Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media

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1.Introduction

Background & Motivation

- For the pros, the institution of analysis risks becoming de-professionalized.
- Instead of relying on expert advice, consumers increasingly turn to fellow customers when choosing among products and this peer opinions have also begun to play a greater role in financial markets.
- **The goal of this study** is to assess the performance of investors-turned-advisors and to test whether investors can turn to their peers for genuine, useful investment advice.

1.Introduction

Question

- Can peer opinions predict the stocks' future performance? **OR** Do peer opinions actually impart value-relevant news?

Yes

- What are the mechanisms behind this predictability?

There are two main mechanisms

1.Introduction

Research content

Can peer opinions predict the stocks' future performance?

Do peer opinions actually impart value-relevant news?

What are the mechanisms behind this predictability?

The return predictability of the fraction of negative words in articles/comments

Control the variable: number of comments

Re-estimate the main equations but focus on the fundamental variable. (earnings surprise)

The mechanisms

The positive feedback effects

The interaction between author and followers

1.Introduction

Related researches

- Das and Chen (2007); Li (2008); Loughran and McDonald (2011); Davis, Piger (2011) and Sedor 2012: suggests that the frequency of negative words used in an article captures the tone of the report.
- Loughran and McDonald(2011): provide the negative words list for texture analyzing.
- Tetlock (2007); Tetlock, Saar Tsechansky, and Macskassy (2008): DJNS articles can predict stock future performance.

1.Introduction

Contribution

- Our paper relates to the literature on the usefulness of peer-based advice and proves that social media outlets play a valuable role in the domain of financial markets.
- We adds to the literature on professional forecasters.
- Our study also contributes to the literature analyzing the media's effect on the stock market.
- we propose a new laboratory for investigating questions about social interactions and investing.

2.Data

Type:

- Text data: Seeking alpha (articles and comments); Dow Jones News Service (articles)
- Financial analyst data: IBES
- Financial-statement and financial market data: CRSP

Sample period: 2005-2012

Details:

- We just focus on the single-ticker articles and the comments written within the first two days of article publication.
- For the DJNS articles, we require the stock name should appear at least in the first 50 words of the article.

2. Data

A "Negative" Article about Google (12 negative words, 494 total words, NegSA = 2.43%):

Does Google Uphold 'Do No Evil' with shareholders?

January 12, 2010 | about: GOOG

Author: Ravi Nagarajan (http://seekingalpha.com/author/ravi-nagarajan)
Article URL: http://seekingalpha.com/article/182037-does-google-uphold-do-no-evil-with-shareholders

Wonderful Timing, Just Not For Shareholders
As the Wall Street Journal reminds us Monday, in early 2009 Google re-priced a large number of options at much lower strike prices. 7.6 million options with an average strike price of $522 were exchanged for an equivalent number exercisable at $308.57. This narrowly **missed** the low for the year of $282.75. Google now trades at just under $600.
Google's founders were supposedly influenced by Warren Buffett when they published an "owner's manual" shortly before Google's IPO. It is, therefore, even more surprising that management reacted to what proved to be a temporary share price **decline** by massively re-pricing options at the expense of Google's shareholders.

Descriptive statistics of Seeking Alpha and Dow Jones News Service articles

	Seeking Alpha (SA) Articles	Seeking Alpha (SA) Comments	Dow Jones News Service (DJNS) Articles
Panel A: Single-Ticker SA Articles, SA Comments and DJNS Articles			
Total # Stock tickers	7,422	5,031	4,507
Total # Articles (or Comments)	97,070	459,679	322,046
Avg. # Words per article	675	82	380
StDev. # Words per article	466	104	934
Avg. % Negative words	1.25%	1.75%	1.48%
StDev % Negative words	0.96%	2.74%	1.49%
Panel B: SA and DJNS Articles with Word Stem "*Earn*" and Corresponding SA Comments			
Total # Stock tickers	5,054	3,406	3,889
Total # Articles	45,239	200,546	100,403
Avg. # Words per article	741	79	455
StDev. # Words per article	520	101	836
Avg. % Negative words	1.20%	1.63%	1.49%
StDev % Negative words	0.88%	2.62%	1.20%

