Opposites Attract and Likes Repel: Social Media Assimilation Effects in Analysts

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Abstract

This study examines how analysts incorporate social media information, focusing on how analysts benchmark to Seeking Alpha sentiment of other firms in the analysts' portfolio. We use SA sentiment of other firms in the portfolio as it may better capture analysts' habitual and possibly unconscious behavior when performing an important but recurring task like forecasting. We find that analysts shift their forecasts in the direction of SA sentiment about other firms in their portfolio. This contrasts with previous findings where analysts benchmark away from traditional forecast errors. Additional cross-sectional tests where we vary the degree of information ambiguity of the focal firm presents evidence of an even stronger positive relationship between SA sentiment and both forecast errors and forecast optimism. This suggests analysts may be basing benchmarking decisions on their familiarity with the information medium. Specifically, they can easily identify and separate inaccurate components in traditional analyst forecasts but incorporate the information in SA sentiment because they are unable to completely distinguish the useful components from the noise. The study contributes by identifying a new decision heuristic—familiarity with the content and form of information—that influences analysts' benchmarking behavior.

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1. Introduction

In the process of making forecasts, analysts rely on a combination of information and heuristics. This study explores one such decision heuristic. With the rising popularity of social media, additional channels for information communication have emerged. Numerous studies have found these channels to be informative (Bartov et al. 2018; Chen et al. 2014; Jame et al. 2016; Drake et al. 2023; Huang et al. 2020). Contrarily, some studies have discussed that social media could also lead to misinformation (Jia et al. 2020; Clarke et al. 2020; Luca and Zervas 2016). Consequently, the role of social media in capital markets remains debated. In this paper, we investigate one significant contributor to information production and dissemination in capital markets: analysts, and their relationship with social media financial advice. Specifically, we examine how analysts perceive information from online sources compared to traditional sources and how social media estimates manifest in one of the primary outputs of analysts' efforts—their forecasts.

We use Seeking Alpha (SA) as a representative source of social media information that analysts may consider. Founded in 2004, SA was designed as a forum where the investment community could share stock recommendations and alpha-generating ideas, as its name suggests. Over time, it has evolved into a multi-functional platform offering a wide range of tools, including investment advice articles, earnings call transcripts, stock and bond monitoring, and discussions on investment strategies. For this study, we focus on the articles published on the SA platform. Our focus on SA articles is based on several reasons related to the higher likelihood that analysts would consider these articles compared to other social media content. First, all published articles on SA are screened by an editorial board, which enhances their credibility and filters out some of the noise and ulterior motives that are present in other social media platforms like Twitter (Merkley et al. 2024) or Reddit (Bradley et al. 2024), which

lack similar screening mechanisms. Second, SA articles are comparable in length and format to traditional media articles, such as those in the Wall Street Journal. Therefore, they are similar to the types of public financial information that analysts would be exposed to on a daily basis. Finally, articles on SA are tagged by ticker symbols, enabling up-to-date alerts and convenient monitoring of firms in analysts' portfolios.

We aim to jointly test whether analysts would consistently pay attention to opinions from social media and the direction of their forecast response to these opinions. Drake et al. (2023) find that SA articles published in the 7 days leading up to the publication of a subsequent analyst report on the same firm subsume some of the stock market effect of the analyst report. Our study differs from that of Drake et al. (2023) in a couple of ways. First, while Drake et al. (2023) examines the direct effect of SA information on the focal firm in analysts' portfolios, we investigate whether SA sentiment on other firms within an analyst's portfolio influences forecasts for the focal firm. This is a conscious decision as it is an open question whether analysts would even care about other information about other firms when producing forecasts. Additionally, investigating the consideration of other information may better capture analysts' habitual and possibly unconscious behavior when performing an important but recurring task like forecasting. Second, whereas Drake et al. (2023) focus on the presence of an SA article, we match the directional SA sentiment to the direction of the forecast response.

In summary, we explore a facet of analysts' decision-making that may not be entirely conscious yet has implications for the quality of their output. We consider this inquiry to be a worthwhile endeavor as we should be aware of the implicit assumptions in the forecasting process when we are attempting to discern information and value from analyst reports. Furthermore, our findings provide insights into how analysts may behave when incorporating new information sources, which has

broader implications for understanding their decision-making processes in a rapidly evolving information landscape.

To investigate whether analysts are influenced by SA (Seeking Alpha) opinions, we collect 350,095 SA articles from the platform. Using natural language processing, we code each article based on a combination of business events and general sentiment to calculate an overall sentiment score. We then regress analyst focal firm forecast error and forecast optimism on the past-quarter SA sentiment of other firms in the analyst's portfolio. These regressions control for past-quarter traditional analyst forecast errors on other firms and the analyst's own past forecast errors. Similar to Kumar et al. (2022), the regressions also included earnings announcements and firm-analyst fixed effects, which account for common and firm-specific factors that influence forecasts and the analyst's average forecast error, respectively. In essence, we sought to isolate the effect of SA sentiment related to other firms in the analyst's portfolio on the focal firm, ruling out both the informational impact of the focal firm itself and the influence of traditional analysts, including the analyst's own past behavior.

