Seeking Alpha: More Sophisticated Than Meets the Eye

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Abstract

This study investigates the information content of articles from the crowd-sourced investment advice platform Seeking Alpha (SA), its timeliness, and its relevance for more sophisticated investors. Textual analysis is employed to extract positive sentiment, negative sentiment, and directional sentiment contents of economic events in coding SA documents. Immediate market returns and 90-day drift returns follow the directional sentiment of SA articles, incremental to the information in the most recent earnings surprise and earning announcement return. This information is new to the stock and options market, suggesting it is timely for both retail and more sophisticated investors. Option volatility spread and volatility skew changes follow publication of SA articles. In addition, SA information seems incremental to common risk factors. A hedged portfolio strategy buying the most positive SA sentiment firms and selling the most negative earns positive monthly returns after controlling for size, market-to-book, and momentum.

Keywords: Seeking Alpha, social media, textual analysis, options market

1. Introduction

With the universality of the internet, more channels of communication and information dissemination have emerged. This era of investor democratization also raises new questions about social media as a source of value relevant firm information for capital market participants. Some consider social media as more of an information dissemination facilitator (Blankespoor et al. [2014], Jung et al. [2018]) while others claim it can be the source for new information (Tang [2018], Huang et al. [2020]). We investigate one such type of social media that caters to the investment community – Seeking Alpha. Seeking Alpha was created in 2004, and as the name suggests, was designed as a forum where the investment community would be able to post their stock recommendations and alpha-generating ideas. It has evolved into a multi-functional platform offering a multitude of tools for the user, including reading investment advice articles, viewing earnings call transcripts, monitoring stocks and bonds, and discussing investment strategies.

Earlier research on Seeking Alpha has found that Seeking Alpha has informational value for returns (Chen et al. [2014], Campbell et al. [2019], Drake et al. [2023]). However, their analyses focus on either the average Loughran and McDonald [2011] word sentiment revealed by all Seeking Alpha articles about a firm in a period or the number of articles. We slightly differ in our methodology and study Seeking Alpha information on an article-by-article basis. We consider article sentiment also important to explore, as an article scoring mimics how human readers would consume Seeking Alpha information.

We explore the research question whether Seeking Alpha article sentiment provides directional information for returns that is incremental to other publicly available sources of information. To categorize article sentiment, we use Natural Language Processing (NLP) textual analysis to code phrases that contain positive and negative business information. These phrases cover more than 50 business events types, such as product announcements, mergers and acquisitions and workforce. We then assign a net score, *READER SENTIMENT*, based on the difference between the positive and negative mentions. Using Fama-MacBeth regressions, we test the relationship between the rank of *READER SENTIMENT*, *SASCORE*, and excess returns controlling for size, market-to-book, and momentum. We find that the *SASCORE* of Seeking Alpha articles positively correlates with immediate [-1, +1] stock market returns, after controlling for the information released in the prior earnings announcement and earnings surprise. We also document incremental explanatory power of *SASCORE* for [+2, +90] drift returns after controlling for earnings news and earnings surprise. In reference to the contradicting evidence of Chen et al. [2014] and Campbell et al. [2019] who find significant correlation and no correlation, respectively, between Seeking Alpha sentiment and [+3, +60] returns, our results support Chen et al. [2014]. There is a persistent correlation between Seeking Alpha sentiment and returns without reversal. Seeking Alpha sentiment seems to be informative for future stock returns.

We further investigate characteristics of Seeking Alpha information. Informed trading (Amin and Lee [1997], Roll et al. [2010], Pan and Poteshman [2006], Hu [2014], Kacperczyk and Pagnotta [2019], Lei et al. [2020]) and price discovery (Chakravarty et al. [2004]) also happens in the options market. We explore if Seeking Alpha sentiment is also value relevant for options market measures. The measures we use are the options volatility spread and skew. A more positive volatility spread has been shown to correlate with good news (Cremers and Weinbaum [2010], Jin et al. [2012], Han and Li [2021], Atilgan [2014], Lei et al. [2020], Hayunga and Lung [2014], Lin and Lu [2015]) while a higher volatility skew is an indicator of bad news (Xing et al. [2010], Hayunga and Lung [2014], Lin and Lu [2015]). Changes in options market volatility spread and volatility skew correlate positively and negatively, respectively, with the net NLP tone *SASCORE* in Seeking Alpha articles, incremental to the earnings news and earnings surprise. Together, the stock and options market results suggest Seeking Alpha information rates highly on the timeliness factor. Seeking Alpha publication leads changes in both the stock and options markets. In additional analyses, we document that a hedged Seeking Alpha portfolio strategy that buys the most positive Seeking Alpha *SASCORE* firms and sells the most negative Seeking Alpha *SASCORE* firms generates approximately 50 basis points return per month after controlling for risk factors including size, market-to-book, and momentum.

The first contribution this study makes to the literature is that to the best of our knowledge, this is the first paper that looks at the options market consequences of Seeking Alpha. In addition to prior studies focusing on stock market reactions (Chen et al. [2014], Farrell et al. [2022], Campbell et al. [2019], Drake et al. [2023], Gomez et al. [2022]), we find responses to Seeking Alpha sentiment in the options market where experienced capital market participants trade such as investment banks (Lowry et al. [2019]), those who receive early information from analysts (Lin and Lu [2015]), and those who seek higher levels of leverage (Pan and Poteshman [2006]). The option volatility spread and skew changes in the direction of Seeking Alpha sentiment after publication of article, suggesting Seeking Alpha information is value-relevant for options trading. Extant research has mostly focused on gains to retail investors from Seeking Alpha (Farrell et al. [2022]; Gomez et al. [2022]). We show that Seeking Alpha sentiment leads both the stock and options markets, where informed trading and price discovery exist (Chakravarty et al. [2004]), Amin and Lee [1997], Roll et al. [2010], Pan and Poteshman [2006], Hu [2014], Kacperczyk and Pagnotta [2019], Lei et al. [2020]. Therefore, Seeking Alpha sentiment seems to reflect information before most of the market reacts. It is also timely for more sophisticated investors.

This study's second contribution is that it provides insight into individual investors' information but disentangles it from their trading activities. It adds to the debate whether individual investors have unique information about firms (Ivković et al. [2009], Ivković and Weisbenner [2005], Boehmer et al. [2021]), or have limited information and exist mostly to provide liquidity to their counterparts such as institutions (Lakonishok et al. [2006], Bauer et al. [2009], Barber et al. [2008], Barber and Odean [2000], Kaniel et al. [2008], Seasholes and Zhu [2010], Grinblatt and Keloharju [2000]). In accordance with Barber and Odean [2000], we show that individual investors' trading does not equate to their information. The aggregate knowledge from a social media platform, of which more than half originate from individual writers (Campbell et al. [2019])[1] is informative for both the stock and options markets. A hedged portfolio strategy buying the best Seeking Alpha-rated firms and selling the worst Seeking Alpha-rated firms also earns a significant 50 basis point per month return. It may be the frequent trading of individuals or their overconfidence (Barber and Odean [2000], Dorn and Huberman [2005]) that renders their trading unprofitable.

The remainder of the paper is organized as follows; Section 2 gives a brief overview of the Seeking Alpha platform, then outlines what has already been studied in the literature about Seeking Alpha and how this paper extends it. Section 3 describes the data and the textual analysis methodology used. Section 4 explains the methodology and results including the price informativeness of Seeking Alpha articles for the stock and options market, relevance of Seeking

[1] Campbell et al. [2019] tabulate that of all the articles published on Seeking Alpha between 2004 and July 2015, 56% of the author aliases are individuals, 16% are companies, and the rest are anonymous.

Alpha around the earnings announcement, and Seeking Alpha sentiment used as a hedged portfolio strategy. Finally, Section 5 provides a concluding discussion.

2. Literature Review and Background

2.1 Institutional Background

Owing to the rise of computers and the internet, investors are able to search and obtain more varied firm information. They need not rely on firm narratives that are either scheduled, such as earnings announcements, or voluntary disclosures, such as management forecasts. With the proliferation of computers, social media has emerged as an information source for capital market participants. Recent studies on social media have found it to contain information that is value-relevant for investors. Jame et al. [2016] have shown that crowd-sourced earnings forecasts from the online platform Estimize have incremental information content over traditional analyst forecasts from the IBES database for predicting next-period EPS. Tang [2018] finds that product information on Twitter correlates with firm sales. Tweets posted on Twitter in a short window before the earnings announcements have relevance for the earning surprise and earnings announcement return (Bartov et al. [2018]). Blankespoor et al. [2014] document that Twitter also helps disseminate firm information that has been published, thereby lowering bid ask spreads and decreasing information asymmetry. Al Guindy [2021] finds that firms that have a Twitter presence enjoy lower costs of capital, corroborating the argument that Twitter may lower information asymmetry. Research has also shown that employee reviews on firms from the site, Glassdoor.com, can reveal additional information about sales, operating income, earnings surprises (Hales et al. [2018]), as well as earnings announcement returns and return on assets (Huang et al. [2020]).

While there are many social media channels for information dissemination and search, this paper focuses on information from Seeking Alpha, which is a crowd-sourced investment advice online platform. As the name suggests, Seeking Alpha started as a forum in 2004 for users to post their stock “alpha” ideas, but has gradually evolved into a multi-functional site. On the site, users are able to browse investment advice articles, read earnings conference call transcripts, publish their interpretations of public reports and announcements, and monitor a plethora of investment products. Seeking alpha differs from other social media types in several ways. First, Seeking Alpha information pieces are longer in length. Although the community may use Seeking Alpha for other purposes such as to view earnings conference call transcripts, we focus on the repository of contributor-generated Seeking Alpha articles. The articles may be of varying degrees of writer sophistication. Some are similar to analyst reports, some seem to be written by experts and contain technical language of the industry, and others read like major news outlet reports. Two examples of Seeking Alpha articles are included in Appendix 3. The Methodology section describes the content of the two articles in detail and uses them show how sentiment is calculated. Seeking Alpha articles are similar in length to news in traditional media such as the *Wall Street Journal*. This is in contrast to Twitter which has a limit of 280 characters[2] and Estimize which consists of a monetary estimate of earnings. Glassdoor.com allows more discretion for contributors when they post employer reviews, but a quick survey through the site shows most reviews are less than 200 words in length. Moreover, prior research has focused on reviews of firm business outlook (Hales et al. [2018], Huang et al. [2020]), which is a Likert scale item.

[2] https://developer.twitter.com/en/docs/counting-characters

Seeking Alpha is also different from other types of social media as it specializes in providing investment advice and all published articles are screened by an editorial board. Glassdoor.com and Estimize are also business social media. However, they provide employer reviews and earnings forecasts, respectively. Twitter is general interest social media, posts on the platform include a variety of topics in addition to business including sports, entertainment, and politics. To the best of our knowledge, Seeking Alpha is the only platform that uses an editorial board to review articles before publication. In their own words, this is to screen articles for "clarity, consistency and impact"[3]. Estimize also uses a screening tool, but it does not seem to check for content. Instead, it is more targeted towards filtering away earning estimates that are not in a realistic range[4]. Having an editorial board does not ensure articles contain accurate information or that articles are free from falsification. Clarke et al. [2020] find that the editorial board does not always distinguish between articles authored by individuals who were being compensated by companies for rating them favorably and articles with no conflict of interest. However, the presence of an editorial board is an additional check on the relevance of firm information, compared to other social media without these checks.

2.2 Price Informativeness of Seeking Alpha

As Seeking Alpha is different than other social media, the first question we ask is whether the firm information in Seeking Alpha articles is value-relevant to capital market participants. Seeking Alpha does not require any qualifications for individuals to become a Seeking Alpha article contributor. This is different than fund managers (Chevalier and Ellison [2002], Kacperczyk et al. [2014], Jagannathan et al. [2010]) and star analysts (Stickel [1992],

[3] https://about.seekingalpha.com/editorial-principles
[4] https://www.estimize.com/faq

Clement [1999]) who also provide investment advice but have more requirements and tests for qualification into the profession. Seeking Alpha may have many individual investors serving as contributors. According to Barber and Odean [2000] and Grinblatt and Keloharju [2000], individual investors, on average, underperform compared to institutional investors in equity markets. Bauer et al. [2009] also show that individual investors generate losses on average in the options market. Therefore, if Seeking Alpha articles are mostly authored by individual investors with no other qualifications, the advice in them may contain limited information content.