Summary statistics: Firm/calendar year level

		N	Mean	Std. Dev.	25^{th} Pctl	50^{th} Pctl	75^{th} Pctl
3,300	*Size*	7,773	10,291	29,424	529	1,930	7,204
0.82	*BM*	7,773	0.640	1.080	0.274	0.470	0.760
7.7%	*Past Return*	7,773	0.140	1.300	−0.200	0.070	0.310
	Coverage	7,773	10.870	7.840	5.000	10.000	16.000
	Retail Holdings	7,773	0.260	0.230	0.083	0.210	0.390

3. Main Results

(1) SA and abnormal return

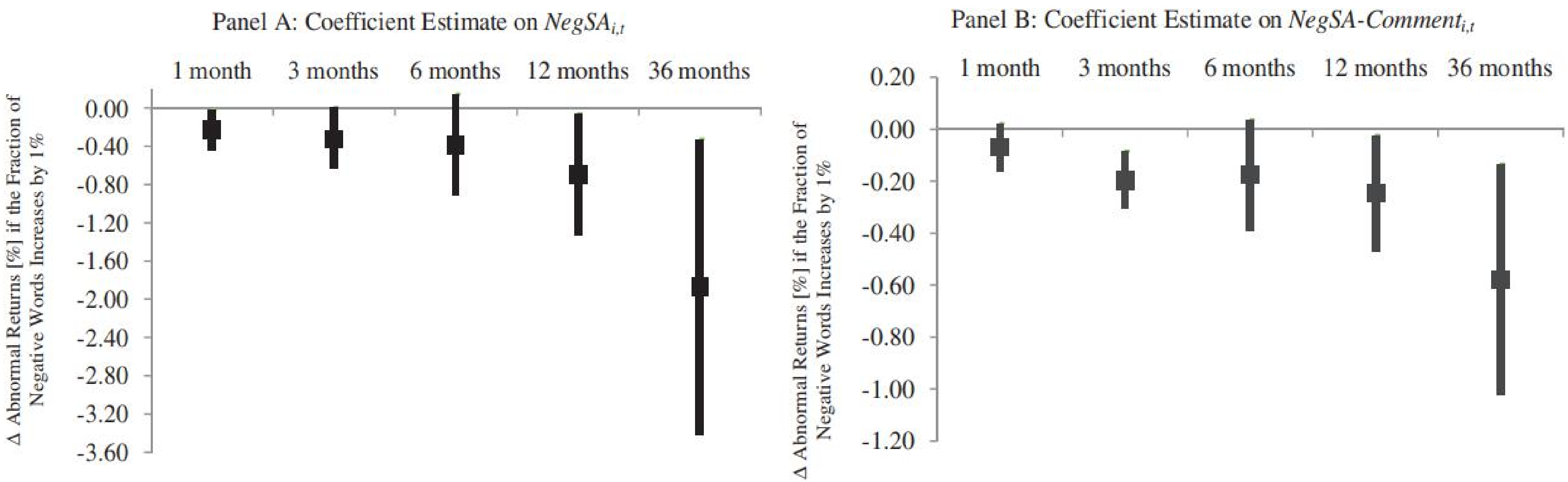
$$ARet_{i,t+3,t+60} = \alpha + \beta_1 NegSA_{i,t} + \beta_2 NegSA\text{-}Comment_{i,t} + \delta X + \varepsilon_{i,t}$$

- $NegSA_{i,t}$($NegSA\text{-}Comment_{i,t}$): the fraction of negative words in the SA article about company i published in day t. (the average fraction of the negative words across SA comments posted over days t to $t+1$)
- $ARet_{i,t+3,t+60}$: three-month holding period returns from trading day $t+3$ to $t+60$.
- Abnormal returns is the difference between raw returns minus returns on a value-weighted portfolio of firms with similar size, book-to-market ratio, and past returns.

