Does Perception Matter in Asset Pricing? Modeling Volatility Jumps and Returns Using Twitter-Based Sentiment Indices

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Questions

- How do we model sentiments?
- Do sentiments affect stock returns?
- Do sentiments affect volatility jumps?

Motivation

How investors are using social media to make money

Bryan Borzykowski, special to CNBC.com
Thursday, 9 Jun 2016 | 10:15 AM ET

CNBC

While most Twitter users post about news they've seen or what they're doing during the day, a number of hedge funds and financial firms are doing something else with the site: They're looking for information that can help them make money.

If they can find out what the masses are thinking about a particular company, or if they can be first to react to a news event, then maybe they can get an edge over their competition.

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The Twitter accounts investors need to follow in 2017

Published: Dec 30, 2016 10:54 a.m. ET

These financial tweeters will make you money or at least make you laugh.

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It's easy to get the financials on a particular stock, but it wasn't always easy to get real-time sentiment. What are people thinking right now? What information might they have that is swaying their views of a company?

Last October, Wong wanted to build his portfolio for clients on the U.S. housing recovery theme.

"To get a sense of what investors are thinking — the intangible kind of feel for the company — that's what I use Twitter for," Wong says. He says he simply used the Twitter stock tag "$" with the stock's ticker to research investor interest in PulteGroup PHM, -1.17% . That led him to a story featuring an interview with the CEO. Today, he owns Pulte, Home Depot HD, +0.46% and Louisiana Pacific LPX, -1.72% to complete his housing-market-recovery portfolio. He bought PulteGroup at $17 in November, and it's now at over $20, up about 21%.

Motivation

MARKETS | MARKETS MAIN

Retail Traders Wield Social Media for Investing Fame

Dispensing stock tips on Twitter, Facebook and online brokerage sites, some build a following; 'If you're wrong, people will know it.'

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146

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Why Are We Here?

- Question: Can we explain short term asset returns and/or volatility jumps?
    - what information (or variable) might explain the so-called short-term "noise" in asset returns?
    - what information (or variable) might explain changes in volatility and/or jumps in asset returns?

- Answer: Forecast firm-specific returns AND volatility jumps using Twitter-based sentiment index
    - Return intuition – "wisdom of the crowd" argument – do consumers like/hate your product/company
    - Volatility intuition – shifts in aggregate sentiment (e.g. positive to negative) signals sudden uncertainty toward specific company

Example - United Airlines Sentiment April 10, 2017

Literature Review (Short)

Return Modeling:

- Baker and Wurgler, "Investor sentiment and the cross-section of stock returns" *JoF* (2006)
- Boudoukh, Feldman, Kogan, and Richardson, "Which News Moves Stock Prices? A Textual Analysis" *NBER WP* (2013)
- Cen, Lu, and Yang, "Investor Sentiment, Disagreement, and the Breadth–Return Relationship" *MS* (2013)

Volatility Modeling:

- Manela and Moreira, "News implied volatility and disaster concerns" *JFE* (2017)
- Bekaert and Wu, "Asymmetric Volatility and Risk in Equity Markets" *NBER WP* (1997)

Issues: cross-sectional asset pricing, no volatility jump modeling, use dichotomous variables, expert-based.

Sentiment Index Distribution

What affects stock returns and volatilities?

Consumer/Investor Sentiment

Use Twitter to determine overall consumer/investor sentiment:

- Classify words as positive, negative, or neutral (e.g. long, short, hold)
- Score words from -3 to +3 to obtain sentiment distribution (e.g. exceptional > good)
    - Relationship between positive and negative sentiments
    - Distribution
    - Look at different "bins" in distribution

Sentiment Index - Two Dictionaries

Words and associated scores come from two sources:

- Bill McDonald's word list – finance terms ranked as positive or negative
- Finn Årup Nielsen – 8,000 words scored from -3 to +3

McDonald Dictionary Example

What does positive or negative mean?