In addition, it is not clear what motivates individuals and investment organizations to write Seeking Alpha articles. If the information was highly relevant to the firm and required substantial costs in its acquisition, in the model of Grossman and Stiglitz [1980] the acquirer should trade on the information directly rather than disclose it publicly. Seeking Alpha does not seem to offer substantial monetary compensation to render the disclosure decision highly profitable. As an example, in an article in 2014[5], Seeking Alpha discloses it pays contributors $270,000 in total per month, and 2,454 contributors have been active in the last six months. As a conservative estimate[6], each contributor would be paid approximately $340 per month, which does not seem to be a substantial amount. An argument in favor of the decision to disclose on Seeking Alpha could be that the writer may have already taken advantage of market timing to trade and discloses the information shortly after, which has been observed in the market for another type of disclosure – shareholder activism (Norli et al. [2015], Collin-Dufresne and Fos [2015]). Moreover, the writer may need to publicize the information to receive even greater gains as in the case of short sellers (Ljunqvist and Qian [2016]).

[5] https://seekingalpha.com/article/2134803-how-much-does-seeking-alpha-pay-its-contributors

[6] We assume each contributor posts at least in two of the six months, which would imply approximately 800 active contributors per month.

Finally, one may be concerned about the speed at which Seeking Alpha reflects firm information. If Seeking Alpha's primary role is to widely distribute news that has already been published elsewhere, i.e., stale news, then price discovery effects may be limited. In prior research on traditional media, the role of media in creating as opposed to just disseminating information is contingent on the degree of staleness, i.e., the lack of new information presented in the article (Bushee et al. [2010], Blankespoor et al. [2018], Guest [2021], Drake et al. [2014]). Guest [2021] shows the higher the degree of editorial content, in other words the deviation from repetition of already known analyst forecasts, returns, and earnings numbers, the higher the market response. It is an empirical question whether Seeking Alpha articles offer new and differentiated information, one that we aim to quantify using textual analysis. There is also mixed evidence about whether social media can be the source for new information (Tang [2018], Huang et al. [2020]) or primarily serves as a dissemination tool (Blankespoor et al. [2014], Jung et al. [2018]).

Literature on Seeking Alpha articles have also found them to be relevant for returns, but use either sentiment averaged over all articles for a firm in a specified period or the number of articles published. Chen et al. [2014] find that the more negative the sentiment in Seeking Alpha articles about a firm the more negative the returns in the next 60 days and the earnings surprise. The negative sentiment measure is calculated as the number of negative words in all articles about a firm in a particular period divided by the total number of words in all articles about a firm in a particular period. They do not study the role of positive words in Seeking Alpha articles. Campbell et al. [2019] show that more positive (negative) Seeking Alpha article sentiment is correlated with more positive (negative) day [0, +1] firm returns. They use a similar methodology to Chen et al. [2014] in calculating sentiment. Specifically, positive (negative) sentiment is calculated as the fraction of positive (negative) words in all articles for a firm on a single day. Drake et al. [2023] document that the publication of at least one Seeking Alpha article in the week before sell-side analyst reports subsumes some of the market reaction of the analyst reports, suggesting some analyst information is pre-empted in Seeking Alpha articles. They do not examine the sentiment of the Seeking Alpha articles except to test if they agree or disagree with the sell-side analyst report.

We consider it also important to examine the net positive minus negative sentiment on an article basis. An article-by-article evaluation of the firm may more closely emulate how Seeking Alpha articles are used by the investment community in reality[7]. Moreover, it is not a given that those who trade on Seeking Alpha information will read all articles about a firm in a day. This seems to be the underlying assumption in Chen et al. [2014] and Campbell et al. [2019] since the score for a firm is averaged over all articles published about a firm in a day. As an example of the number of articles published, four articles were submitted on Tesla for April 25, 2017 and another four articles were published on April 26, 2017. We investigate the relationship that Seeking Alpha article sentiment has with both immediate and drift returns, calculated as [-1,+1] of publication date and [+2, +90] of publication date, respectively. In Campbell et al. [2019], drift returns are not correlated with positive minus negative Seeking Alpha sentiment, in contrast to Chen et al. [2014] who find that drift returns are correlated with negative Seeking Alpha sentiment. One explanation may be that Loughran and McDonald [2011] word lists are less

[7] Article by article consumption seems to be the type of consumption envisioned by the Seeking Alpha management team, as the fee structure is also based on free access up to a certain amount of articles, and paid subscriptions after the article limit: https://seekingalpha.com/article/4396836-important-update-for-seeking-alpha-users

precise at capturing the positive words (Loughran and Mcdonald [2016]), which Campbell et al. [2019] use in addition to negative words.

In this study, we use a textual analysis methodology based on NLP that includes recognition of business events to explore the relationship between Seeking Alpha article sentiment and immediate and drift returns. It is an empirical question whether Seeking Alpha article sentiment has a relationship with immediate and drift returns. Therefore, we state our first hypothesis in the null form: This forms the basis of our first research question:

H1a: Seeking Alpha article sentiment does not correlate with immediate [-1, +1] firm returns.

H1b: Seeking Alpha article sentiment does not correlate with drift [+2, +90] firm returns.

2.3 Seeking Alpha Information in the Options Market

Prior research has focused on Seeking Alpha's relevance for retail traders and investors (Farrell et al. [2022], Gomez et al. [2022]). Farrell et al. [2022] find more retail trading in the hours immediately after article publication and retail order imbalances in the direction of the article information. Article information is expressed by either article Loughran and McDonald [2011] tone or disclosure of position in the stock discussed. Gomez et al. [2022] document that the publication of Seeking Alpha articles helps reduce information asymmetry, proxied by spikes in bid-ask spreads immediately after the earnings announcement.

We ask if Seeking Alpha could also be useful for more sophisticated investors and more timely reflection of information. Although one does not know the identity of the article writers on this anonymous platform, prior research has shown that many users seem to be experienced capital market participants and still derive value from Seeking Alpha. Levy et al. [2023] explore a different function of Seeking Alpha – the ability to create a watchlist to monitor stock patterns.

They tabulate the profiles of users that create watchlists and find 14% are executives, 24% are full-time investors, and 42% are finance professionals. Drake et al. [2023] also document that the market reacts less to sell-side analyst information if a Seeking Alpha has been published before it. They take that as evidence Seeking Alpha reflects some information at an earlier date than sophisticated analysts, although the timeliness of Seeking Alpha disappears for firms with low retail trading.

In the options market, there is documented presence of price discovery (Chakravarty et al. [2004]) and informed trading (Amin and Lee [1997], Roll et al. [2010], Pan and Poteshman [2006], Hu [2014], Kacperczyk and Pagnotta [2019], Lei et al. [2020]). The level of informational activity in the options markets may be attributed to the leverage offered (Black [1975], Ge et al. [2016]) or short-sell constraints diverting bad news to the options markets (Diamond and Verrecchia [1987], Johnson and So [2012], Xing et al. [2010]). Prior literature has shown that options market measures is a forerunner of stock returns (Amin and Lee [1997], Cremers and Weinbaum [2010], Xing et al. [2010], Jin et al. [2014], Ge et al. [2016], Hu [2014], Lin and Lu [2015], Han and Li [2021], Bollerslev et al. [2009], Atilgan [2014], Lei et al. [2020]). Particularly, the options market seems to have predictive ability before corporate news events including earning announcements (Roll et al. [2010], Jin et al. [2012], Atilgan [2014], Lei et al. [2020]), mergers and acquisitions (Lowry et al. [2019]), analyst forecasts (Hayunga and Lung [2014], Lin and Lu [2015]), and other unscheduled events (Jin et al. [2012]).

To test the timeliness of Seeking Alpha, we explore whether there is an option market response around the publication of Seeking Alpha articles. If Seeking Alpha articles are timely, their publication should coincide with options market measures in the direction of the revealed sentiment. If Seeking Alpha articles are also shown to be timely in the stock return tests, the analysis then shows that Seeking Alpha information is not stale. It is decision relevant as it precedes movements in both the stock and options markets. Recent research has shown that the option implied volatility contains information relevant for future returns (Cremers and Weinbaum [2010], Xing et al. [2010], Jin et al. [2012], Atilgan [2014], Hayunga and Lung [2014], Lin and Lu [2015], Kacperczyk and Pagnotta [2019], Lei et al. [2020], Han and Li [2021]). As such, the two options market indicators we consider are the option volatility spread and the option volatility skew, both are calculated using implied volatility.

Prior research has found the option volatility spread to contain information (Cremers and Weinbaum [2010], Jin et al. [2012], Han and Li [2021], Atilgan [2014], Lei et al. [2020], Hayunga and Lung [2014], Lin and Lu [2015]). Cremers and Weinbaum [2010] show that the volatility spread predicts future returns. The volatility spread's directional predictive ability for earnings announcement returns (Jin et al. [2012], Atilgan [2014]; Lei et al. [2020]), macroeconomic conditions (Han and Li [2021]), analyst forecasts (Hayunga and Lung [2014], Lin and Lu [2015]), and unscheduled event returns which include a sample of client and product news, management changes, and litigation (Jin et al. [2012]). Distinct from the research that focus on volatility spread's explanatory power before events, Jin et al. [2012] also find volatility spread to correlate with stock returns after the unscheduled events sample, suggesting option traders have superior ability to process information when the news is unanticipated.

The second options market measure we use is the option volatility skew. Bates [1991] first documented the relatively expensiveness of out-of-the-money (OTM) puts before the 1987 stock market crash and connected it to option traders' negative perceptions of the market. Xing et al. [2010] extend the volatility skew measure to individual stocks and find the implied volatility of OTM puts relative to at-the-money (ATM) calls is correlated with stock underperformance.

Bollen and Whaley [2004] find this difference in implied volatilities to be informationally driven. With the arrival of positive news, prices and implied volatilities of calls increase relative to puts; with the arrival of negative news, prices and implied volatilities of puts increase relative to calls. Jin et al. [2012] observe volatility skew predicts returns of both scheduled and unscheduled announcements. Volatility skew also predicts analyst news and returns around analyst news days (Hayunga and Lung [2014], Lin and Lu [2015]).

Whether option volatility spread and skew correlate with sentiment in Seeking Alpha articles depends on whether there is new information in these publications. The timing of information arrival is also important. Options market responses would only be observed in the case where traders have not yet fully incorporated such information. We state our hypotheses in the null form:

H2a: Seeking Alpha article sentiment does not correlate with changes in option volatility spread.

H2b: Seeking Alpha article sentiment does not correlate with changes in option volatility skew.

3. Data and Methodology

3.1 Methodology

Using textual analysis (Loughran and McDonald [2011], Li [2008]), we code sentences in the article in two steps. In the first coding step, the natural language processing (NLP) algorithm scans the entire article on a sentence basis looking for parts of the sentence to code for positive and negative business events. In this step, the coded parts are longer on average than the second step, as business events require more words or phrases to be described accurately. The NLP algorithm has about 3,000 rules that it recognizes and categorizes as positive and negative business events. These rules also recognize and differentiate parts-of-speech such as noun, adjective, verb, adverb, etc., in a sentence. The 3,000 rules are classified into more than 50 different events, such as product announcements, mergers and acquisitions and workforce.