Seeking Alpha and abnormal returns

	(1)	(2)	(3)
$NegSA_{i,t}$	−0.379	−0.332	−0.320
	(−2.24)	(−2.03)	(−1.98)
$NegSA\text{-}Comment_{i,t}$		−0.194	−0.196
		(−3.44)	(−3.55)
$I(SA\text{-}Comment_{i,t})$		0.001	0.001
		(0.25)	(0.17)
$NegDJNS_{i,t}$			−0.254
			(−1.44)
$I(DJNS_{i,t})$			0.009
			(1.33)
$Upgrade_{i,t}$	0.003	0.003	0.003
	(0.59)	(0.60)	(0.50)
$Downgrade_{i,t}$	−0.005	−0.005	−0.005
	(−1.08)	(−1.06)	(−1.10)
$PosES_{i,t}$	0.0014	0.001	−0.002
	(0.38)	(0.35)	(−0.41)
$NegES_{i,t}$	−0.004	−0.004	−0.006
	(−0.44)	(−0.49)	(−0.66)
$Volatility_{i,t}$	−0.044	−0.043	−0.042
	(−0.52)	(−0.50)	(−0.49)
$ARet_{i,t}$	−0.068	−0.070	−0.071
	(−1.64)	(−1.68)	(−1.71)
$ARet_{i,t-1}$	−0.077	−0.077	−0.077
	(−2.00)	(−2.00)	(−2.01)
$ARet_{i,t-2}$	−0.021	0.022	−0.022
	(0.35)	(0.37)	(−0.38)
$ARet_{i,t-60,t-3}$	−0.021	−0.022	−0.022
	(−1.41)	(−1.42)	(−1.43)
# Obs.	40,946	40,946	40,946
Adj. R^2	1.20%	1.23%	1.24%

Seeking Alpha and abnormal returns over different holding periods



DJNS articles are news articles and, as such, can be expected to have more of an immediate impact on prices. **SA articles**, on the other hand, resemble analyst reports (both in terms of format and character) and reflect more of a medium- or long-term view.

Why not most of the abnormal performance after a recommendation upgrade (downgrade) accrues around the date of the recommendation change?

3. Main Results

One question: whether the selection of stocks also is associated with abnormal stock market performance?

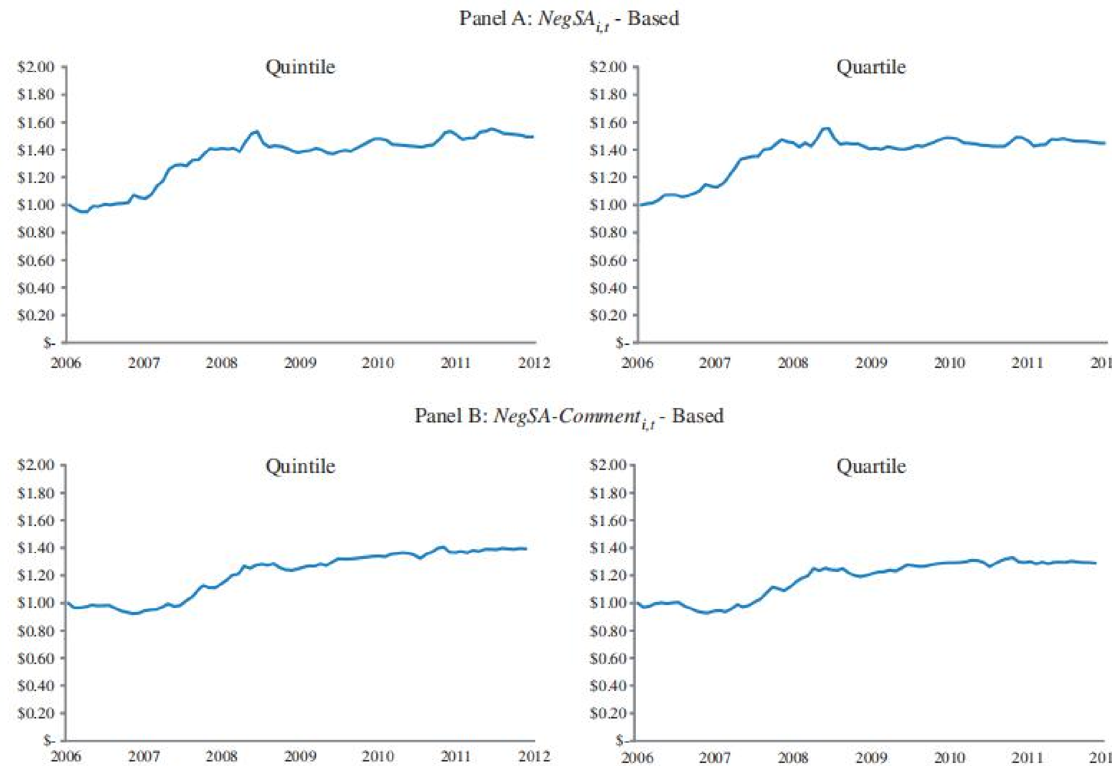
$$ARet_{i,t+3,t+60} = \alpha + \beta_0 indicator_{i,t} + \beta_1 NegSA_{i,t} + \beta_2 NegSA\text{-}Comment_{i,t} + \delta X + \varepsilon_{i,t}$$

- $indicator_{i,t}$ equals one if the stock is covered by SA on a particular trading day t, and zero otherwise.