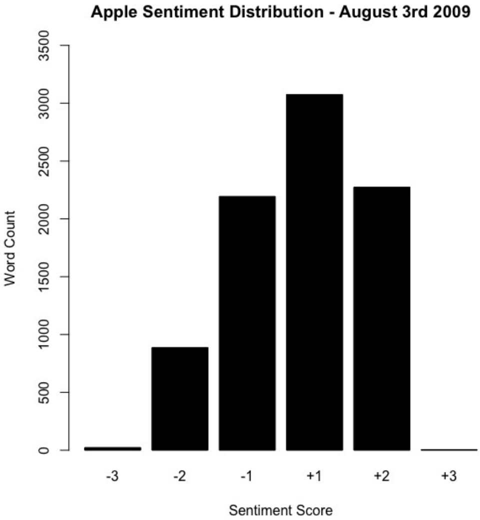
- Positive (5/14/2017): "#Apple's next iPhone #iPhone8 might worth more than $1,000 and may send the $apple stock soaring"
  - "[...] $apple stock **soaring**" $\implies$ score of +1
- Negative (4/11/2017): "$apple #apple US Stock over extended, too high to buy based on supply and demand #nasdaq #sp500 #dowjones"
  - "[...] **too high** to buy [...]" $\implies$ score of -1

Nielsen Dictionary Example

What does positive or negative mean?

- Positive (5/14/2017): "#Apple's next iPhone #iPhone8 might worth more than $1,000 and may send the $apple stock soaring"
  - "[...] $apple stock **soaring**" $\Longrightarrow$ score of +3
- Negative (4/11/2017): "$apple #apple US Stock over extended, too high to buy based on supply and demand #nasdaq #sp500 #dowjones"
  - "[...] **too high** to buy [...]" $\Longrightarrow$ score of -2

Example: Tweets about Apple



Data

Price data:

- Data source: Wharton Research Data Services (WRDS) databases
- Returns and volatility data: CRSP
- Two sample periods:
  - June 2009 - September 2018 (paper)
  - Jun. 2009–Dec. 2009 (presentation) – why?
    - Only period with population of tweets – do not miss important tweets
    - Long to analyze – sentiment analysis on 600,000 Apple tweets takes about a half day

Data (cont'd)

Twitter-based sentiment:

- Subsample of 450 million tweets scraped from Twitter for 2009
- Subsetted by firm
- Using seven months of data

Firms analyzed:

- Thirteen randomly selected firms analyzed:
- Apple, Google, Exxon, FedEx, Ford, JP Morgan, Lockhead Martin, Microsoft, Pepsi, Pfizer, Verizon, Wells Fargo, and Wal-Mart
- For this presentation, focus on Apple results
- Other results available for discussion
- All tweets for 7 months would take about 375 days

Results: Daily Regressions, Returns, McDonald

Regression Equation: $r_t = \alpha + \sum_{i=1}^{6} \beta_{t-1,i} z_{t-1,i} + \epsilon_t$

	Model 1	Model 2	Model 3
(Intercept)	-0.0540	-0.0516^{**}	-0.1576^{***}
	(0.0403)	(0.0191)	(0.0409)
Proportion VV Negative		$1.6742^{\dagger}$	0.2430
		(0.8926)	(0.8891)
Proportion V Negative		0.1427	0.2304^{*}
		(0.1160)	(0.1134)
Proportion Negative		0.1544^{*}	0.1699^{**}
		(0.0612)	(0.0615)
Proportion Positive	0.1167^{*}		0.1579^{**}
	(0.0583)		(0.0505)
Proportion V Positive	0.0286		0.1316^{*}
	(0.0754)		(0.0646)
Proportion VV Positive	6.1016^{*}		
	(2.3933)		
R^2	0.0815	0.0761	0.1225
Num. obs.	138	138	138

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table: Apple tweets June–August 2009 (≈600,000 tweets)

Results: Daily Regressions, Volatility Jumps, McDonald

Regression Equation: $\sigma_t = \alpha + \beta skew_{t-1} + \epsilon$

	Regime 1	Regime 2
(Intercept)	0.0181^{***}	0.0147^{***}
	(0.0002)	(0.0002)
$skew_{t-1}$	0.0046^{***}	0.0016^{*}
	(0.0007)	(0.0007)
R^2	0.4435	0.0539
Num. obs.	138	138

