ANTICIPATING MARKET REACTIONS TO FED POLICY

USING NLP TO FORECAST CURRENCY RETURNS FROM FOMC STATEMENTS

BEN ROUNDS

"BUY THE RUMOR, SELL THE NEWS"

THE QUESTION

- Can natural language processing on Fed policy statements reveal insights

Process

- Seek to distill individual statements (8/year) into aggregate sentiment values by word count
- Test aggregate counts of various sentiment-laden words to forecast returns to US dollar

THE WALL STREET JOURNAL.
WSJ.com

December 16, 2015, 12:01 PM ET

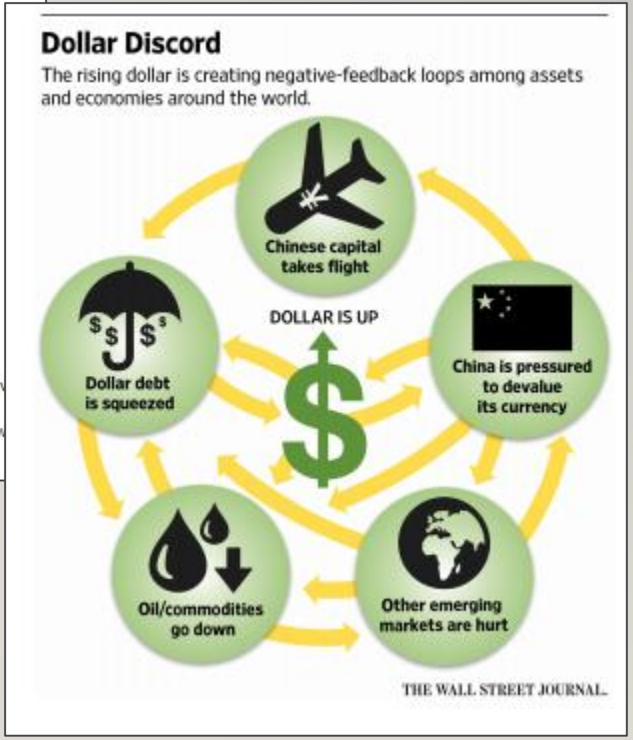
Fed Interest-Rate Decision and Janet Yellen's Press Conference—Recap

BySudeep Reddy, Josh Zumbrun and Jeffrey Sparshott

Fed Chairwoman Janet Yellen announces that the Fed will raise its benchmark interest rate for the first time since 2008 on Wednesday in Washington, D.C.

CHIP SOMODEVILLA/GETTY IMAGES

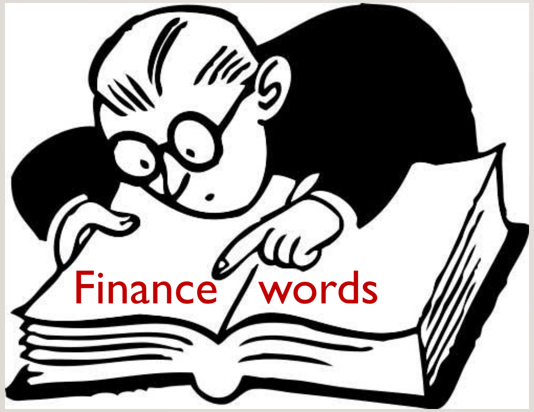
The **Federal Reserve** decided Wednesday to lift its interest-rate target from near zero, sev years after it pushed its benchmark rate to the floor during the financial crisis. In a press conference after a two-day meeting, Fed Chairwoman Janet Yellen said the central bank w move gradually in raising rates further in coming years.



THE DATA – A TALE OF TWO DATASETS

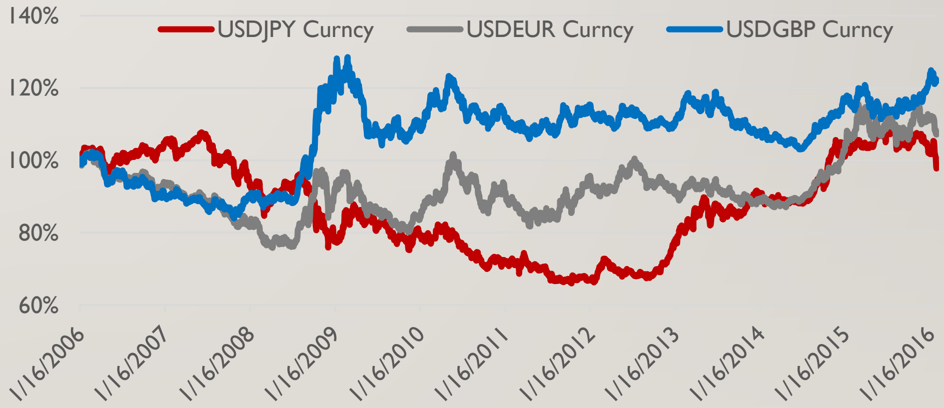
Fed policy statements

- Policy statements are tokenized and matched to a dictionary of financial words and corresponding sentiment scores