In Appendix 2, we provide some examples of the types of positive and negative business events that are coded from Seeking Alpha articles in the sample. In the first example, there is a rule under the mergers and acquisitions event type that captures parts of a sentence with the adjective "potential" and the noun "acquisition". The word "potential" determines the polarity of the business event and prevents a similar acquisition phrase with a different adjective such as "forced" being included as a positive business event. Another advantage of NLP is that there can be additional modifiers between keywords in the rules. This allows more varied combinations of words in a sentence to be captured with the correct event type and sentiment. In the mergers and acquisition example, there is a company name, Alibaba, in between "potential" and "acquisition". However, in the NLP schema, the adjective "potential" is still referring to the "acquisition" and neither "spin-off" in the earlier part of the sentence nor "likelihood" in the latter part. Therefore, the NLP algorithm can recognize the completion of the rule and increase the count for positive merger and acquisition event. Similarly, in the third example, there are many words between the verb "secure" and noun "contract". Since the NLP algorithm recognizes "long-term", "fuel-cell", and "supply" are adjective modifiers of "contract", it increases the counter for positive contract event.

The second example illustrates NLP's ability over a word-based approach to capture polarity more precisely. The keywords in this rule are the noun "default" and the adjective "rising". The rule also includes a few more synonyms of "rising" such as "increasing", but the content is the same. The adjective must mean an increase in the "default". In the case of a word-based approach, "default" is a negative-sentiment word (Loughran and McDonald [2011]). In some cases, it may be preceded by another word such as "reduced", and "reduced defaults" should change the polarity of the mention from negative to positive. NLP makes these types of refined classifications possible. In the rule mentioned above, the NLP algorithm checks for a modifier signifying increases before the noun "default", and only when it finds an adjective related to "increase" will it increase the counter for negative default event.

In the second coding step, the algorithm scans the entire article again to capture any words and phrases that may represent general sentiment. The NLP algorithm also has sets of rules that categorize financial results, earnings guidance, and words from the Loughran and McDonald [2011] word lists. Examples of sentiment mentions not associated with business events could be "earnings increased", or "impair" (Loughran and McDonald [2011]). These mentions are coded separately for positive and negative sentiment, and referred to as general sentiment.

For each article, a Seeking Alpha document score coded using NLP that approximates a human reader's sentiment, *READER SENTIMENT* is created. It is calculated as the standardized net sentiment of the document. We subtract the positive mentions from the negative mentions and standardize by the total mentions (positive and negative mentions). The positive mentions are calculated as an aggregate of positive business event mentions and positive general sentiment mentions, where business event mentions are weighted more heavily than positive general sentiment mentions. The negative mentions are aggregated similarly using negative business event and general sentiment mentions. *READER SENTIMENT* takes on values between -1 and +1 where a positive article would have a score (0,1) and a negative article would have a score [-1,0]:

$$\frac{f(Positive\ Score_{General}, Positive\ Score_{Event}) - f(Negative\ Score_{General}, Negative\ Score_{Event})}{f(Positive\ Score_{General}, Positive\ Score_{Event}) + f(Negative\ Score_{General}, Negative\ Score_{Event})}$$

where $f(x)$ is a weighting scheme that assigns more weight to event sentiment mentions than general sentiment mentions.

In Appendix 3, we include two examples of how NLP extracts the sentiment from Seeking Alpha articles. The first example was published on August 16, 2013, and describes the toy manufacturer Mattel's market position compared to its competitors. The writer acknowledges that the market for dolls has been in a slump. However, the author predicts that the downward trend will reverse soon. Moreover, within this industry, the author considers Mattel the industry leader. Mattel not only learned from the successes of competitor, MGA Entertainment's, and launched its own line of unconventional dolls, it is also the manufacturer of the top three doll category brands by market share at the time of writing. MGA Entertainment owns the top fourth and top fifth brands. This article seems to praise the positives of Mattel more than criticizing the negatives, which is closely captured by the *READER SENTIMENT* score of 0.6875. In contrast, the Loughran and McDonald [2011] word list tone rates the article as -0.091, a net negative score. The second example was published on August 20, 2015, and offers a short analysis on a firm that was watched closely by the investment community at the time, Shake Shack. When the article was published, Shake Shack was just about half a year past its IPO date. The article negatively assesses Shake Shack's growth plans. The author thinks Shake Shack is over-ambitious with its plans to increase locations and expand internationally. Shake Shack operates on a franchise-model, and it will not be able to manage its growth and maintain quality control. The author is also not optimistic because of insider selling shortly after IPO. This article received a *READER SENTIMENT* score of -0.3158. In this case, it is corroborated by the Loughran and McDonald [2011] tone of -0.333. This is in accordance with Loughran and McDonald [2011, 2016] that excerpts with negative sentiment are often easier for deriving meaning than excerpts with positive sentiment when using word lists. The English language convention of including a negative word in front of a positive word to denote negation makes counting positive words (in addition to negative words) noisier than (just) counting negative words (Loughran and McDonald [2016]).

The Seeking Alpha sentiment measure we create, *READER SENTIMENT*, and the data expand on earlier findings about the type and precision of information extracted from the Seeking Alpha articles. Chen et al. [2014] report on only negative sentiment extracted from articles following the Loughran and McDonald [2011] word list. Firstly, *READER SENTIMENT* is calculated using both positive and negative mentions in Seeking Alpha articles. This methodology informs on the question of whether positive sentiment information may also be value relevant for firms, in addition to negative sentiment information. Secondly, *READER SENTIMENT* captures mentions in the Loughran and McDonald [2011] word list but also goes beyond it with thousands of rules that measure positive and negative business events as well as economic-context sentiment. We employ NLP to capture more precisely the business events and economic context discussed in Seeking Alpha articles. Thirdly, we are interested in the persistence of Seeking Alpha information. In consideration of possible news sentiment reversals (Tetlock [2007]), we extend the measurement period for the effect of Seeking Alpha articles to 3 months from the 2-week interval (Drake et al. [2023]; Farrell et al. [2022]).

3.2 Data

We compile all Seeking Alpha articles written from the establishment of the site, i.e., 2004, through October 1, 2018. In total, 350,095 articles are included covering 5,635 companies. One article may be coded as relating to multiple companies if it is a comparison piece or industry analysis. Returns data are from CRSP and could be matched to all companies. We use abnormal returns for the analysis. Since the goal is to investigate the incremental information of Seeking Alpha articles, the abnormal firm return is the residual return after considering the effects of common risk factors such as size, market-to-book, and momentum. To achieve this, abnormal return is calculated as the difference between the firm return and a matched portfolio sorted on size, market-to-book, and momentum, 27 portfolios are used with 3 size ranks, 3 market-to-book ranks, and 3 momentum ranks. Earnings surprise data and announcement returns are gathered for 5,267 and 5,635 companies, respectively. They are collected from IBES and CRSP. Finally, we collect options data from OptionMetrics.

4. Results

4.1 Descriptive Statistics

Table 1 Panel A presents descriptive statistics on firms that are mentioned in Seeking Alpha articles. Descriptions of all variables used in the analysis are included in Appendix 1. Seeking Alpha firms appear to be bigger in size (log mean = 7.766), have higher market-to-book (mean = 7.966), and greater analyst following (mean = 8.615) than the typical Compustat firm (Chen et al. [2014], Drake et al. [2023]). These firms have volatility spread and skew, *VOLSPREAD* and *VOLSKEW* respectively, comparable to the average firm which have traded options (Jin et al. [2012]). As expected, the volatility spread is negative (value = -0.011) as the options market incorporates more negative news overall because of the presence of short-sale constrained firms (Figlewski and Webb [1993]).

Table 1 Panel B shows descriptive statistics on an article basis. The regression results use observations on an article basis. This is different than observations on a firm basis as there could be multiple articles published about a firm on a single day[8]. The mean immediate return, *IMMEDIATE RET*, and drift return, *DRIFT RET*, of Seeking Alpha articles is not statistically different from zero. This is unsurprising, as the observations include both positive and negative articles. The average score of a Seeking Alpha article, *READER SENTIMENT*, is positive-toned (mean=0.138, median=0.158). However, once ranked on a monthly basis through the variable *SASCORE*, the mean is zero and the median is -0.056. The interpretation is that although the average article is more positive toned than negative toned, when ranked on a monthly basis, the average article is ranked between the 5th and 6th deciles[9]. Mean change in volatility spread, *CHG VOLSPREAD*, and mean change in volatility skew, *CHG VOLSKEW*, is also not statistically different from zero.

We also explore the timing of Seeking Alpha articles compared to the scheduled public earnings announcement disclosure. The mean and median number of days between earnings announcement and any published Seeking Alpha article, *DAY DIFF*, is 42.4 and 41, respectively. Figure 1 shows the number of articles published by days from earnings announcement. There are more articles published around the earnings announcement, particularly immediately after the announcement. Even outside the earnings announcement period, there is still substantial Seeking Alpha activity. Articles are continuously published away from the earnings announcement date. Specifically, Publication interest appears to return to normal levels approximately 2 weeks after the earnings announcement date. In this context, the mean of 42.4 days between Seeking Alpha

[8] An article could also mention multiple firms, especially in comparison-type articles. However, single articles that mention more than five firms are eliminated from the sample. The assumption is that in these articles, there is not enough information attributable to each individual firm mentioned.
[9] *SASCORE* is calculated the decile rank of the Seeking Alpha article, divided by 9 and then subtracted by 0.5. *SASCORE* takes on values between -0.5 and +0.5. See Appendix 1 for detailed description.

article and earnings announcement seems reasonable. It is slightly shorter than halfway through the quarter, 45 days, owing to more articles published soon after announcements.

In Table 1 Panel C, we sort the Seeking Alpha document sentiment, *READER SENTIMENT*, into decile ranks. The immediate return is monotonically increasing in decile ranks. The drift return and change in spread is also generally increasing with higher ranks. The results suggest the more positive the information revealed in the Seeking Alpha article, the more positive the immediate, drift return, and the option volatility spread. There seems to be a positive relationship between Seeking Alpha information and stock and option pricing. The change in skew corroborates this finding. The negative change in option volatility skew is higher in magnitude in the top half of decile ranks than the lower half, meaning as the Seeking Alpha information becomes more positive, the volatility skew also becomes less negative.

4.2 Seeking Alpha Information and Returns

To explore whether Seeking Alpha articles contain useful information for explaining returns, we compare the scaled document sentiment score, *READER SENTIMENT*, for each Seeking Alpha article to all other Seeking Alpha articles published in the month. We then calculate the decile rank of each Seeking Alpha article, *SASCORE*. From the rank of each Seeking Alpha article, we divide by 9 (decile ranks are from 0 to 9) and subtract by 0.5 to obtain the standardized rank between -0.5 and +0.5[10]. Since we collect Seeking Alpha articles published from 2004 to 2018 and articles written on many firms, the data is both cross-sectional and time-series. To produce estimates and standard errors that are corrected for cross-sectional correlation over different years (i.e., if all firms were rated poorly in 2005 because of instability from

[10] This is for ease of economic interpretation. The coefficient on the Seeking Alpha score in a regression of returns on Seeking Alpha score can be interpreted as the returns to a hedged portfolio.

Hurricane Katrina), we follow a Fama-MacBeth regressions specification. Specifically, we regress returns on the standardized Seeking Alpha rank for each year-month:

$$R_{[-1,+1]or[+2,+90]} = \alpha + \beta_1 SASCORE + \varepsilon$$

Then, the cross-sectional coefficient is averaged across months. Two types of returns are included in the analysis. The first is the immediate returns [-1, +1] around publication date. The second return is the [+2, +90] drift, which observes returns behavior in the longer period after publication. It is useful in identifying noise in the immediate period if reversals occur in the 90-day period. We consider the drift return to be more informative and value relevant as it measures Seeking Alpha's persistent price impact until the next quarterly update in 90 days. As mentioned in the Data section, we are interested in exploring Seeking Alpha's information about firm value beyond the known risk factors. As such, immediate and drift returns are abnormal returns calculated as the difference between the firm return and a similar portfolio matched on size, market-to-book, and momentum. Using this method, correlation between *SASCORE* and returns suggests articles contain incremental information about returns, beyond information about size, market-to-book, or momentum factors.

