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Could crowdsourced financial analysis replace the equity research by investment banks?

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COULD CROWDSOURCED FINANCIAL ANALYSIS REPLACE THE EQUITY RESEARCH BY INVESTMENT BANKS?

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Abstract

Equity research is gaining popularity in crowd-sourced information sharing platforms. This study analyses S&P 100 companies stock recommendations and user-contributed articles published on Seeking Alpha platform over a three-year period; and investigates whether investment banks' rating consensus or the sentiment of single-ticker articles published by Seeking Alpha contributors can predict future abnormal returns more accurately. We find that both analyst groups underperform the market. Trading strategies based on the sentiment of the opinion articles perform worse than trading strategies designed around the recommendations of security analysts. Analyst recommendations are expected to remain relevant, there is no immediate pressure from crowd-sourced equity research for changing the business model.

JEL codes: C22, G11, G14, G24

Keywords: stock recommendation; investment bank; crowdsourced financial analysis; sentiment; stock returns

1. Introduction

New types of services, such as peer-to-peer lending, crowdfunding and robo-advisory disrupt the conventional business models in the financial industry. This study analyses the impact of crowd-sourced investment advice; a new investment advisory service which may render the dominance of investment banks in the field. Equity research is seeing a rise in crowd-sourced information sharing platforms that could shake the industry by making analysis and information more accessible to the masses; on social media platforms information is shared faster and received by a larger crowd. A prominent example for such platform is Seeking Alpha, where both professional as well as amateur investors may present their analysis in the form of opinion articles.

This research aims at comparing whether analyst recommendations or Seeking Alpha sentiment can predict future excess stock returns more accurately. In particular, we investigate whether the sentiment of single-ticker articles published by Seeking Alpha contributors or investment banks' rating consensus is able to predict future abnormal returns more precisely. The novelty of the research lies in judging the predictive ability of contributions on Seeking Alpha platform and investment banks' equity research jointly. Previous research has covered the performance of social media platforms and investment banks' equity research separately; this study creates a link between the two sources of information for the first time in the literature.

Seeking Alpha is one of the largest social media platforms offering crowd-sourced investment advice; this platform is the top destination for stock market opinions and analyses on the internet, and it is widely read by finance professionals and dedicated individual investors. The platform offers everyone the possibility to share views on stocks in the form of opinion articles. The site has more than four million registered users, over ten million unique monthly visitors, it covers more than 8 000 stocks, and it has over 15 000 contributing authors (Seeking Alpha, 2017).

Research on the performance of investment banks' recommendations generally suggests that investors can earn abnormal returns by trading on valuable information provided by analysts (Stickel, 1995; Womack, 1996; Barber et al. 2001; Moshirian, Ng, & Wu, 2009). Only a few studies report that investors cannot earn positive abnormal returns by following analyst recommendations (Barber et al. 2003; Boni & Womack, 2006). Empirical evidence on the performance of social media platforms is mixed. On the one hand, several studies suggest that investors cannot earn abnormal returns by following the advice of social media sites (Dewally, 2000; Tumarkin & Whitelaw, 2001; Antweiler & Frank, 2004; Sabherwal, Sarkar & Zhang 2011). On the other hand, numerous studies show that articles posted on social media sites have the ability to predict future stock performance (Wysocki, 1999; Bollen, Mao and Zheng, 2011; Chen, De, Hu & Hwang, 2014).