Currency returns and volatility

- Currency returns observed over 1 day, 1week, and 1 month
- Volatility is 1-month rolling



TEXT MATCHING – A CLOSER LOOK

FEDERAL RESERVE press release

Release Date: January 31, 2006

For immediate release

The Federal Open Market Committee decided today to raise its target for the federal funds rate by 25 basis points to 4-1/2 percent.

Although recent economic data have been uneven, the expansion in economic activity appears solid. Core inflation has stayed relatively low in recent months and longer-term inflation expectations remain contained. Nevertheless, possible increases in resource utilization as well as elevated energy prices have the potential to add to inflation pressures.

The Committee judges that some further policy firming may be needed to keep the risks to the attainment of both sustainable economic growth and price stability roughly in balance. In any event, the Committee will respond to changes in economic prospects as needed to foster these objectives.

Voting for the FOMC monetary policy action were: Alan Greenspan, Chairman; Timothy F. Geithner, Vice Chairman; Susan S. Bies; Roger W. Ferguson, Jr.; Jack Guynn; Donald L. Kohn; Jeffrey M. Lacker; Mark W. Olson; Sandra Pianalto; and Janet L. Yellen.

In a related action, the Board of Governors unanimously approved a 25-basis-point increase in the discount rate to 5-1/2 percent. In taking this action, the Board approved the requests submitted by the Boards of Directors of the Federal Reserve Banks of Boston, New York, Philadelphia, Cleveland, Richmond, Atlanta, Chicago, St. Louis, Kansas City, Dallas, and San Francisco.

Search for and aggregate words in dictionary:

Negative	Positive	Uncertainty	Litigious	Constraining	Superfluous	Interesting
0	1	.	0	0	0	0

+

Negative	Positive	Uncertainty	Litigious	Constraining	Superfluous	Interesting
0	0	1	0	0	0	0

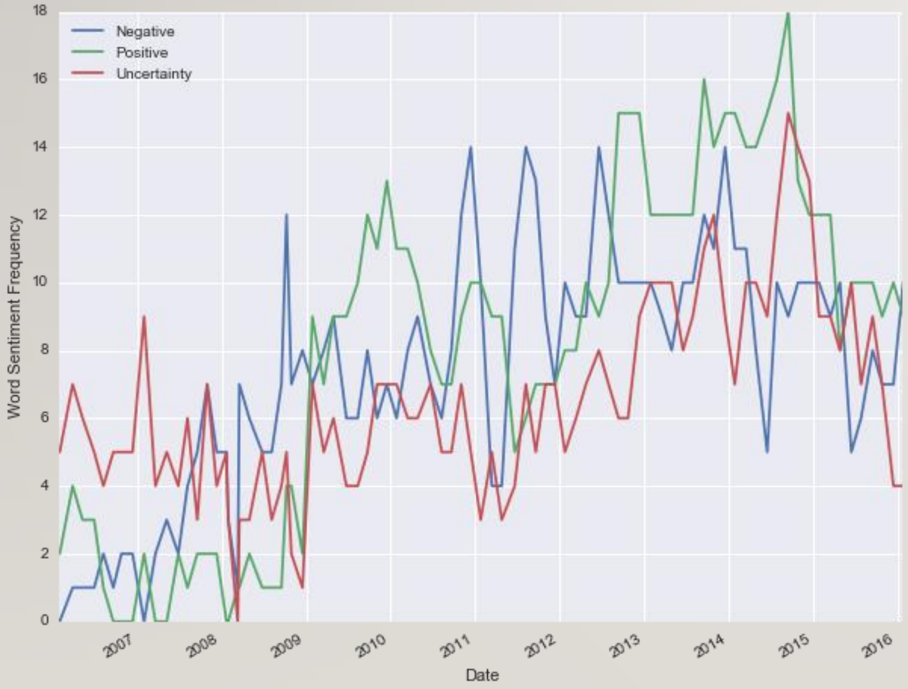
+

Negative	Positive	Uncertainty	Litigious	Constraining	Superfluous	Interesting
0	0	1	0	0	0	0