Table 2 Panels A and B show that Seeking Alpha sentiment information has significant explanatory power for both immediate and drift returns (immediate coefficient = 0.0210767, t-statistic = 21.04; drift coefficient = 0.0084762, t-statistic = 3.54). Since scores are scaled between -0.5 and +0.5, the immediate and drift return translates into an economically significant 211 and 85 basis point return per month, respectively. Seeking Alpha is highly accessible to both institutional and retail investors (Farrell et al. [2022]). Therefore, we also run separate regressions for the period before, during, and after the 2009 Financial Crisis (measured as June 2008 until December 2009, which may affect results because of market unpredictability in the period). On the one hand, retail investors may be more likely to seek additional information, perhaps on Seeking Alpha, in periods of uncertainty. This would increase the value-relevance of Seeking Alpha. On the other hand, market uncertainty may cause articles to contain less information, decreasing Seeking Alpha's value relevance. We find that although information in articles significantly correlates with immediate market returns during the financial crisis (coefficient = 0.0286955, t-statistic = 10.41), they are not significantly associated with drift market returns. On the other hand, both immediate and drift returns are positively correlated with Seeking Alpha information post-Financial Crisis (immediate coefficient = 0.016249, t-statistic = 27.56; drift coefficient = 0.009326, t-statistic =4.46). This suggests that Seeking Alpha articles are not as informative about firms during the financial crisis but have recovered their informativeness since 2010.

4.3 Seeking Alpha Information and Public Disclosures

Having established the correlation between Seeking Alpha sentiment information and returns up to 90 days after issue of an article, we are more interested if Seeking Alpha provides any information not revealed through other publicly available sources. We extract earnings surprise and returns information from the public scheduled earning announcement, which is one of the most reliable sources of firm information (Foster [1977], May [1971, Jones and Litzenberger [1970]]. Then, we test if Seeking Alpha produces incremental information not contained in the earnings announcement. For this reason, we regress returns on Seeking Alpha scores and two other indicators:

$$R_{[-1,+1]or[+2,+90]} = \alpha + \beta_1 SASCORE + \beta_2 SURPRISE + \beta_3 EA\_NEWS + \varepsilon$$

where *SURPRISE* is the rank of the most recent quarter's earnings surprise and *EA NEWS* is the rank of the immediate [-1, +1] return around the most recent quarterly earnings announcement.

These two measures have been shown to predict returns behavior (Ball and Brown [1968]; Jones and Litzenberger [1970]; Foster et al. [1984]; Bernard and Thomas [1989]). Additionally, prior research has found that the information dissemination effect of traditional media (Bushee et al. [2010]), online media (Drake et al. [2017]), and Twitter (Blankespoor et al. [2017]) is particularly prevalent around the [-1, +1] day of earnings announcements. Therefore, by controlling the earnings announcement return, we also partly control the effects of other types of non-Seeking Alpha information on the return.

Table 2 Panel C shows that the direction of the market response still tracks closely with directional sentiment of Seeking Alpha in the immediate period around an article publication (coefficient = 0.0174891, t-statistic = 22.22) after controlling for earnings surprise and announcement return. For the drift return, though, the relationship with Seeking Alpha sentiment is not consistent across all periods. Table 2 Panel D outlines the analysis. After the financial crisis, which consists of the majority of the sample, both earnings surprise and announcement return contain information that correlate with subsequent returns. Most importantly, there is incremental information in Seeking Alpha sentiment for explaining drift returns (coefficient = 0.0047611, t-statistic =2.26). The interpretation of the coefficient is that after controlling for earnings surprise and announcement return, Seeking Alpha information retain a 48-basis point monthly excess return. During the financial crisis, the coefficient on *SASCORE* is negative and significant at the 10% level (coefficient = -0.0174044). The negative coefficient suggests that the initial response to Seeking Alpha information (coefficient when regressing on immediate returns = 0.0263901) experiences a partial reversal news in the subsequent 90 days. Seeking Alpha information was not as reliable during the financial crisis of 2009.

4.4 Seeking Alpha Information and Options Indicators

The prior results have established Seeking Alpha's ability to explain stock market movements. We now explore how Seeking Alpha's information content may be reflected in options indicators. We regress the volatility spread or volatility skew on the ranked Seeking Alpha score:

$$CHG\ VOLSPREAD = \alpha + \beta_1 SASCORE + \varepsilon,$$

$$CHG\ VOLSKEW = \alpha + \beta_1 SASCORE + \varepsilon,$$

where $CHG\ VOLSPREAD$ is the change in volatility spread and $CHG\ VOLSKEW$ is the change in volatility skew from before to after the article publication. Following Cremers and Weinbaum [2010], we calculate volatility spread as the weighted average of the difference in implied volatilities for call-put option pairs matched on exercise date and strike price. The weighting scheme uses the open interest of the call-put option pair with the same date and strike price over open interest of all call-put option pairs on the day. Following Jin et al. [2012] we calculate option skew as the implied volatility of OTM puts minus the implied volatility of ATM calls. OTM puts are determined by the option delta closest to -0.3 and between [-0.15, -0.45]. ATM calls are determined by the option delta closest to +0.5 and between [+0.4, +0.7]. We focus on the change in volatility skews and spreads from day [-10, -5] before article publication to day [+1, +5] after article publication. In another specification, we add controls for information in the earnings surprise and announcement return:

$$CHG\ VOLSPREAD = \alpha + \beta_1 SASCORE + \beta_2 SURPRISE + \beta_3 EA\_NEWS + \varepsilon$$

$$CHG\ VOLSKEW = \alpha + \beta_1 SASCORE + \beta_2 SURPRISE + \beta_3 EA\_NEWS + \varepsilon$$

Table 3 Panel A reports the univariate regressions and Tabel 3 Panel B reports the multivariate regressions. We will focus on Panel B, as Panel B is more useful for exploring the incremental information of Seeking Alpha articles since it controls for other public disclosure. We will also draw particular attention to the post-financial crisis period. Seeking Alpha gained traction in the investment community post-financial crisis, evidenced by the majority of observations collected from the post-financial crisis period. Additionally, general market uncertainty during the financial crisis may elicit capital market participant behavior that is different from any other period.

Table 3 Panel B show that the incidence of Seeking Alpha articles correlates with both changes in spread and changes in skew post-financial crisis. Article sentiment, *SASCORE*, is positively correlated with changes in spread (coefficient = 0.0016317, t-statistic = 3.19). The more positive the spread, the more the implied volatilities of calls increase on average relative to implied volatilities of puts. In other words, the more positive the Seeking Alpha sentiment, the more positive the expectations of firms reflected in the volatility spread (Cremers and Weinbaum [2010]). The same pattern is repeated in the volatility skew. Seeking Alpha sentiment is negatively correlated with the volatility skew (coefficient = -0.000850347, t-statistic = -1.73), which proxies for the extent options on the firm are negatively skewed. A less negative skew means the implied volatility of OTM puts decreases relative to the implied volatility of ATM calls. This can be translated into a less negative outlook on the firm (Xing et al. [2010]). The positive *SASCORE* coefficient on the regression of volatility spread and the negative *SASCORE* coefficient on the regression of volatility skew means the converse is also true. The more negative the SA sentiment, the more negative is the spread and the larger the negative skew – both indicators of negative news (Cremers and Weinbaum [2010]; Xing et al. [2010]). Economically, as the mean daily volatility spread and skew for sample firms are -0.011 and 0.026, respectively, the best and worst rated Seeking Alpha firms have a difference of 15% of the mean for volatility spread (0.0016317/0.011) and a difference of 3% of the mean for volatility skew (0.000850347/0.026).

To summarize, Table 3 suggests that Seeking Alpha information is not only incremental to earnings announcement information but also timely. Article publication date coincides with changes in options market measures, and the directional sentiment in articles corresponds with the directional change in volatility spread and volatility skew. Even though the options market is a leading indicator of firm performance (An et al. [2014]; Cremers and Weinbaum [2010]) and many sophisticated traders participate in the options market (Chakravarty et al. [2004]), Seeking Alpha information manages to be at least as timely as options market information.

4.5 Additional Analyses

4.5.1 Seeking Alpha Portfolio Strategy

We also look at the viability of Seeking Alpha articles as a valuation indicator and returns predictor from the perspective of its success as a trading strategy. We first rank firms based on their monthly Seeking Alpha sentiment, *READER SENTIMENT*[11]. Then, we form twenty portfolios for the cross-section of firms by year-month[12]. In any given month, there are about 105 firms in the top-ranked portfolio and 86 firms in the bottom-ranked portfolio (untabulated). Data is available for 161 year-months in total. On average, a hedged portfolio buying firms in the highest-ranked portfolio and selling firms in the lowest-ranked decile earns 70 basis points per

[11]For firms with multiple Seeking Alpha articles published in the month, we take the average *READER SENTIMENT* and rank the average

[12] Since ranking is completed on a year-month basis, each rank does not have the same number of observations. We rank observations into 20 groups so that there are a reasonable of observations for the highest and lowest ranked portfolios. The highest and lowest ranked portfolios each consists of approximately 10% of the observations in the total sample.

month as raw return, significant at the 5% level (Table 5 Panel A). A similar hedged strategy[13] earns 62 basis points per month abnormal return, significant at the 5% level, after adjusting for the size, market-to-book, and momentum factors (Fama and French [1993]; Carhart [1997]).

The portfolio analysis suggests information from Seeking Alpha articles contains additional explanatory power for returns over the size, market-to-book, and momentum factors. we regress monthly returns from the Seeking Alpha portfolio on the risk factors directly to explore if Seeking Alpha indeed provides incremental information. The expected return models we use are the market model, Fama and French 3 Factor (1993), and Carhart (1997)[14]:

$$R_{SA\ Hedged} - R_f = \alpha + \beta_1(R_{mkt} - R_f) + \varepsilon$$

$$R_{SA\ Hedged} - R_f = \alpha + \beta_1(R_{mkt} - R_f) + \beta_2 R_{SMB} + \beta_3 R_{HML} + \varepsilon$$

$$R_{SA\ Hedged} - R_f = \alpha + \beta_1(R_{mkt} - R_f) + \beta_2 R_{SMB} + \beta_3 R_{HML} + \beta_4 R_{MOM} + \varepsilon$$

As before, we rank firms into 20 portfolios based on their monthly Seeking Alpha article sentiment, *READER SENTIMENT*. we then create a hedged portfolio buying the best-ranked portfolio and selling the worst-ranked portfolio.

The results are reported in Table 5. Seeking Alpha appears to provide information incremental to that captured by the risk factors (Market Model α=0.00779, t-statistic = 2.39; Fama French 3 α= 0.00675, t-statistic =2.12; Carhart α= 0.00568, t-statistic =2.05,). The negative loading on *HML* in the Fama and French 3 Factor model and the positive loading on the momentum factor suggest Seeking Alpha is more likely to cover growth firms and firms that exhibit momentum. This links to article-writing incentives. Although writers are awarded a fixed

[13] In untabulated results, hedged portfolios are created only for the post-financial crisis period. The hedged return is still positive and highly significant.

[14] In untabulated results, we also regress the Seeking Alpha portfolio on the Fama and French 5 Factor (2015) model, the Fama and French 5 Factor (2015) plus momentum model, and replicate results restricting the time period to post-financial crisis. The alphas in the specifications are highly significant.

amount for publishing articles for firms on the under covered list, the fundamental payment structure is variable and based on the number of times an article is read[15]. It is plausible that high momentum and high growth firms are followed more closely by the capital markets, and more articles on these firms will be published because of their financial potential for article writers. From the portfolio analysis, Seeking Alpha articles seem to include unique contents of information not captured by the common risk factors, warranting its following by some capital market participants.