Equity research by investment banks and brokerage firms has been a substantial and important source of information for both retail and institutional investors. There are several reasons why specialized social media platforms might break the exclusivity currently enjoyed by investment banks in equity research. First, social media platforms offer a quick and cheap way of gathering information about stocks. Second, free-of-charge information about stocks reaches a wide audience including many potential investors; articles posted on these platforms are often shared on other platforms, including the traditional media. Third, social media platforms became professional news and analysis aggregators. The platforms are used by both private retail investors as well as professionals; the U.S. Securities and Exchange Commission had to issue a risk alert reminding registered investment advisors to follow compliance and disclosure regulations (SEC, 2012). As several professionals publish their views on social media sites, the analysis might be as reliable and valuable as the one disclosed by investment banks. Fourth, people having limited time to analyse stocks, tend to purchase the stocks they hear about resulting in naïve buying or selling pressure (Barber & Loeffler,1993; Barber & Ordean, 2008; Dougal et al. 2012). Fifth, recommendations of investment banks and brokerage firms have been associated with conflict of interest on multiple occasions, rendering the reliability of their stock recommendations (Michaely & Womack, 1999; Barber, Lehavy & Trueman, 2007; Agrawal & Chen, 2008; Kadan et al. 2009). All in all, it is worth investigating whether the model of user-contributed investment recommendations performs as good as investment banks' analyst recommendations.

2. Data and methodology

2.1 Data

The sample consists of stocks in Standard & Poor's 100 index as of 31 October 2016. S&P 100 tracks the largest, most liquid stocks across multiple industry groups. These leading stocks are widely known and being covered in several articles by both investment banks and Seeking Alpha contributors.

The sentiment projected in Seeking Alpha articles is based on single-ticker articles—articles assessing a single company rather than multiple companies. In total, 25 986 single-ticker articles were retrieved from SeekingAlpha.com covering a three-year period (January 2014 to December 2016). The most frequently covered stock was Apple with 2 117 articles published in three years, followed by General Electric with 813 articles and Intel with 805 articles (Online Supplementary Material, Table 1). Median number of articles retrieved per company was 148. Despite high market capitalization, some companies did not attract wide interest from Seeking Alpha contributors and followers.

2.2 Seeking Alpha sentiment variable

For each article published on Seeking Alpha, a numerical value for the mood sentiment is extracted by performing a contextual analysis. RapidMiner's text mining tools is used for the contextual analysis. As a first step, we identify the total number of words (positive, negative and neutral) in each article. Afterwards, we compare the content of each article with the pre-produced lists of negative and positive words to identify the total number of either negative or positive words in the article. Similar to Chen et. al. (2014), we use the glossary of Loughran and McDonald (2014) which was specifically created for researching sentiment in financial markets. Finally, we compute the negative sentiment of each article by dividing the number of negative words with the total number of words.

$$Sentiment\ SA = \frac{Negative\ words}{Negative\ words + Positive\ words + Neutral\ words} \qquad Eq.\ 1$$

Sentiment SA variable ranges from 0 to 1; the higher the fraction of negative words, the higher the sentiment variable. Several stocks are not covered frequently by contributors; articles are written every couple of weeks or even less frequently. As a result, Seeking Alpha sentiment variable $Sentiment\ SA_{i,t}$ is computed as an average of sentiment values of each article written for each stock *i* in quarter *t*.

2.3 Investment bank consensus variable

Daily data on investment bank stock recommendations was obtained from Thomson Reuters Eikon from January 2014 to December 2016. Investment bank analysts may rate each stock in the sample on a scale of 1 to 5 as follows: 1 (sell), 2 (underperform), 3 (hold), 4 (buy) and 5 (strong buy). It is reasonable to assume that if analysts leave the rating unchanged, it does not convey new information to the readers, whereas change in recommendation indicates change in the analyst's sentiment. In this research, in order to measure the change in the sentiment in a more pronounced way only those recommendations were included where the analysts changed the rating compared to the previous one. To allow comparison with the sentiment variable, analyst ratings are normalized to [0,1]. The investment bank recommendation variable ($IB\ Consensus_{i,t}$) is calculated by considering all ratings available by analysts on Thomson Reuters Eikon for stock *i* in period *t*:

$$IB\ Consensus = \frac{(Maximum\ rating - Mean\ rating\ of\ period\ t)}{(Maximum\ rating - Minimum\ rating)} \qquad \textit{Eq. 2}$$

In Eq. 2 the maximum rating is 5, whereas the minimum is 1. By construction, if the investment banks' consensus on the rating deceases in period *t* as compared to the period *t-1*, variable *IB Consensus* increases.