Main variables	Coefficient	*t*-statistic
$indicator_{i,t}$	0.008 ~ 0.009	1.46 ~ 1.92
$NegSA_{i,t}$	-0.245 ~ -0.278	-2.21 ~ -2.43
$NegSA\text{-}Comment_{i,t}$	-0.161 ~ -0.162	-2.07 ~ -2.11

Generally, the positive abnormal profits are viewed not exclusive to a brief time period, which suggests that our results hold more generally across time

Calendar-time trading strategy based on Seeking Alpha



Variable\portfolio	Quintile	Quartile
$NegSA_{i,t}$	2.6 (2.87)	2.4 (2.89)
$NegSA\text{-}Comment_{i,t}$	2.2 (1.87)	1.7 (2.92)

(2) Number of comments:

Seeking Alpha, abnormal returns, and number of Seeking Alpha comments

	(1)	(2)
$NegSA_{i,t}$	−0.393	−0.381
	(−1.95)	(−1.92)
$NegSA\text{-}Comment_{i,t}$	−0.120	−0.122
	(−1.74)	(−1.77)
$NegSA\text{-}Comment_{i,t} * Rank(\#SA\text{-}Comment_{i,t})$	−0.196	−0.196
	(−2.18)	(−2.21)
$Rank(\#SA\text{-}Comment_{i,t})$	0.009	0.009
	(1.93)	(2.05)
$NegDJNS_{i,t}$		−0.226
		(−1.05)
$I(DJNS_{i,t})$		0.007
		(0.98)

We then re-estimate our main regression with the addition of this new tercile-rank variable and its interaction term with $NegSA\text{-}Comment_{i,t}$, the tercile-rank variable either equals zero, one, or two.

3. Main Results

(3) Noise or value-relevant information?:

- There are two channel behind this predictability: predictability channel or clout channel.
- Earnings surprise is the difference between reported quarterly EPS and the consensus EPS forecast across all analysts issuing earnings estimates from 30 to three calendar days prior to the earnings announcement.
- SA views predicting future earnings surprises would, thus, point more towards the predictability channel.

Seeking Alpha and earnings surprises

	(1)	(2)	(3)	(4)	(5)
$NegSA_{i,t-30,t-3}$	−0.266	−0.232			
	(−2.45)	(−2.27)			
$NegSA\_EA_{i,t-30,t-3}$			−0.306	−0.267	−0.229
			(−2.54)	(−2.34)	(−1.72)
$I(NegSA\_EA_{i,t-30,t-3})$			0.001	0.001	0.005
			(0.72)	(0.64)	(1.62)
$NegSA\_NoEA_{i,t-30,t-3}$			−0.209	−0.193	0.020
			(−1.48)	(−1.43)	(0.18)
$I(NegSA\_NoEA_{i,t-30,t-3})$			0.000	0.001	0.002
			(0.15)	(0.36)	(0.61)
$NegSA\text{-}Comment_{i,t-30,t-3}$	−0.095	−0.094			
	(−1.72)	(−1.72)			
$I(SA\text{-}Comment_{i,t-30,t-3})$	−0.002	−0.002			
	(−1.43)	(−1.31)			
$NegSA\text{-}Comment\_EA_{i,t-30,t-3}$			−0.146	−0.144	−0.100
			(−2.25)	(−2.28)	(−1.59)
$I(SA\text{-}Comment\_EA_{i,t-30,t-3})$			0.000	0.000	0.000
			(0.45)	(0.49)	(0.05)
$NegSA\text{-}Comment\_NoEA_{i,t-30,t-3}$			−0.023	−0.019	−0.008
			(−0.30)	(−0.25)	(−0.08)
$I(SA\text{-}Comment\_NoEA_{i,t-30,t-3})$			−0.003	−0.003	0.001
			(−1.75)	(−1.66)	(0.25)
$NegDJNS_{i,t-30,t-3}$		−0.113			
		(−1.52)			
$I(DJNS_{i,t-30,t-3})$		−0.001			
		(−0.57)			
$NegDJNS\_EA_{i,t-30,t-3}$				−0.127	−0.073
				(−1.68)	(−1.50)
$I(DJNS\_EA_{i,t-30,t-3})$				0.001	0.001
				(0.78)	(0.99)
$NegDJNS\_NoEA_{i,t-30,t-3}$				−0.039	−0.110
				(−0.63)	(−0.78)
$I(DJNS\_NoEA_{i,t-30,t-3})$				−0.002	−0.001
				(−1.35)	(−0.31)