Statement	Negative	Positive	Uncertainty	Litigious	Constraining	Superfluous	Interesting
2006-01-31	0	1	2	0	0	0	0

AGGREGATING WORD OCCURRENCE

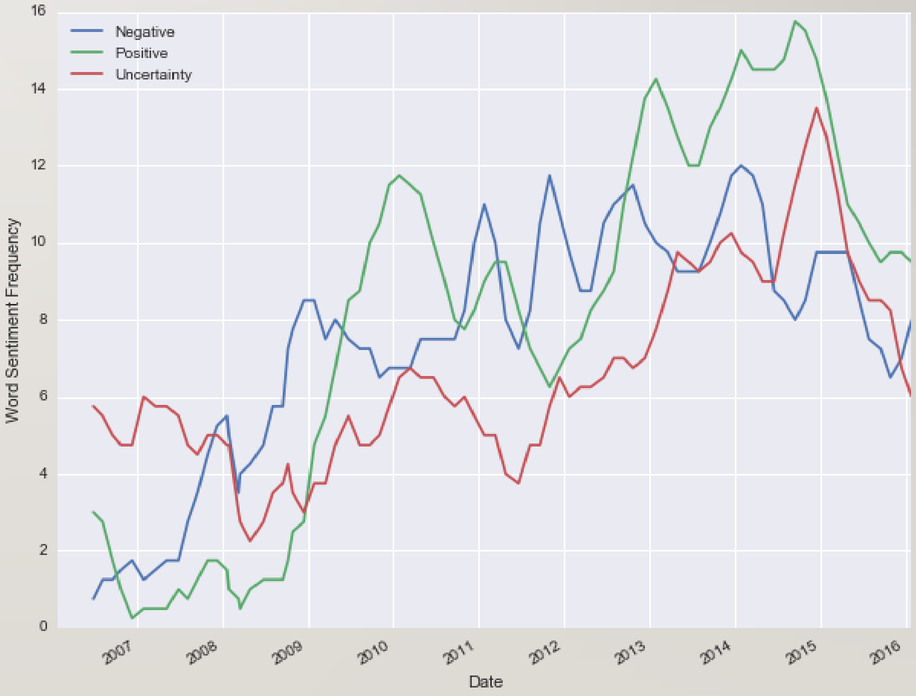
Raw word occurrence overtime



4 statement (~6 month)