4.5.2 Seeking Alpha and Options Market Measures Around Earnings Announcement

Next, we examine if there is differential treatment from the options market for Seeking Alpha articles published in response to the earnings announcement. Jin et al. [2012], Atilgan [2014], and Lei et al. [2020] document that options traders engage more before earnings announcements, suggesting an anticipatory effect of the options trades. Trades in this period are also more impactful for future returns, perhaps benefitting from the rich information environment around earnings announcements (Atilgan [2014], Lei et al. [2020]). we use the specification:

$$CHG\ VOLSPREAD = \alpha + \beta_1 SASCORE + \beta_2 SASCORE \times PREEA + \varepsilon,$$

$$CHG\ VOLSKEW = \alpha + \beta_1 SASCORE + \beta_2 SASCORE \times PREEA + \varepsilon,$$

where $PREEA$ is an indicator variable equal to 1 if the Seeking Alpha article is published between [-10, -1] of the earnings announcement date and equal to 0 if the articles is published more than 10 days before earnings announcement date[16]. Table 6 Panel A reports the results.

[15] https://about.seekingalpha.com/article-payments

[16] We have also tested different specifications such as [-20, -5], [-20, -2], and [-10, -2] before the earnings announcement. Articles published immediately before the earnings announcement do not seem to be incrementally informative for options market measures.

Post financial crisis, the sentiment in Seeking Alpha articles, *SASCORE*, is statistically significant in explaining both volatility spread (coefficient = 0.0019376, t-statistic = 3.81) and volatility skew (coefficient = -0.000873143, t-statistic = -1.84). However, the articles published immediately before earnings announcement do not have incremental explanatory power for volatility skew and spread compared to any other period. The coefficients on $SASCORE \times PREEA$ are insignificant.

Similarly, we also test for the information content of Seeking Alpha sentiment immediately after earnings announcement employing the specification:

$$CHG\ VOLSPREAD = \alpha + \beta_1 SASCORE + \beta_2 SASCORE \times POSTEA + \varepsilon,$$

$$CHG\ VOLSKEW = \alpha + \beta_1 SASCORE + \beta_2 SASCORE \times POSTEA + \varepsilon,$$

where $POSTEA$ is an indicator variable equal to 1 if the Seeking Alpha article is published between [0, +10] of the earnings announcement date and equal to 0 if the articles is published more than 10 days before earnings announcement date. In Table 6 Panel B, the coefficient on Seeking Alpha reader sentiment, *SASCORE*, is significant for both volatility spread (coefficient = 0.0011593, t-statistic = 2.15) and volatility skew (coefficient = -0.000821334, t-statistic = -1.69) post financial crisis. Seeking Alpha sentiment consistently explains changes in volatility spread and skew. Interestingly, the coefficient on $SASCORE \times PREEA$ is also significant (coefficient = -0.0064069, t-statistic = 2.63) for post-financial crisis changes in volatility spread. Seeking Alpha articles published immediately after the earnings announcement have incremental explanatory power for changes in volatility spread. This may be because Seeking Alpha articles provide superior analysis of earnings announcement information, similar to traditional analysts providing interpretive insights after earnings announcements

(Livnat and Zhang [2012]). Thus, articles published in the period immediately after earnings announcement have a stronger correlation with volatility spread.

4.6 Robustness Checks

4.6.1 Sensitivity of SA around Earnings Announcements

Figure 1 which graphs the number of Seeking Alpha articles against weeks since earnings announcement shows that there is a significant number of Seeking Alpha articles released in the week immediately after the earnings announcement. There may be concerns that Seeking Alpha reader sentiment's significant relationship on the stock and options market is driven by those articles published around the earnings announcement. we repeat the analysis without Seeking Alpha articles published [-10, +10] days of the earnings announcement while controlling for the information in the most recent earnings announcement using *RSURPRISE*, earnings surprise, and *REANEWS*, earnings announcement news. As Table 7 shows the coefficients are still significant. In particular, Seeking Alpha articles post-financial crisis incrementally explain immediate (coefficient = 0.0099115, t-statistic = 17.45) and 90-day drift (coefficient = 0.0047209, t-statistic = 2.03) returns. In Table 8, we replicate Table 7 replacing the dependent variables with change in volatility spread and skew. Seeking Alpha articles post-financial crisis significantly predicts changes in both volatility spread (coefficient = 0.0019080, t-statistic = 3.23) and skew (coefficient = -0.0011479, t-statistic = -2.47).

4.6.2 Ranked Options Market Measures

The descriptive statistics (Table 1 Panel B) show that the mean of volatility skew is not zero and that the distribution is slightly non-symmetric (mean = -0.001, 25^{th} percentile = -0.014, 75th percentile = -0.013). To mitigate the effect of outliers, we provide additional results where we use the quartile ranking of the change in volatility spread and volatility skew divided by 3 and subtract 0.5 from the number, which essentially creates a scaled ranking. Table 9 shows that the ranked results do not change in significance. Post-financial crisis ranked changes in volatility spread (coefficient = 0.0107414, t-statistic = 3.25) and skew (coefficient = -0.0069839, t-statistic = -1.78) are significantly correlated with Seeking Alpha sentiment, *SASCORE*, incremental to the earnings surprise and announcement return.

5. Conclusion

Using textual analysis which captures both general sentiment and business event-based sentiment, we study the information content of Seeking Alpha articles and test the timeliness of Seeking Alpha information. We find Seeking Alpha sentiment can explain short-term movements in stock prices [-1, +1] day of article publication and predict changes in returns up to the [+2, +90] day of article publication. This explanatory power is in addition to information already revealed through the most recent earnings surprise and earnings announcement return. In addition to the stock market, Seeking Alpha article sentiment predicts changes to options trading behavior. *SASCORE* has a positive relationship with option volatility spread and a negative relationship with option volatility skew. The directional relationship between Seeking Alpha article sentiment and both stock and options market measures suggest the response is information driven. It also shows Seeking Alpha information is timely, as it leads both the stock and options markets. Seeking Alpha news appears to be new and incremental to publicly available news as the stock and options markets respond to Seeking Alpha separately to their reaction of earnings announcements and risk factors. Finally, we document evidence that Seeking Alpha used as a hedged portfolio strategy can be a consistent return generator earning more than 50 basis points per month. In summary, Seeking Alpha appears to incremental and timely information to the stock and options market, representing a new source of value-relevant firm information.

This study extends the literature by providing some evidence on the extent of Seeking Alpha's information advantage. In addition to corroborating earlier findings on Seeking Alpha's value relevance for the stock market, it adds to the literature by exploring options traders' response to Seeking Alpha information. Moreover, the results enrich the debate on whether individual investors should be considered noise (Lakonishok et al. [2006], Bauer et al. [2009], Barber et al. [2008], Barber and Odean [2000], Kaniel et al. [2008], Seasholes and Zhu [2010], Grinblatt and Keloharju [2000]) or informed traders (Ivković et al. [2009], Ivković and Weisbenner [2005], Boehmer et al. [2021]). The observations in this study suggest even though individual investors may not achieve superior returns by trading, their collective knowledge aggregated through a social media platform provides incremental information for pricing in the stock and options markets.

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Figure 1: Seeking Alpha Articles by Week Around Earnings Announcements

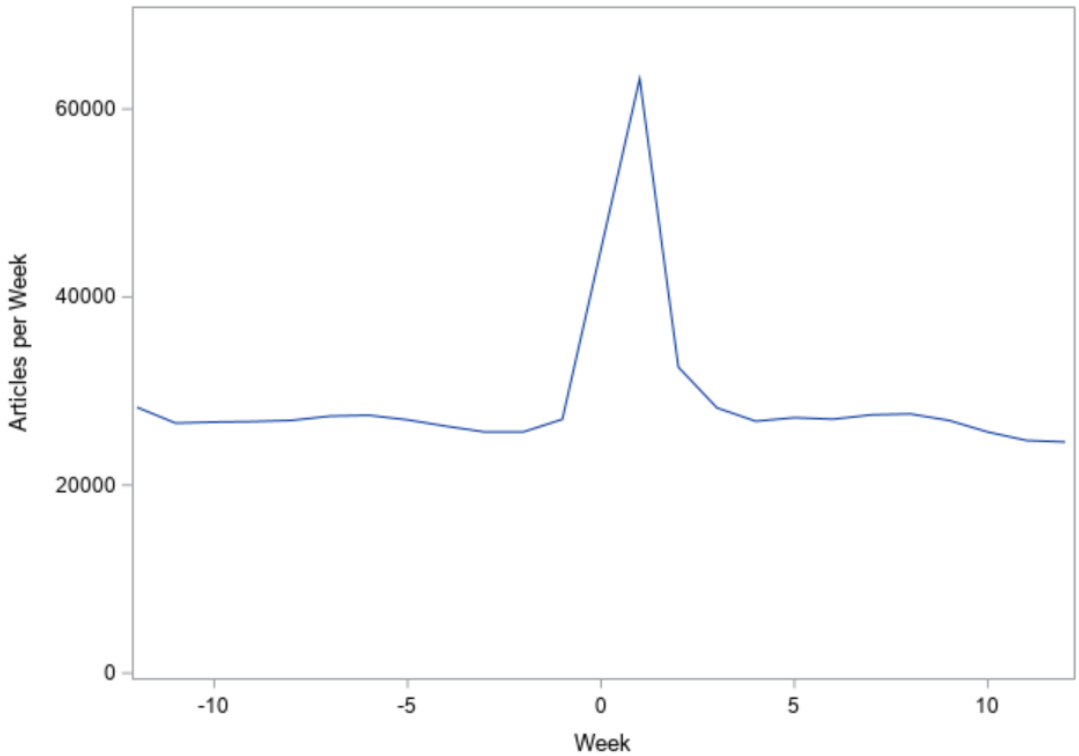


Table 1: Descriptive Statistics for SA Articles

Sample is drawn from 350,095 Seeking Alpha articles extracted. MTB, # FORECASTS, SURPRISE, and EA NEWS are measured on a quarterly basis. VOLSPREAD and VOLSKEW are measured daily. All other variables are tabulated by article.

Panel A: Descriptive Statistics by Seeking Alpha Firm

	Mean	*Median*	*STD*	*25%*	*75%*
SIZE	7.766	7.755	2.231	6.189	9.234
MTB	7.966	2.191	896.322	1.232	3.992
# FORECASTS	8.615	6	7.274	3	12
SURPRISE	-0.128	-0.023	4.815	-0.735	0.666
EA NEWS	0.001	-0.001	0.088	-0.038	0.038
VOLSPREAD	-0.011	-0.007	0.129	-0.04	0.021
VOLSKEW	0.026	0.02	0.1	-0.001	0.047

Panel B: Descriptive Statistics by Seeking Alpha Article

	Mean	*Median*	*STD*	*25%*	*75%*
IMMEDIATE RET	0	0	0.062	-0.015	0.015
DRIFT RET	-0.002	-0.004	0.19	-0.079	0.066
DAY DIFF	42.448	41	29.984	15	67
READER SENTIMENT	0.138	0.158	0.553	-0.27	0.583
SA SCORE	0	-0.056	0.32	-0.278	0.278
CHG VOLSPREAD	0	0	0.077	-0.018	0.018
CHG VOLSKEW	-0.001	-0.001	0.07	-0.014	0.013

Panel C: Descriptive Statistics by Seeking Alpha Article

READER SENTIMENT	*IMMEDIATE RET*	*DRIFT RET*	*CHG VOLSPREAD*	*CHG VOLSKEW*
Lowest Rank	-0.00981	-0.00321	-0.00030	-0.00079
2	-0.00763	-0.00519	-0.00028	-0.00113
3	-0.00518	-0.00371	-0.00039	-0.00170
4	-0.00253	-0.00253	0.00023	-0.00073
5	-0.00054	-0.00187	0.00036	-0.00122
6	0.00183	-0.00053	0.00041	-0.00144
7	0.00336	-0.00016	0.00003	-0.00111
8	0.00568	0.00207	0.00011	-0.00167
9	0.00612	0.00340	0.00115	-0.00136
Highest Rank	0.00684	0.00276	0.00121	-0.00167