2.4 Time series regression with Newey-West standard errors

Time-series regression models are used for investigating whether the Seeking Alpha sentiment and the investment bank consensus variables are statistically significant in explaining the abnormal returns of stocks. The regression model without control variables is specified as follows:

$$AR_{i,t+1} = \beta_0 + \beta_1 Sentiment\ SA_{i,t} + \ \beta_2 IB\ Consensus_{i,t} + \epsilon_{i,t}, \qquad \textit{Eq.3}$$

where $AR_{i,t+1}$ is the 3-month abnormal return of stock *i* in time period *t+1* calculated as a sum of daily excess returns based on Fama-French 3-factor model. Similar to several papers in empirical asset pricing literature, monthly overlapping values are used (Fama & French, 1988; Howe et al., 2009). The Newey-West correction is applied to overcome potential autocorrelation and conditional heteroscedasticity in the regressions (Newey & West, 1987). Assuming advice in line with company fundamentals, if the value of $Sentiment\ SA$ and/or the value of $IB\ Consensus$ increases, that is, the sentiment is more negative and/or the investment banks' rating is less favourable, the stock is expected to underperform the market and has negative excess returns. In contrast, if the sentiment is more positive and/or the investment banks' rating is more favourable (variables $Sentiment\ SA$ and/or $IB\ Consensus$ decreases), the stock is expected to have positive abnormal returns. Thus, coefficients β_1 and β_2 shall be negative. To test for the outperformance of particular analyst groups (contributors on Seeking Alpha versus investment banks analysts), t-tests are conducted on the equality of regression coefficients.

Control variables are selected by relying on the model of Howe et al. (2009); the authors assess the predictive content of aggregate analyst recommendations while controlling for macroeconomic variables identified as predictors of future market excess returns in asset pricing literature (Fama & Schwert, 1977; Keim & Stambaugh, 1986; Campbell, 1987; Fama & French, 1988, 1999). The model of Howe et al. (2009) is modified and fitted to the firm-specific data of this research. Instead of two macroeconomic control variables, we include two stock specific control variables: the default spread corporate bond variable is replaced by the cost of debt of each stock, while market dividend yields are replaced by individual dividend yields. Control variables are defined in Table 1. The regression model with control variables is specified as follows:

$$AR_{t,t+1} = \beta_0 + \beta_1 Sentiment\ SA_{i,t} + \beta_2 IB\ Consensus_{i,t} + \beta_3 Div\ Yield_{i,t} + \beta_4 T\text{–}bill_t + \beta_5 T\text{–}spread_t + \beta_6 CoD_{i,t} + \epsilon_{i,t} \qquad \textit{Eq. 4}$$

Table 1: Control variables: abbreviation and definitions

Abbreviation	Definition
$Div\ Yield_{i,t}$	Average dividend yield for time period *t* of stock *i*.
$T\text{–}bill_t$	Average three-month treasury bill rate for the time period *t*.
$T\text{–}spread_t$	Average 10-year US bond yield less the 3-month US treasury bill rate for time period *t*.
$CoD_{i,t}$	Average cost of debt of stock *i* for the time period *t*.

Data for the control variables were retrieved from Thomson Reuters Eikon on 26.02.2017.

Robustness tests are performed by modifying the variable of $Sentiment\ SA$ as defined in Eq. 5. This sentiment measure considers the words being identified as either positive or negative in each article only.

$$Sentiment2\ SA = \frac{Negative\ words}{(Negative\ words + Positive\ words)} \qquad \textit{Eq. 5}$$

3. Results and discussion

Ten stocks were removed from the dataset due to lack of data; over multiple quarters there were either no articles published on Seeking Alpha or no ratings provided by the analysts. In addition, regression diagnostics were performed to identify outliers. Regression diagnostics included analysing residual-versus-fitted, added-variable, component-plus-residual, leverage-versus-residual-squared plots, quantile plots and Cook's distance (Chen, Ender, Mitchell & Wells, 2003). The Cook's distance values revealed eight observations with high distortive effect on the regression estimates; these observations were removed from the dataset.