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Table: Apple tweets June–December 2009 (≈600,000 tweets)

$$P = \begin{bmatrix} p_{L,L} & p_{L,H} \\ p_{H,L} & p_{H,H} \end{bmatrix} = \begin{bmatrix} 0.9598 & 0.0241 \\ 0.0402 & 0.9759 \end{bmatrix}$$

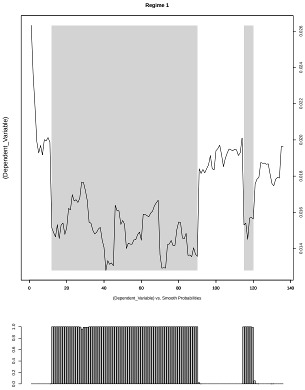

Figure: Apple Volatility – Regime 1

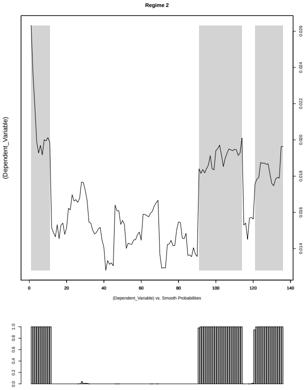

Figure: Apple Volatility – Regime 2

Cautionary Tale!

There is always a need for diligence.

Updated Investor Alert: Social Media and Investing -- Stock Rumors

Nov. 5, 2015

The U.S. Securities and Exchange Commission's (SEC) Office of Investor Education and Advocacy ("OIEA") is issuing this Investor Alert to warn investors about fraudsters who may attempt to manipulate share prices by using social media to spread false or misleading information about stocks.

Conclusion

- Constructed sentiment indices from tweets;
- Sentiment indices can be used to model short-term asset returns;
- Sentiment indices can be used to model volatility jumps.

Thank you!

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Appendix – Additional Results

Firm: Microsoft with about 100,000 tweets

	Regime 1	Regime 2
(Intercept)	0.0125^{***}	0.0217^{***}
	(0.0002)	(0.0006)
$skew_{t-1}$	-0.0009^{**}	-0.0031^{***}
	(0.0003)	(0.0008)
R^2	0.1128	0.2208
Num. obs.	138	138

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table: Apple tweets June–December 2009 (≈600,000 tweets)

Appendix – Additional Results

Firm: Google with about 1,000,000 tweets

	Regime 1	Regime 2
(Intercept)	0.0079^{***}	0.0155^{***}
	(0.0005)	(0.0004)
$skew_{t-1}$	0.0013^{**}	-0.0010^{*}
	(0.0005)	(0.0004)
R^2	0.1443	0.06875
Num. obs.	138	138

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table: Apple tweets June–December 2009 (≈600,000 tweets)

Appendix – Additional Results

Firm: Ford with about 900,000 tweets

	Regime 1	Regime 2
(Intercept)	0.0148^{***}	0.0353^{***}
	(0.0019)	(0.0012)
$skew_{t-1}$	0.0094^{***}	-0.0037^{*}
	(0.0022)	(0.0015)
R^2	0.2967	0.1052
Num. obs.	138	138

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table: Apple tweets June–December 2009 (≈600,000 tweets)

Results: Daily Regressions, Volatility, McDonald

Regression Equation: $\Delta\sigma_t = \alpha + \sum_{i=1}^{6} \beta_{t-1,i} z_{t-1,i} + \epsilon_t$

	Model 1	Model 2	Model 3
(Intercept)	$-0.0003^{\dagger}$	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)
VV Negative	0.1838		0.9056
	(1.7266)		(1.7128)
V Negative	-0.2706^{*}		0.0543
	(0.1332)		(0.1750)
Negative	0.1530^{*}		0.1946^{**}
	(0.0598)		(0.0707)
Positive		-0.1814^{**}	-0.2582^{***}
		(0.0539)	(0.0682)
V Positive		0.2289^{***}	0.1503^{*}
		(0.0660)	(0.0705)
VV Positive		10.2847^{*}	10.1482^{*}
		(4.5090)	(4.5306)
R^2	0.0589	0.1057	0.1599
Num. obs.	137	137	137

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table: Apple tweets June–August 2009 (≈600,000 tweets)