READER SENTIMENT	*SIZE*	*MTB*	*FORECASTS*	*DAY DIFF*	*SURPRISE*	*EA NEWS*
Lowest Rank	9.730	11.545	15.163	43.466	-0.279	-0.015
2	9.653	13.391	15.458	42.797	-0.313	-0.015
3	9.570	8.206	15.505	42.438	-0.229	-0.011
4	9.521	10.911	15.520	42.265	-0.140	-0.007
5	9.474	11.995	15.226	42.283	-0.157	-0.003
6	9.449	13.182	15.122	42.013	-0.148	0.000
7	9.393	12.569	14.982	41.759	-0.084	0.004
8	9.395	20.089	15.016	42.273	0.002	0.007
9	9.356	17.009	14.624	42.134	0.041	0.010
Highest Rank	9.417	5.852	14.407	42.975	-0.030	0.010

Table 2: SA Score and Returns

Regression coefficients are estimated cross-sectionally every month between September 2004 – October 2018. Then, coefficients are averaged over the months. Months with less than 50 observations are removed. Observations report the number of articles within the period. Results are reported separately for all observations (Column 1), observations pre-2009 Financial Crisis (Column 2), during 2009 Financial Crisis (Column 3), and post-2009 Financial Crisis (Column 4). Dependent variable is either immediate returns, measured as [-1, +1] of article publication date, or drift returns, measured as [+2, +90] of article publication date. Any immediate return in excess of +/-1 is replaced by +/-1. Any drift return in excess of +/-3 is replaced by +/-3. Variable of interest SASCORE, is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. SA score is then ranked into deciles by year-month and scaled to be between -0.5 and +0.5. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between immediate [-1, +1] returns and SA score

	(1) All	(2) Pre-FC	(3) FC	(4) Post-FC
SASCORE	0.0210767***	0.0307022***	0.0286955***	0.0160788***
	(21.04)	*(10.52)*	*(10.41)*	*(27.56)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	165	40	19	106
Observations	487,778	23,995	32,241	431,542
Average R^2	0.0134765	0.0263142	0.0116128	0.0089661

Panel B: Relationship between drift [+2, +90] returns and SA score

	(1) All	(2) Pre-FC	(3) FC	(4) Post-FC
SASCORE	0.0084762***	0.0175388**	-0.0092857	0.0082401***
	(3.54)	*(2.53)*	*(-0.95)*	*(4.46)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	165	40	19	106
Observations	487,778	23,995	32,241	431,542
Average R^2	0.0026736	0.0061841	0.0024043	0.0013971

Panel C: Relationship between immediate returns and SA score with controls

	(1) All	(2) Pre-FC	(3) FC	(4) Post-FC
SASCORE	**0.0174891*** **	**0.0241699*** **	**0.0263901*** **	**0.0134077*** **
	(22.22)	***(12.11)***	***(11.07)***	***(23.85)***
RSURPRISE	-0.000911457	-0.0035102	0.0030034	-0.00069801
	(-0.83)	*(-0.92)*	*(0.72)*	*(-1.07)*
REANEWS	0.0327126***	0.0526852***	0.0385257***	0.0243848***
	(14.07)	*(6.85)*	*(6.4)*	*(17.32)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	158	37	19	102
Observations	391,075	19,700	25,738	345,637
Average R^2	0.0534853	0.1112474	0.0403819	0.0349732

Panel D: Relationship between drift returns and SA score with controls

	(1) All	(2) Pre-FC	(3) FC	(4) Post-FC
SASCORE	**0.0019082**	**0.0039608**	**-0.0174044***	**0.0047611****
	(0.67)	***(0.42)***	***(-1.98)***	***(2.26)***
SURPRISE	0.0079347*	0.0124119	-0.0324991*	0.0138425***
	(1.84)	*(1)*	*(-1.85)*	*(4.19)*
REANEWS	0.0017815	-0.00218	-0.0127268	0.005921*
	(0.4)	*(-0.16)*	*(-0.72)*	*(1.76)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	158	37	19	102
Observations	391,075	19,700	25,738	345,637
Average R^2	0.0176199	0.0404834	0.0173299	0.0093803

Table 3: SA and Option Market Indicators

Regression coefficients are estimated cross-sectionally every month between September 2004 – October 2018. Then, coefficients are averaged over the months. Months with less than 50 observations are removed. Observations report the number of articles within the period. Results are reported separately for all observations (Column 1&2) and post-2009 Financial Crisis (Column 3&4). Dependent variable is change in either volatility spread or volatility skew, measured as the difference between base period [-10, -5] and post period [+1,+5] of article publication date. Variable of interest SASCORE, is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. SA score is then ranked into deciles by year-month and scaled to be between -0.5 and +0.5. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between changes in volatility spread/skew and SA score

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
SASCORE	0.0011981**	-0.0012254**	0.0014138***	-0.0014329***
	(2.45)	*(-2.42)*	*(3.05)*	*(-3.17)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	162	158	106	106
Observations	530,241	469,799	472,752	419,584
Average R^2	0.0010231	0.0015532	0.000584225	0.000759526

Panel B: Relationship between changes in volatility spread/skew and SA score with controls

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
SASCORE	**0.0012012****	**-0.000749918**	**0.0016317*****	**-0.000850347***
	(2.22)	***(-1.45)***	***(3.19)***	***(-1.73)***
RSURPRISE	-0.000239144	0.000873811	-0.000339976	-0.000182386
	(-0.25)	*(0.98)*	*(-0.59)*	*(-0.34)*
REANEWS	0.0010427	0.000544918	0.0010045	0.000071032
	(1.12)	*(0.73)*	*(1.34)*	*(0.10)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	157	154	102	102
Observations	382,847	338,227	339,279	300,690
Average R^2	0.0068433	0.0084240	0.0027150	0.0031620

Table 4: Monthly (*t+1*) SA Score Portfolio Returns

Portfolios are formed by sorting on 20 portfolios of average monthly Seeking Alpha score. In consideration of portfolio rebalancing timing, articles published within 2 days of month end are disregarded. Seeking Alpha score is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. In Panel A, raw returns are shown. In Panel B, returns are adjusted for size, market-to-book, and momentum. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A: Monthly raw returns sorted on SA score

	Year-Months	*Return*	*t-stat*
95th Percentile (High)	161	0.01441***	3.06
5st Percentile (Low)	161	0.00743	1.23
High - Low	161	0.00698**	2.11

Panel B: Monthly returns adjusted for size, market-to-book, and momentum sorted on SA score

	Year-Months	*Return*	*t-stat*
95th Percentile (High)	161	0.00525***	2.87
5st Percentile (Low)	161	-0.00094	-0.35
High - Low	161	0.00619**	2.29

Table 5: SA Score Portfolio and Expected Return Models

Portfolios are formed by sorting on 20 portfolios of average monthly Seeking Alpha score. In consideration of portfolio rebalancing timing, articles published within 2 days of month end are disregarded. Seeking Alpha score is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. Monthly portfolio returns of a hedged portfolio of the best (95th percentile) minus worst (5th percentile) firms are regressed on factors from different expected return models. Expected return models include the market model in Column 1, Fama and French 3 factor (1993) in Columns 2, and Carhart (1997) in Column 3. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

	(1) Market	(2) FF3	(3) Carhart
α	0.00779**	0.00675**	0.00568**
	(2.39)	*(2.12)*	*(2.05)*
β	-0.24420***	-0.17072**	-0.04308
	(-3.08)	*(-2.12)*	*(-0.57)*
SMB		-0.00168	-0.00804
		(-0.01)	*(-0.06)*
HML		-0.42773***	-0.10277
		(-3.35)	*(-0.86)*
MOM			0.49511***
			(7.16)
Observations	161	161	161
R^2	0.0563	0.1195	0.3374

Table 6: SA Information for EA and Option Market Indicators

Regression coefficients are estimated cross-sectionally every month between September 2004 – October 2018. Then, coefficients are averaged over the months. Months with less than 50 observations are removed. Observations report the number of articles within the period. Results are reported separately for all observations (Column 1&2) and post-2009 Financial Crisis (Column 3&4). Dependent variable in Panel A is change in either volatility spread or volatility skew, measured as the difference between base period [-10, -5] and post period [+1,+5] of article publication date. In Panel B, change in either volatility spread or volatility skew is sorted into quartile ranks by year-month. Variable of interest SASCORE, is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. PREEA is an indicator variable, 1 for articles published -10 to -1 days of the earnings announcement date and 0 otherwise. POSTEA is an indicator variable, 1 for articles published 0 to +10 days of the earnings announcement date and 0 otherwise. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. SA score is then ranked into deciles by year-month and scaled to be between -0.5 and +0.5. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A: Option Indicators Before EA

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
PREEA	-0.0016253	-0.0018214	0.000787480	-0.0039546
	(-1.11)	*(-1.02)*	*(0.58)*	*(-1.60)*
SASCORE	**0.0017800*** **	**-0.000793956**	**0.0019376*** **	**-0.000873143***
	(3.05)	***(-1.57)***	***(3.81)***	***(-1.84)***
SASCORE×PREEA	**0.000499317**	**0.000413578**	**0.000074187**	**0.0037158**
	(0.20)	***(0.11)***	***(0.03)***	***(0.69)***
RSURPRISE	-0.000352049	0.000935878	-0.000524361	-0.000010258
	(-0.40)	*(1.17)*	*(-0.96)*	*(-0.02)*
REANEWS	0.000960980	0.000736204	0.000962838	0.000094648
	(1.06)	*(0.99)*	*(1.37)*	*(0.13)*
Intercept	Yes	Yes	Yes	Yes
Portfolios	157	154	102	102
Observations	368,770	325,840	326,350	289,360
Average R^2	0.0104552	0.0129132	0.0045117	0.0062076

Panel B: Option Indicators After EA

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
POSTEA	-0.000547429	-0.0059761***	-0.000676858	-0.0052705***
	(-0.62)	*(-6.91)*	*(-0.84)*	*(-6.52)*
SASCORE	**0.000882769**	**-0.000858035**	**0.0011593****	**-0.000821334***
	(1.56)	***(-1.46)***	***(2.15)***	***(-1.69)***
SASCORE×POSTEA	**0.0060373*****	**-0.000968777**	**0.0064069*****	**-0.0015603**
	(3.15)	***(-0.56)***	***(2.63)***	***(-0.79)***
RSURPRISE	-0.000332743	0.000619069	-0.000591989	-0.000131163
	(-0.37)	*(0.80)*	*(-1.08)*	*(-0.26)*
REANEWS	0.000886136	0.000557785	0.000875350	0.000108381
	(0.97)	*(0.77)*	*(1.25)*	*(0.15)*
Intercept	Yes	Yes	Yes	Yes
Portfolios	157	154	102	102
Observations	368,770	325,840	326,350	289,360
Average R^2	0.0117154	0.0169285	0.0050281	0.0073478

Table 7: SA and Returns Excluding [-10, +10] of Earnings Announcement

Regression coefficients are estimated cross-sectionally every month between September 2004 – October 2018. Then, coefficients are averaged over the months. Months with less than 50 observations are removed. Observations report the number of articles within the period. Results are reported separately for all observations (Column 1&2) and post-2009 Financial Crisis (Column 3&4). Dependent variable is either immediate returns, measured as [-1, +1] of article publication date, or drift returns, measured as [+2, +90] of article publication date. Any immediate return in excess of +/-1 is replaced by +/-1. Any drift return in excess of +/-3 is replaced by +/-3. Variable of interest SASCORE, is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. SA score is then ranked into deciles by year-month and scaled to be between -0.5 and +0.5. Articles published within 10 days of the earnings announcement are omitted from the sample. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between immediate returns and SA score for articles away from earnings announcement

	(1) All	(2) All	(3) Post-FC	(4) Post-FC
SASCORE	**0.0141050*** **	**0.0136539*** **	**0.0102989*** **	**0.0099115*** **
	(15.50)	***(15.96)***	***(17.33)***	***(17.45)***
RSURPRISE		0.000785117		0.000859052
		(0.90)		*(1.39)*
REANEWS		-0.000067995		0.000534533
		(-0.08)		*(0.73)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	149	149	98	98
Observations	263,298	255,324	233,445	226,385
Average R^2	0.0083462	0.0135564	0.0053825	0.0088463