For each stock, the mean length of articles, the mean number of positive versus negative words, and the median quarterly abnormal returns are displayed in the Online Supplementary Material, Table 1.

Bivariate correlation analysis revealed that none of the independent variables shall be excluded from the multiple regression analysis; the correlation between the variables of $Sentiment\ SA$ and $IB\ Consensus$ is very weak (0.14). The results of the time series regressions using Newey-West estimators are displayed in Table 2. The model without the control variables (*Eq. 3*) shows that both analyst groups (contributors on Seeking Alpha versus investment banks analysts) have statistically significant impact on the following quarter's excess returns with positive β_1 and β_2 coefficients. If negative news is revealed about the company, as a result of which the negative sentiment of the articles increased, and/or the investment banks' rating became less favourable, the results signal that investors should buy stocks; they are expected to earn positive abnormal returns. Thus, investors cannot outperform the market by trading based on the sentiment extracted from Seeking Alpha articles or following the advice of investment bank analysts. The trading strategy based on the sentiment of Seeking Alpha articles performs significantly worse than the one based on analyst recommendations.

Table 2. Time series regression with Newey-West standard errors

	Regression without control variables	**Regression with control variables**
Constant	-0.061 *(***)*	-0.097 *(***)*
Sentiment SA	2.006 *(***)*	1.843 *(***)*
IB Consensus	0.044 *(**)*	0.034
CoD		-0.008
Div Yield		0.006 *(*)*
T-bill		5.439
T-spread		1.807
Test if $Sentiment\ SA = IB\ Consensus$		
Prob > F	(0.000***)	(0.000***)

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

When control variables are added to the regression, the coefficient of $Sentiment\ SA$ has slightly decreased, while the coefficient for the $IB\ Consensus$ variable became insignificant. The probability of $Sentiment\ SA$ being equal or smaller than $IB\ Consensus$ is still negligible. None of the control variables provide information regarding the excess returns. This result is consistent with the efficient market hypothesis; publicly available information is embedded in the stock price. Robustness tests are performed by modifying the $Sentiment\ SA$ variable (Table 3). The test results confirm the above findings; Seeking Alpha contributors are worse in predicting future stock returns than investment bank analysts.

Table 3. Robustness test: time series regression with Newey-West standard errors

	Regression without control variables	**Regression with control variables**
Constant	-0.070 (***)	-0.099 (***)
Sentiment2 SA	0.114 (***)	0.104 (***)
IB Consensus	0.048 (**)	0.035 (*)
CoD		-0.010
Div Yield		0.006 (*)
T-bill		5.926
T-spread		1.727
Test if *Sentiment SA* = *IB Consensus*		
Prob > F	(0.000***)	(0.000***)

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

The underperformance of Seeking Alpha sentiment is in line with studies suggesting that investors cannot earn excess returns by forming a trading strategy based on opinion articles (Dewally, 2000; Tumarkin & Whitelaw, 2001; Antweiler & Frank, 2004; Sabherwal, Sarkar & Zhangm 2011). Our findings, however, contradict the results of Chen et al. (2014); the authors find that views expressed in Seeking Alpha articles predict future stock returns over multiple time periods. Different research designs might explain the contradicting findings; Chen et al. (2014) investigate the performance of value weighted portfolios, while this research analysed the performance of single stocks.

