Adair Morse, and Annette Vissing-Jorgensen (2016). "Stock returns over the FOMC cycle". In: (cit. on p. 9).

Giannini, ROBERT, PJ Irvine, and T Shu (2014). "Do local investors know more? A direct examination of individual investorsâ information set". In: *working paper* (cit. on pp. 11, 12).

Hoberg, Gerard and Vojislav Maksimovic (2015). "Redefining financial constraints: A text-based analysis". In: *Review of Financial Studies* 28.5, pp. 1312–1352 (cit. on p. 9).

Bibliography III

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala (2014). "Product market threats, payouts, and financial flexibility". In: *The Journal of Finance* 69.1, pp. 293–324 (cit. on p. 9).

Jegadeesh, Narasimhan and Di Andrew Wu (2017). "Deciphering fedspeak: The information content of fomc meetings". In: (cit. on p. 9).

Li, Xiaodong et al. (2014). "News impact on stock price return via sentiment analysis". In: *Knowledge-Based Systems* 69, pp. 14–23 (cit. on pp. 35–41).

Lucca, David O and Emanuel Moench (2015). "The Pre-FOMC Announcement Drift". In: *The Journal of Finance* 70.1, pp. 329–371 (cit. on p. 9).

Bibliography IV

- Nardo, Michela, Marco Petracco, and Minás Naltsidis (2016). "Walking down wall street with a tablet: a survey of stock market predictions using the web". In: (cit. on pp. 35–41).
- Pang, Bo, Lillian Lee, et al. (2008). "Opinion mining and sentiment analysis". In: *Foundations and Trends® in Information Retrieval* 2.1–2, pp. 1–135 (cit. on pp. 11, 12, 35–42).
- Plakandaras, Vasilios et al. (2015). "Market sentiment and exchange rate directional forecasting". In: *Algorithmic Finance* 4.1-2, pp. 69–79 (cit. on p. 42).
- Tetlock, Paul C (2007). "Giving content to investor sentiment: The role of media in the stock market". In: *The Journal of Finance* 62.3, pp. 1139–1168 (cit. on pp. 9, 35–41).

Bibliography V

Wilkerson, John D and Andreu Casas (2017). "Large-Scale Computerized Text Analysis in Political Science: Opportunities and Challenges". In: *Annual Review of Political Science* 20.1 (cit. on p. 42).