Panel B: Relationship between drift returns and SA score for articles away from earnings announcement

	(1) All	(2) All	(3) Post-FC	(4) Post-FC
SASCORE	**0.0021212**	**0.000696166**	**0.0051876*** *	**0.0047209*** *
	(0.77)	***(0.27)***	***(2.20)***	***(2.03)***
RSURPRISE		0.0091898*		0.0151847***
		(1.85)		*(3.82)*
REANEWS		-0.0050912		0.0037918
		(-0.97)		*(0.95)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	149	149	98	98
Observations	263,298	255,324	233,445	226,385
Average R^2	0.0030689	0.0192882	0.0019277	0.0122116

Table 8: SA and Options Market Excluding [-10, +10] of Earnings Announcement

Regression coefficients are estimated cross-sectionally every month between September 2004 – October 2018. Then, coefficients are averaged over the months. Months with less than 50 observations are removed. Observations report the number of articles within the period. Results are reported separately for all observations (Column 1&2) and post-2009 Financial Crisis (Column 3&4). Dependent variable is change in either volatility spread or volatility skew, measured as the difference between base period [-10, -5] and post period [+1,+5] of article publication date. Variable of interest SASCORE, is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. SA score is then ranked into deciles by year-month and scaled to be between -0.5 and +0.5. Articles published within 10 days of the earnings announcement are omitted from the sample. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A: Changes in volatility spread/skew for SA articles away from EA

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
SASCORE	0.0021622***	-0.000768475	0.001882***	-0.0012061***
	(3.36)	*(-1.4)*	*(3.23)*	*(-2.65)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	149	147	98	98
Observations	243,566	214,800	216,168	191,105
Average R^2	0.0017309	0.0027393	0.000996957	0.000875443

Panel B: Changes in volatility spread/skew for SA articles away from EA with controls

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
SASCORE	**0.0021126*** **	**-0.000777634**	**0.0019080*** **	**-0.0011479** **
	(3.25)	***(-1.41)***	***(3.23)***	***(-2.47)***
RSURPRISE	0.0010617	-0.000089188	0.000634920	0.000245251
	(0.93)	*(-0.14)*	*(0.90)*	*(0.46)*
REANEWS	-0.000660502	-0.000380469	-0.0014816*	-0.000219888
	(-0.62)	*(-0.51)*	*(-1.81)*	*(-0.31)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	148	146	98	98
Observations	236,983	209,934	210,434	186,944
Average R^2	0.0087953	0.0090274	0.0039032	0.0039362

Table 9: SA Score and Ranked Option Market Indicators

Regression coefficients are estimated cross-sectionally every month between September 2004 – October 2018. Then, coefficients are averaged over the months. Months with less than 50 observations are removed. Observations report the number of articles within the period. Results are reported separately for all observations (Column 1&2) and post-2009 Financial Crisis (Column 3&4). Dependent variable is ranked change in either volatility spread or volatility skew, measured as the difference between base period [-10, -5] and post period [+1, +5] of article publication date. Quartile ranks are determined by year-month. Variable of interest SASCORE, is calculated according to the method mentioned in Section 3 and take on continuous values between -1 and +1. Documents with less than 5 positive and negative mentions altogether are considered no news articles and eliminated from the sample. SA score is then ranked into deciles by year-month and scaled to be between -0.5 and +0.5. ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between changes in volatility spread/skew rank and SA score

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
SASCORE	0.0130522***	-0.0124828***	0.0184306***	-0.0147246***
	(3.85)	*(-3.19)*	*(5.71)*	*(-3.86)*
Intercept	Yes	Yes	Yes	Yes
Portfolios	162	158	106	106
Observations	440,997	389,400	390,316	345,524
Average R^2	0.0014736	0.0018776	0.0010537	0.0012684

Panel B: Relationship between changes in volatility spread/skew rank and SA score with controls

	(1) Spread All	(2) Skew All	(3) Spread Post-FC	(4) Skew Post-FC
SASCORE	**0.0059995**	**-0.0094853****	**0.0107414*****	**-0.0069839***
	(1.57)	***(-2.18)***	***(3.25)***	***(-1.78)***
RSURPRISE	-0.0020763	0.0062049	-0.000844162	-0.0010465
	(-0.42)	*(1.15)*	*(-0.22)*	*(-0.23)*
REANEWS	0.0162062***	0.0103376*	0.0136078***	-0.000553382
	(3.33)	*(1.76)*	*(3.17)*	*(-0.12)*
Intercept	Yes	Yes	Yes	Yes
Year-Month Portfolios	157	154	102	102
Observations	368,770	325,840	326,350	289,360
Average R^2	0.0072138	0.0091150	0.0035219	0.0041978

Appendix 1: Variable Definitions

SIZE	The log of total assets of the firm from Compustat
MTB	The ratio of market value to book value of the firm from Compustat
# FORECASTS	Number of forecasts issued on the firm in the quarter from I/B/E/S
DAY DIFF	Number of days between quarterly earnings announcement and publication of Seeking Alpha article
SURPRISE	The actual EPS from I/B/E/S subtracted by either the average of all analyst forecasts in the 90 days before earnings announcement or the time series of prior analyst forecasts of the quarter counting back in 4 quarter increments if most recent analyst forecasts are not available
RSURPRISE	Decile rank by year-month of the actual EPS from I/B/E/S subtracted by either the average of all analyst forecasts in the 90 days before earnings announcement or the time series of prior analyst forecasts of the quarter counting back in 4 quarter increments if most recent analyst forecasts are not available, rank is standardized between [-0.5, +0.5] i.e., rank is a number 0-9, divide the number by 9 and subtract 0.5
EA NEWS	The [-1,+1] abnormal return of the firm around quarterly earnings announcement; abnormal return is calculated as the difference between the firm return and a matched portfolio sorted on size, market-to-book, and momentum, 27 portfolios are used with 3 size ranks, 3 market-to-book ranks, and 3 momentum ranks
REANEWS	Decile rank by year-month of the [-1,+1] abnormal return of the firm around quarterly earnings announcement; abnormal return is calculated as the difference between the firm return and a matched portfolio sorted on size, market-to-book, and momentum, 27 portfolios are used with 3 size ranks, 3 market-to-book ranks, and 3 momentum ranks; rank is standardized between [-0.5, +0.5] i.e., rank is a number 0-9, divide the number by 9 and subtract 0.5
IMMEDIATE RET	[-1,+1] abnormal trading day return of the firm around Seeking Alpha article publication date, if return is more than 1, then replace with 1; abnormal return is calculated as the difference between the firm return and a matched portfolio sorted on size, market-to-book, and momentum, 27 portfolios are used with 3 size ranks, 3 market-to-book ranks, and 3 momentum ranks
DRIFT RET	[+2, +90] abnormal trading day return of the firm after Seeking Alpha article publication date, if return is more than 3, then replace with 3; abnormal return is calculated as the difference

	between the firm return and a matched portfolio sorted on size, market-to-book, and momentum, 27 portfolios are used with 3 size ranks, 3 market-to-book ranks, and 3 momentum ranks
READER SENTIMENT	Scaled sentiment score between [-1, +1] of Seeking Alpha article, calculated as $\frac{Positive\ Score_{General+Event} - Negative\ Score_{General+Event}}{Positive\ Score_{General+Event} + Negative\ Score_{General+Event}}$, positive and negative mentions are calculated using NLP, see examples in Appendix 2
SASCORE	Scaled sentiment score between [-1, +1] of Seeking Alpha article, calculated as $\frac{Positive\ Score_{General+Event} - Negative\ Score_{General+Event}}{Positive\ Score_{General+Event} + Negative\ Score_{General+Event}}$, sentiment score is then ranked into deciles by year-month and standardized between [-0.5, +0.5] i.e., rank is a number 0-9, divide the number by 9 and subtract 0.5
VOLSPREAD	Volatility spread is calculated as the weighted average of the difference in implied volatilities of call-put pairs matched on strike price and exercise date, weighted by open interest of the pair divided by open interest of all pairs on the day, for ranked volatility spread the ranking is in quartiles by year month
VOLSKEW	Volatility skew is calculated as implied volatility of out-of-the-money (OTM) puts minus the implied volatility of at-the-money (ATM) calls, for OTM puts take option with delta closest to -0.3 and between [-0.45, -0.15] and for ATM calls take option with delta closest to +0.5 and between [+0.4, +0.7], for ranked volatility skew the ranking is in quartiles by year month
CHG VOLSPREAD	Change in volatility spread from [-10, -5] to [+1, +5] of publication date, volatility spread is calculated as the weighted average of the difference in implied volatilities of call-put pairs matched on strike price and exercise date, weighted by open interest of the pair divided by open interest of all pairs on the day, for ranked volatility spread the ranking is in quartiles by year month
CHG VOLSKEW	Change in volatility skew from [-10, -5] to [+1, +5] of publication date, volatility skew is calculated as implied volatility of out-of-the-money (OTM) puts minus the implied volatility of at-the-money (ATM) calls, for OTM puts take option with delta closest to -0.3 and between [-0.45, -0.15] and for ATM calls take option with delta closest to +0.5 and between [+0.4, +0.7], for ranked volatility skew the ranking is in quartiles by year month

PREEA	Indicator variable, 1 if Seeking Alpha article is published within [-10, -1] days of quarterly earnings announcement and 0 otherwise
POSTEA	Indicator variable, 1 if Seeking Alpha article is published within [0, +10] days of quarterly earnings announcement and 0 otherwise
α	Alpha of the expected return model
β	Beta of the expected return model, coefficient of regressing $R_i - R_f$ on $R_{mkt} - R_f$, R_{mkt} and R_f are provided by the Fama French Data Library
SMB	Size factor, calculated as the average return of small stock portfolios subtracted by the average return of large stock portfolios, provided by the Fama French Data Library
HML	Value factor, calculated as the average return of the value portfolios minus the growth portfolios, provided by the Fama French Data Library
MOM	Momentum factor, calculated as the average return on the strong momentum portfolios minus the average return on the weak momentum portfolios, provided by the Fama French Data Library

Appendix 2: NLP Business Event Examples

Event Type	Excerpt	Sentiment
Mergers and Acquisitions	The eBay spin-off can be relevant for the timing of a **potential Alibaba acquisition** as well as the potential likelihood.	POS
Default	Canadian banks will be required to immediately cut their dividends under **rising defaults** as shown below, with all banks cutting their dividends entirely in 2018 due to losses from rising defaults.	NEG
Contract	Late last year, Ballard announced that the company **secured a long-term fuel-cell supply contract** from PLUG, which includes providing fuel-cell stacks for use in Plug Power’s GenDrive systems deployed in forklift trucks.	POS
Workforce	These **include headcount reductions**, reengineering our products and processes, improving efficiencies and raw material pricing…	NEG
Supply and Demand	The company is growing its fleet to service the **increasing demands for** air travel in the region.	POS

Appendix 3: Seeking Alpha Article Examples

Why Mattel Continues To Dominate The Dolls Category

Aug. 16, 2013 2:34 PM ET | **Mattel, Inc. (MAT)** | HAS

Lutz Muller
912 Followers

Dolls, Dolls, Dolls - Through Ups and Downs, the Doll Market Perseveres

If you just look at the overall sales picture of dolls and plush in the United States, you see a picture so dismal you would want to emigrate. This is what NPD numbers tell us:

Source NPD

However, when you look a little closer, you will see that there is still life in this category.