The underperformance of investment bank analysts contradicts previous literature (Stickel, 1995; Womack, 1996; Barber et al. 2001; Moshirian, Ng, & Wu, 2009). The significance of the respective coefficients in our models with control variables is, however, quite low: it is either insignificant (Table 2) or significant at 10% level only (Table 3). Diverging findings are most probably attributable to aggregation; recommendations were averaged over three-month period hindering the measurement of the immediate impact, an approach commonly adopted in previous studies. This aggregation was nevertheless inevitable for comparing analyst recommendations with the sentiment of opinion articles.

For the first time in the literature, this research provides empirical evidence of investment bank analysts delivering superior information as compared to Seeking Alpha sentiment; their negative excess returns are smaller. The large negative excess returns of investors trading on the sentiment of articles published by Seeking Alpha contributors signal that investors might profit from a contrarian trading strategy, trading against the Seeking Alpha sentiment.

Finally, several caveats should be noted. First, as several stocks in S&P 100 index were not covered widely by Seeking Alpha contributors, we pooled data together and analysed the three-month average sentiment. Second, this analysis is based on large-cap companies—the conclusions might not be generalizable for the entire US market and for global stock markets. For smaller firms, information from analysts and contributors might be more valuable as it is harder to obtain. Third, causality was not tested due to limited number of observations and uneven groups. Fourth, in each quarter change in investment bank recommendations might have influenced the Seeking Alpha sentiment—influence being disregarded in this study.

4. Conclusions

In this research we investigated whether the sentiment of articles published by Seeking Alpha contributors and recommendations from investment bank analysts can predict future excess stock returns. We showed that both analyst groups underperform the market; investors trading in line with the sentiment reflected in Seeking Alpha articles would earn larger negative excess return than investors following the recommendations of investment bank analysts. As a result, crowd-sourced equity research does not challenge the dominant role of investment banks and brokerages in the equity research market.

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Appendix, Table A1. Descriptive statistics of the Seeking Alpha dataset

Ticker	No. articles	Article length (mean)	Number of negative words (mean)	Number of positive words (mean)	Quarterly abnormal return (median)	Ticker	No. articles	Article length (mean)	Number of negative words (mean)	Number of positive words (mean)	Quarterly abnormal return (median)
AAPL	2117	653.6	15.6	13.6	0.4%	**JPM**	270	502.4	15.6	12.3	1.6%
ABBV	133	651	14	13.6	2.7%	**KMI**	556	593.2	16.3	11.2	1.2%
ABT	99	596.2	11.9	14.3	2.4%	**KO**	381	632.5	15.3	15.4	-2.2%
AGN	108	689.7	20.2	11.6	-0.6%	**LLY**	63	562.6	14.6	11.5	1.7%
AIG	184	504.3	15.5	13.6	0.5%	**LMT**	121	584.7	13.3	15.7	-1.0%
AMGN	126	791.3	19.4	19.7	-2.8%	**LOW**	112	542.8	9.9	20	-1.4%
AMZN	801	580.4	13.4	12.6	6.5%	**MA**	94	575.1	11.9	14.9	-0.9%
AXP	131	564	16.9	14.7	1.6%	**MCD**	581	548.9	15.9	12.8	1.6%
BA	451	222.9	4.7	4.8	2.0%	**MDLZ**	75	635.4	15.5	19.2	-0.1%
BAC	761	538.8	19.8	12.2	0.3%	**MDT**	67	551.2	10.3	14.4	-2.7%
BIIB	95	735.7	17.6	17.4	-2.6%	**MET**	57	485.2	13.6	11.6	-2.5%
BLK	43	602	10	16.6	-1.4%	**MMM**	171	591.3	12.4	17.6	-1.9%
BMY	88	629.2	14.5	14.9	4.3%	**MO**	271	589.9	11.4	14.4	0.9%
C	375	545.8	19.3	11.9	1.6%	**MON**	93	599.9	15.3	14.1	-2.2%
CAT	266	553.1	20.5	13.5	-0.7%	**MRK**	80	576.6	13.6	12.7	1.0%
CELG	98	818.4	18.5	20.6	3.0%	**MS**	75	551.9	15.3	14.1	1.8%
CL	114	648.7	12.4	18.1	-0.7%	**MSFT**	755	568	11.6	13.8	3.3%
CMCSA	182	527.7	10.1	12.5	0.9%	**NKE**	308	550.5	10.7	16.9	0.4%
COP	378	552	14.9	12.8	-1.2%	**ORCL**	197	592.7	13.5	12.9	-3.8%
COST	171	554.3	9.9	16.2	1.9%	**OXY**	105	579.1	11.9	14.8	0.0%
CSCO	328	588.2	13.2	12.9	-1.2%	**PCLN**	130	539.1	9.7	14.9	-4.3%
CVS	138	609.7	10	17.4	-1.7%	**PEP**	215	632.3	12.3	16.5	0.3%
CVX	426	582	16	12.7	-2.6%	**PFE**	171	615.3	14.4	14.6	-4.2%