3. Main Results

(4)The Mechanisms

- First, users could derive significant utility from the attention and recognition.
- **Second**, if the crowd allocates more attention to authors that, historically, have produced good articles, this creates an incentive to share good advice.
- **Third**, social media platforms allow users to directly interact with each other and provide useful feedback.
- Finally, SA have some price impact; informed actors have an incentive to contribute to SA to publicize their investment ideas and to convince other investors to follow their investment approach.

3. Main Results

Time interval: second half of 2012:

$$(1)\ Y_i = \alpha + \beta Consistency_i + \delta X + \varepsilon_i$$

- $PageView_i$: number of page views for articles.
- $Read\text{-}to\text{-}End_i$: the number of times an article is read-to-end
- $Consistency_i$: the fraction of articles published by author i that are consistent.

$$(2)\ \Delta Y_{i,j} = \alpha + \beta Consistency\ Recent\ Article_{i,j-1} + \varepsilon_{i,j}$$

- We set $Baseline\text{-}Y_i$ when the first article was published by author, $\Delta Y_{i,j} = Y_{i,j} - Baseline\text{-}Y_i$
- We require article $j-1$ to have been published at least three months prior to article j

NegSA\ARet	Positive	Negative
Above		Consistent
Below	Consistent	

The mechanisms: Author-track record and following

	Page View (1)	Read-to-End (2)
$Consistency_i$	49.151	27.754
	(2.34)	(2.33)
$Article\ Length_i$	−27.663	−20.523
	(−1.94)	(−2.31)
$NegSA_i$	−570.508	−300.345
	(−0.73)	(−0.66)
$I(Blog_i)$	54.901	31.270
	(3.50)	(3.28)
$I(Company_i)$	−24.978	−12.598
	(−1.33)	(−1.19)
# Obs.	308	308
Adj. R^2	3.75%	4.18%

\$\Delta Y_{i,j}$	$PageView_{i,j}$	$Read\text{-}to\text{-}End_{i,j}$
Coefficient	14.911	9.042
t-statistic	3.37	4.27

Intelligent followers can differentiate between authors that offer historically good versus bad advice and the popularity of these authors changes accordingly.

3. Main Results

- The correlation between $NegSA_{i,t}$ and $NegSA\text{-}Comment_{i,t}$ is 0.170. Here, we examine factors that determine the magnitude of the correlation between this two variables.

  $$(1) Disagreement_i = \alpha + \beta Consistency_i + \delta X + \varepsilon_i$$

- $Disagreement_i$:average author/follower disagreement across all single-ticker articles j published by author i.
- (2) Re-estimate main regression equation and focus on: **A**. there is an disagreement; **B**. author is "poor track record."

NegSA\NegSA-Comment	Above	Below
Above		disagreement
Below	disagreement	

The mechanisms: Author-track record and follower disagreement

	Coefficient Estimate (t-statistic)
$Consistency_i$	−0.004
	(−2.22)
$Article\ Length_i$	−0.002
	(−2.47)
$NegSA_i$	0.240
	(3.08)
$I(Blog_i)$	−0.000
	(−0.12)
$I(Company_i)$	0.001
	(0.94)
# Obs.	265
Adj. R^2	7.51%

The mechanisms: Predictability when author-track record is poor and followers challenge the author

	(1)	(2)	(3)
$NegSA_{i,t}$	−0.013	−0.687	−0.664
	(−0.03)	(−1.21)	(−1.16)
$NegSA\text{-}Comment_{i,t}$		−0.560	−0.557
		(−3.30)	(−3.27)
$NegDJNS_{i,t}$			−0.611
			(−1.15)
$I(DJNS_{i,t})$			0.019
			(1.20)

4.Conclusion

- The Internet has become increasingly popular both as a venue to place trades and as a source of information
- We find that the opinions revealed on this SA strongly predict future stock returns and earnings surprises.
- Our findings point to the usefulness of peer-based advice in financial markets.