rolling average of word occurrence for three possible sentiments

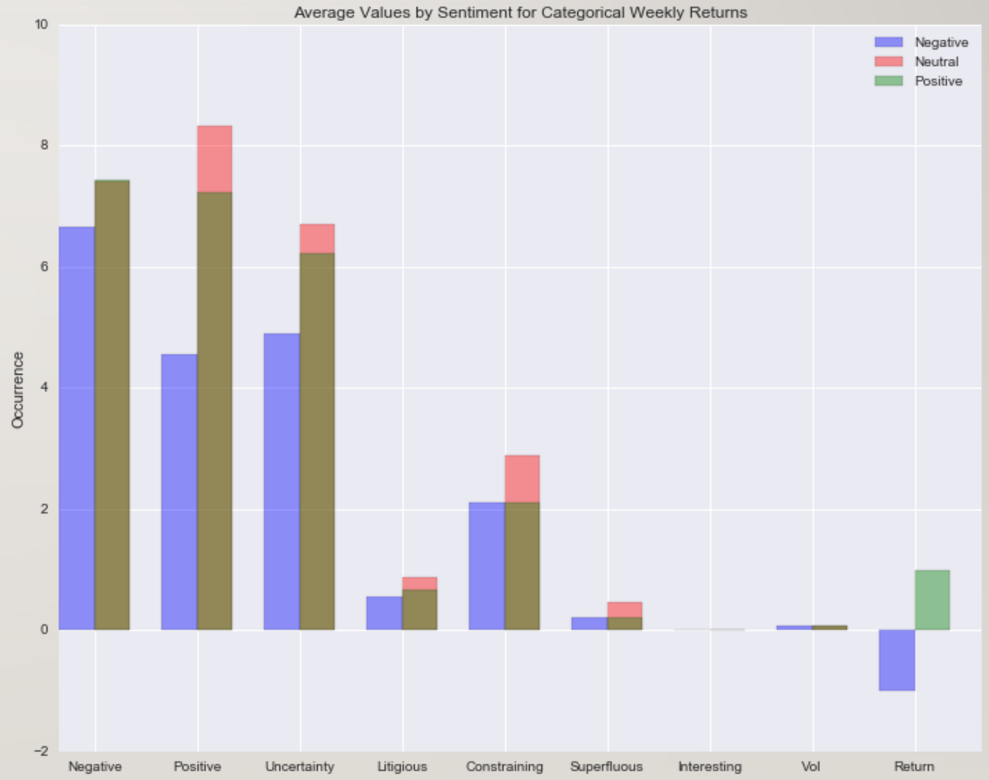
Smoothed word occurrence over time



RETURN CATEGORIZATION

- Returns are transformed from continuous variables into categorical based on the 10th and 90th percentile

```
# Use map function to conditionally change 'Return' variable
d_sentiment_cat['Return'] = map(lambda x: 1 if x > d_sentiment.Return.quantile(0.9)
                                else -1 if x < d_sentiment.Return.quantile(0.1)
                                else 0, d_sentiment.Return)
# Weekly
w_sentiment_cat['Return'] = map(lambda x: 1 if x > w_sentiment.Return.quantile(0.9)
                                else -1 if x < w_sentiment.Return.quantile(0.1)
                                else 0, w_sentiment.Return)
# Monthly
m_sentiment_cat['Return'] = map(lambda x: 1 if x > m_sentiment.Return.quantile(0.9)
                                else -1 if x < m_sentiment.Return.quantile(0.1)
                                else 0, m_sentiment.Return)
```



MODELING

Which models were employed:

Nearest neighbors

Why?

- Explainability
- Relevance

Logistic regression

Why?

- Explainability
- Relevance

Random Forest

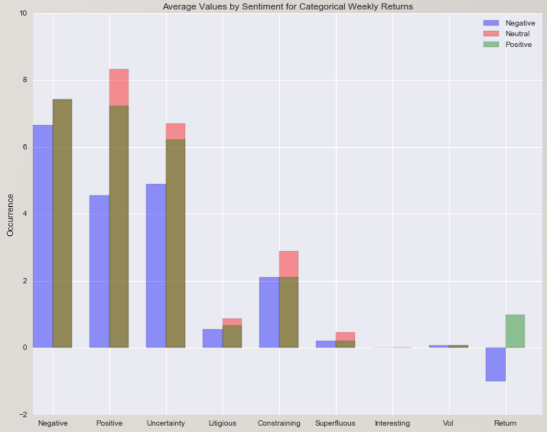
Why?

- Ability to handle correlated features
- Significance scores for predictions made

RESULTS

	Predicted	Actual Binary	Actual Categorical
0	1	1	0
1	1	1	0
2	1	1	0
3	1	1	1
4	1	1	0
5	1	1	0
6	1	1	0
7	1	0	0
8	1	0	0
9	1	1	0
10	1	1	0
11	1	0	0
12	1	0	0
13	1	1	0
14	1	0	0

- No model was able to consistently predict – using any measure of success – currency returns better than the dummy regressor predicting the most common outcome
- Likely a result of little differentiation in word occurrence between return outcomes as well as the categorization of returns
- Exceptional return outcomes were concentrated in the beginning of the period tests (training data) while word counts have increased in the common era; need to find a way to periodically normalize to remove this effect



CONCLUSIONS

After fitting various models under different parameters, I've been unable to consistently form a better prediction than any naive estimator predicting the most common prediction class. This may be for any of a host of reasons, such as:

- Arbitrary classification of returns into top and bottom decile versus middle
- Limited data to FOMC policy statements with a particular html format
- Sentiment data as measured by the utilized dictionary and/or the FOMC statements may simply not be a strong predictor of returns

POSSIBLE EXTENSIONS

Given more time, I would like to extend the project by:

- Using a diverse array of potential return categorizations
- Standardize the predictor variables by de-meaning word occurrence and volatility/sentiment
- Expand the dataset by scraping more Fed statements
- Add additional macroeconomic indicators (potentially something in the realm of "now-casting" using Twitter data)
- Incorporate time series validation