Ticker	No. articles	Article length (mean)	Number of negative words (mean)	Number of positive words (mean)	Quarterly abnormal return (median)	Ticker	No. articles	Article length (mean)	Number of negative words (mean)	Number of positive words (mean)	Quarterly abnormal return (median)
DD	97	576.9	17	13.1	-1.9%	**PG**	321	620.4	16.3	17.2	0.5%
DIS	494	589.5	12.6	15.9	1.5%	**PM**	279	573.9	16.2	14.7	0.6%
DOW	93	596.4	12.9	16.6	0.5%	**QCOM**	340	586.8	14.8	13.6	-2.9%
DUK	99	660.7	12.2	18.3	3.9%	**RTN**	51	557.2	11.4	13.9	-0.5%
EMR	112	660.4	18.1	15.9	-3.8%	**SBUX**	422	544.5	10	16.4	0.3%
EXC	63	662.2	18.7	16.7	-1.0%	**SLB**	178	564.4	16.8	15.6	2.4%
F	682	510.9	14	14.5	1.0%	**SO**	82	621.4	13.7	15	1.1%
FB	753	564.4	11.3	12.4	-1.4%	**T**	624	569.1	11.9	12.9	1.5%
FDX	151	517.3	10.8	14.6	2.0%	**TGT**	325	600.3	18.3	14.5	-0.3%
FOX	80	524.5	10.6	13.5	-0.1%	**TWX**	132	528.5	11	12.1	3.9%
GD	32	582.3	9.9	14.1	2.4%	**TXN**	62	574.4	9.7	17	2.4%
GE	813	548	12.6	13.4	-2.2%	**UNH**	48	532	9.6	13.2	4.0%
GILD	659	718.4	17.5	15.8	-0.2%	**UNP**	203	623.3	15.7	17.3	2.7%
GM	432	538.5	19.4	12.9	0.5%	**UPS**	83	642.4	14.1	18.3	0.1%
GOOG	638	570.5	12.9	12.2	-2.0%	**USB**	50	604.5	13.6	17.5	-0.5%
GS	123	537.2	16.7	11.7	3.9%	**UTX**	98	606.6	12.1	15.3	1.7%
HAL	218	559.5	20	12.9	6.6%	**V**	171	589.6	11.5	16.3	-1.7%
HD	186	498.3	9.6	17.4	-0.1%	**VZ**	314	570.9	11.9	13.2	0.2%
HON	110	528.9	10.9	17.3	-1.7%	**WBA**	144	547.1	10	17.8	-2.0%
IBM	578	646.4	17.8	14.1	3.2%	**WFC**	335	567.4	19.1	13.5	-1.3%
INTC	805	597.2	13.9	13.5	1.0%	**WMT**	528	595.4	15.5	13.9	-2.1%
JNJ	359	610.8	13.1	14.9	2.1%	**XOM**	491	623.4	17.9	14.2	-0.1%