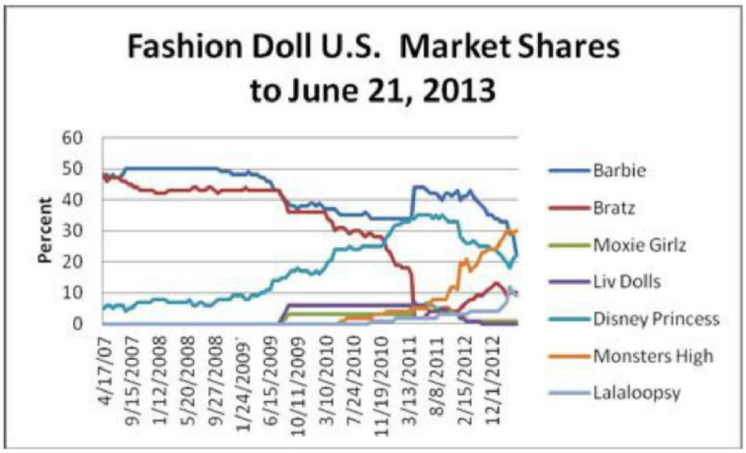
The most important segment of the Doll category is fashion dolls, and as far back as we can remember, Mattel's (NASDAQ:MAT) Barbie has reigned supreme there. Only once was she challenged -- between 2004 and 2007 when MGA Entertainment's Bratz nearly got to a 50% market share in the U.S. fashion doll market. This fight for the No.1 position soon migrated from shelf space battles into court case brawls, which are still ongoing today. In any event, Barbie began to recapture lost market share territory by Summer 2010 and Bratz had virtually disappeared from the shelves by Spring 2011. Since then Bratz has somewhat recovered, but it never got back to where it had been it its heyday.

However, Mattel management had learned a valuable lesson. Yes, Barbie was a nice, wholesome, good girl but MGA proved that not all tween girls wanted a doll that was nice, wholesome and good. They wanted a doll that was edgy, pushy, bratty, and not really well behaved -- in short, Bratz. Mattel responded by creating Monster High in July 2010 and proceeded to make it a major success story. Monster High has overtaken Barbie and is now the No. 1 brand in the U.S.

However, MGA did not stand still. In the same year Mattel created Monsters, MGA launched a new line of rag dolls called Bitty Buttons. Bitty Buttons were very similar in concept to the Raggedy Ann dolls, which were first created in the 1920s and still around today. The line gained traction when MGA decided to change from Bitty Buttons to Lalaloopsy shortly after the brand launched.

While all this was going on, there were other comings and goings. Spin Master launched Liv, which was relatively short-lived, followed by Victorious, which is still hanging in there by the edge of her teeth. MGA had also launched Moxie Girlz as a companion to Bratz, but the range failed to take off and is now slowly vanishing from top retailers' shelves. The most recent ambitious entry was Jakks' (JAKK) Winx Club dolls, released last year and now pretty much on clearance everywhere. Today, there are two new entrants on the horizon -- one is a new version of the original Raggedy Ann, unveiled by Hasbro (HAS) at the 2013 American International Toy Fair and expected to make its appearance on toy shelves this fall. The other is Mooshka by MGA, a range of soft fabric dolls that is set to launch this fall as well..

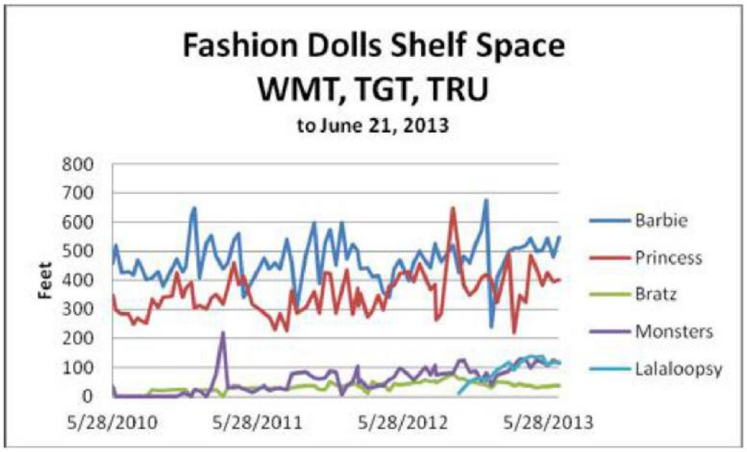
Throughout all this, Mattel's Disney Princess (DIS) sailed like a stately ship through these choppy waters, holding onto its No 2 or No. 3 position regardless of the ups and downs of all the other brands competing for the top spot. The Princess trend is experiencing a mild resurgence due to the very successful entry of Sofia the First, a doll range backed by a 3-D computer-animated TV series released at the beginning of this year on the Disney Channel and Disney Junior.



Source Klosters Retailer Panel

The above graph shows how the top brands have performed in the past six years:

Monsters is #1 with about 30 percent market share, Barbie and Disney Princess are No.2 each with about 20 percent, and Bratz and Lalaloopsy No. 3 each with about 10 percent. This lineup is, interestingly, not reflected in the shelf space each of these brands occupy. This is the picture at Wal-Mart (WMT), Target (TGT) and Toys "R" Us (TOYS):



Source: Klosters Retailer Panel

You would think that the best-selling brand would also have the largest presence on the shelf, yet Monster High is way below Barbie and Disney Princess, holding about the same position as Lalaloopsy, a brand that is selling 66 percent less. How can this be? The reason is that because Monsters sales are growing extremely fast, Mattel cannot keep retailers adequately supplied. The buyers, hence, will not give a higher space allocation to a brand that has continuously empty shelves, unless they are satisfied that these shortages have been fully addressed. This will undoubtedly happen eventually and Monster High will occupy its well-deserved place in the sun.

So, while we can be pretty sure that Mattel will, for the foreseeable future, continue to dominate the fashion doll market in the U.S., the question is what that market is likely to do. Will it continue to decline or will we see a turnaround sometime soon?

Firstly, the buyers at the large retailers think that the negative sales curve for the category over the past decade is coming to an end. They point out that two major drivers are responsible. One is the KGOY [Kids Growing Older Younger] syndrome. The average age of a girl buying a doll a decade ago was about 9 years old, but it is now 6 years old and unlikely to go down any further. The second is that these trend lines denote dollar, not unit, sales. Because of the transition from U.S. manufacturing to China, costs came down and hence the price per unit dropped. In reality, they estimate that the sales in units over the last 10 years are up some 10 percent. Chinese costs are beginning to show a clear tendency to rise, which will result in higher prices and hence higher dollar sales. We will therefore probably see a reversal in direction relatively soon.

Secondly, these buyers are not overly concerned about the influence smartphones and tablets will have on toy sales in general and doll sales in particular. Yes, there are now many apps and online programs that invade doll territory and this trend is likely to continue to increase, at least in the short term. And, yes, the time kids spend on these devices is likely to eat into the time you have for other endeavors. However, the buyers do not think that one replaces the other. As one buyer put it: to play with an app instead of a real doll is the same difference as hugging a photo instead of hugging your girl friend.

Rather, they think that significant future influences on the doll market will come from two different directions. One is the marriage between electronic platforms and physical toys as demonstrated by the Skylanders franchise. This technology will undoubtedly move into doll territory sooner or later, and whoever is first to do so successfully is going to walk away with a really nice market share. The second is the type of precursor technology we do not even see today -- along the lines of 3-D printing -- which will enable consumers to adapt and change toys to their personal preference.

Whatever the case may be, dolls will continue to be around for an extremely long time.

(This article was first published by the Toy Book on August 15, 2013)

Disclosure: I have no positions in any stocks mentioned, and no plans to initiate any positions within the next 72 hours. I wrote this article myself, and it expresses my own opinions. I am not receiving compensation for it. I have no business relationship with any company whose stock is mentioned in this article.

This article was written by

Lutz Muller

912 Followers

Lutz is an acknowledged expert on the toy space. His clients include one of the top three U.S. banks and one of the top three non-public toy companies worldwide. Between 1984 and 2002, Lutz was the CEO at five different ma

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Why I Am Not Yet Nibbling On Shake Shack

Aug. 20, 2015 12:57 PM ET | **Shake Shack Inc. (SHAK)** | 18 Comments

Economics-Based Investor
526 Followers

Summary

Valuation is far too high in the 50s, even with the current growth and expansion plan which is unsustainable in the long-term.

Expansion will almost certainly face a principal-agent problem of maintaining quality food and service both nationally and internationally.

Secondary offering by insiders gives no benefit to the company and should not promote retailers to band-wagon buy.

I am a long-term buyer if it re-enters reality below $40 and will nibble away weekly to dollar-cost average.

SAVORY AND FAST

I have been to a Shake Shack (NYSE:SHAK) one time, in NYC, where I stood in line for over 90 minutes in the park for a burger, fries, and a shake. It was 100% worth it - the best burger I have had and service that moved through hundreds of people during that wait. But it was also their flagship location - thus the quality should be nothing but SHAK's best. And this is where I see the principal-agent problem rising in SHAK's aggressive expansion plan. Adding to this SHAK's recent secondary offer and a very high P/E ratio, I am not a buyer and nor will I be until it returns to reality.

PRINCIPAL-AGENT PROBLEM

The principal-agent problem is well known - the principal (P) gives the agent (A) the right to act on his behalf in exchange for a payment of some sort (money, election to office, or other favors). However, A has his own interests that may cause him to pursue his personal goals over those of the principal and thus shirk P's desires. Most commonly our Congressional representatives fill this problem - voters elect the representative who then may or may not act in the interests of P and knows that P can do little about it until the next election. The monitoring costs are placed upon P who must expend resources to ensure A is meeting the agreed upon expectations. If P will not, or cannot, expend those resources, then the expectation is that A will fulfill enough obligations to keep P somewhat satisfied, but will also find corners to cut or ways to game the system for profit out of self-interest. Franchise-style businesses battle this problem regularly and only those willing to expend adequate resources thrive. There is a reason the franchisees grimace when they know "Corporate representatives" are about to conduct a visit or spot-check on their operations.

And like Howard Penney, this is where SHAK will almost certainly run into issues with its expansion. Adding restaurants will continue its growth and I give kudos to SHAK's management for its aggressive plan; however, they will almost certainly have a Principal-Agent problem as they execute this plan. When the franchises are collocated or all local, monitoring is cheap as management can easily visit the locations to spot-check and ensure quality. However, with its aggressive national and international expansion plan, monitoring costs will sky-rocket. And while it may be able to sustain quality in major cities, the issues will rise as the addiction of extreme growth causes expansion into smaller and more rural areas. Management will almost certainly be unable to handle monitoring each location and quality control measures will slip. .

PRICED FOR PERFECTION, INSIDER'S SELLING

Additionally, SHAK faces a valuation issue that deters me from buying at over $40. The inability to sustain its growth combined with the P-A problem of assuring quality portrays a stock that is run on momentum and a herd mentality. Earnings are what you expect of an expanding company (relatively non-existent). However, the move to do a second offering at $60 on 12 August is by existing shareholders smells of a cash-out. And why should they not, as Michael Ranalli noted their cost basis is well under $1 per share. I am always hesitant of insiders doing this type of activity so close to the IPO after the stock has taken off; it is like the sirens in Ulysses calling in the retail investors.

While sales are increasing at a rapid rate and more locations should yield greater earnings, the market and the herd following the momentum that took the stock from the low of $38 to well over $90 in only a few months has created a company priced for perfection. As seen with LOCO's last earnings, these hyperactive stocks only need to hint at a slow-down to return to a realistic price. Nicholas Mushaike noted that their growth is unsustainable; I agree. It is similar to KORS in 2012-2014 when growth was sizzling…until it was not sizzling and now the stock is over 50% under its all-time high.

CONCLUSION

Let me restate that I am not a buyer at this time and do not recommend it to retail investors. While the company has moved drastically in both directions, I look for long-term investments, not trades; at its current price, SHAK is a trade. If the stock drops back under $40, I will initiate weekly purchases (in a dollar-cost-average manner) as I believe the company will continue to thrive. But as it is currently priced for perfection with an unsustainable level of growth and is taking on an expansion strategy with costs management likely cannot resource, my appetite for this burger company is currently a bit nauseous.

This article was written by

Economics-Based Investor

526 Followers

I am a military officer in the Republic of Korea with 15+ years of personal investing and trading. I gained my knowledge through family and personal research, and remain a long-term horizon investor. I focus primarily on a buy a