Our findings reveal an incremental and significant positive relationship between the average SA sentiment of other firms in the analyst's portfolio and both forecast error and forecast optimism. Analysts are more likely to exhibit forecast errors in the same direction as the past quarter's SA sentiment. This result contrasts with the findings of Kumar et al. (2022), which show that analysts' forecast errors move in the opposite direction of the past-quarter traditional analyst forecast errors for other firms in the portfolio. This divergence, however, is consistent with differences in the sources of influence. Kumar et al. (2022) examine how analysts respond to peer traditional analysts, a setting in which analysts carefully evaluate information based on its merits. In contrast, we examine analysts' responses to social media, where prior research (Kim and Youm, 2017) suggests that analysts pay

attention to social media information but may process it differently. Rather than scrutinizing social media estimates to identify and correct errors, analysts may rely more on the general sentiment conveyed in these platforms. The mechanism underlying this behavior is well explained in the social psychology literature.

Research in social psychology (Herr et al., 1983; Herr, 1986; Herr, 1989; Wänke et al., 1998) suggests that when individuals are exposed to anchoring information, their predictions may shift either closer to or farther away from the anchor. This depends on the degree of alignment between the task at hand—in this case, forecasting—and the anchoring information. In the case of SA articles, these may share familiar features with analysts, such as a format resembling Wall Street Journal articles or earnings reports, and may even be authored by financial professionals or other analysts (Campbell et al. 2019). However, SA articles also differ significantly from traditional analyst earnings forecasts in both form and content—particularly when compared to closer counterparts, such as social media earnings estimates on platforms like Estimize or traditional peer forecasts. The results of our study align with this framework. Analysts are more likely to adjust their forecasts toward SA sentiment due to an overlap between the information required for forecasting and the information provided in SA sentiment. They incorporate the information in SA sentiment because they are unable to completely distinguish the useful components from the noise. Conversely, they adjust their forecasts away from traditional analyst sentiment (Kumar et al. 2022), because they can easily identify and separate inaccurate components—such as forecast errors—when forming improved predictions.

To further test this mechanism, we examine why analysts respond differently to SA sentiment and traditional analyst sentiment by analyzing cross-sections of firm environments characterized by greater information ambiguity. We hypothesize that in such environments, analysts would find it even more

challenging to discern the characteristic differences between SA sentiment and traditional analyst sentiment, making them more likely to adjust their forecasts in the direction of the SA sentiment of other firms in their portfolio (Herr et al. 1983; Herr 1986). The information ambiguity measures we use are analyst dispersion, past negative earnings surprises, and past losses. The results support our hypothesis. The coefficient on the interaction between our measure of information ambiguity and SA sentiment is positive and significant. This finding suggests that in uncertain environments, analysts are even more likely to benchmark their forecasts in the direction of SA sentiment.

We contribute to several strands of literature. First, we provide predictions on how analysts benchmark differently against the opinions of other financial professionals based on their level of familiarity with the processes and information involved in developing estimates. Our findings contrast with those of Kumar et al. (2022), who demonstrate that analysts benchmark away from forecast errors made by their traditional peers. Following the arguments of Herr et al. (1983) and Herr (1986), we find a different result, as analysts appear to be less familiar with the information content and the information production processes underlying social media estimates. Consequently, they face greater difficulty isolating the incremental information embedded in social media estimates compared to traditional analyst forecasts. As a result, analysts exhibit different behavior in benchmarking towards SA sentiment as opposed to benchmarking away from traditional analyst forecast errors. Our findings suggest that analysts adjust their learning processes based on the medium through which they receive information. Specifically, they engage in more critical evaluation when learning from peer analysts but primarily gauge general sentiment when processing information from social media. While prior studies on analyst social categorizations have focused on industry groupings (Cen et al. 2013; Bowers 2015), our paper shifts the focus to the form of the information medium. These findings have broader

implications for how analysts interpret and incorporate new information sources in an evolving informational landscape.

Second, we introduce an additional behavioral component to the process by which analysts develop estimates. In addition to established factors influencing analyst behavior—such as incentives to curry favor with managers (Francis and Philbrick 1993; Lim 2001), analyst boldness (Clement and Tse 2005; Millo et al. 2023), systematic bias (Butler and Lang 1991), reluctance to revise (Bernhardt et al. 2016) and overconfidence (Hilary and Menzly 2006)—we present another heuristic analysts may use: the degree to which they are familiar with the content and form of the information.

Third, we provide evidence on how analysts perceive information from social media. The existing literature on social media and analysts has primarily focused on Estimize (e.g., Jame et al. 2016; Jame et al. 2022; Da and Huang 2020; Schafhäutle and Veenman 2024), as Estimize most closely resembles a repository of analyst earnings estimates in a social media format. We instead focus on SA, which is also a type of financial social media, but not as similar in form and content to traditional analyst estimates as Estimize. These distinctions raise questions about whether analysts incorporate SA as part of their information set when making forecasts. Drake et al. (2023) demonstrate that SA pre-empts content in subsequent analyst reports but do not offer many details regarding the role and significance of SA within analysts' forecasting toolsets. We show that analysts use SA sentiment information, and that they benchmark towards the sentiment revealed in SA.

The remainder of the paper is organized as follows: Section 2 provides a brief overview of the research on social media and analysts and explains how this paper extends this literature. Section 3 outlines the empirical methodology used. Section 4 desribes the data and the textual analysis methodology. Section 5 presents the results. Finally, Section 6 offers a concluding discussion.

2. Research background and hypothesis development

In the literature, there are many instances where analysts predicate their reports and predictions on information from peers. There are studies where analysts learn about firms that they themselves follow (Bowers 2015; Hartzmark and Shue 2018; Cen et al. 2013; Do and Zhang 2020). There are also studies where analysts learn from peers that share some characteristic with the focal firm they are attempting to value (Kumar et al. 2022; Chen et al. 2024).

With the rise of more varied and more accessible sources of firm information, the question has been expanded to whether analysts base their information output on information from social media. Most of the research on analyst reaction to social media are concentrated on Estimize, which is a platform that crowdsources earnings and revenue estimates from anonymous contributors for users to view. Jame et al. (2016) and Schafhäutle and Veenman (2024) find that Estimize contains value-relevant information that has not been reflected in traditional analyst forecasts. However, their findings also suggest that traditional analysts are not paying as much attention to Estimize. If they did, the information in Estimize should have already been incorporated in the analyst forecast and there would be no incremental effect of Estimize information. On the other hand, Jame et al. (2022) later find that traditional analysts may look to Estimize to correct strategic biases. Da and Huang (2020) also find that within the Estimize platform, users are likely to move towards the consensus estimate and away from their prior personal valuations. Assuming some Estimize users are also employed in analyst roles, Da and Huang (2020)'s results would suggest that traditional analysts also assign some weight to online platforms.

Other studies have examined how traditional analysts differ from robo-analysts, Twitter, and

Seeking Alpha. Coleman et al. (2022) find that robo-analysts are more unbiased and more long-term oriented than traditional analysts. Bartov et al. (2018) document that Twitter appears to have predictive ability beyond traditional analyst forecasts, as opinions on Twitter can predict the future earnings surprise. Drake et al. (2023) find that Seeking Alpha (SA), the investment advice platform, also appears to contain information in advance of analyst reports, as they find less of a reaction to analyst reports when a SA article on the same firm has been published in advance of the analyst report.

Our research question imposes even greater attention requirements and asks if traditional analysts would also change their recommendations on a focal stock based on social media perceptions of all other firms in the traditional analysts' portfolio. The reasons for investigating this question is twofold. First, the prior literature has shown that depending on the circumstances and the motivations of the analyst, the analyst may either anchor expectations away from the comparison group (Bowers 2015; Hartzmark and Shue 2018; Kumar et al. 2022) or towards the comparison group (Cen et al. 2013). This has mostly been explored in relation to peer expectations of the focal firm in the analyst's portfolio and how analysts benchmark focal firm reports. Recently, Kumar et al. (2022) find that analyst forecasts of a focal firm are also affected by forecast errors of other firms in an analyst's portfolio. Specifically, analysts adjust their forecasts in the opposite direction of prior forecast errors of other firms in their portfolio. Kumar et al. (2022) explain this finding in terms of analysts learning about peers' forecast errors and adjusting accordingly. However, we propose that analysts may respond differently to social media information because they are less familiar with its underlying production process. As a result, analysts may feel less comfortable critiquing social media information but may still incorporate it into their estimates. In summary, it is an open question whether analysts will benchmark to peers on social media and if so, in which direction.

Second, even though there are studies that explore the interaction between one type of social media and traditional analysts, we are not clear on the circumstances with which the analyst actually extracts information from these types of social media. Using a directional specification, we jointly test whether traditional analysts anchor focal firm expectations on social media opinions of other firms in their portfolio and if so, will they move expectations closer to the peer average or further away from it.

SA is a representative type of social media to study. Unlike Estimize, it is not restricted to providing only numerical estimates – a piece of analysis on a company could be five pages or more. In fact, an observation on SA is significantly longer than most other types of social media such as Twitter, Glassdoor.com[1], and StockTwits. Cookson et al. (2024) show that social media platforms have varying information content even on the same issue, contingent on the user base and the average textual content. In terms of access to content, SA has a paywall restriction[2], which also makes it distinct from other openly-accessible types of social media such as Twitter or Reddit. Users of SA may assign a higher threshold of information content for the benefits of subscription to outweigh its cost. However, it can be argued that compared to StockTwits and Estimize, which have very clear purposes of generating stock picks and earnings forecasts, respectively, SA caters to a wider range of users with different financial investment goals[3]. Therefore, amongst different types of social media, SA strikes a balance between level of presumed professionalism and direct link to offline financial services counterpart. That is, SA has been shown to be value-relevant to capital market participants (Chen et al. 2014), but it is not the social media counterpart to analyst forecasts like Estimize is. These opposing forces make

[1] Twitter has a limit of 280 characters: https://developer.twitter.com/en/docs/counting-characters, and a selection of sample ratings from Glassdoor.com shows most reviews are less than 200 words in length

[2] Complete access to Seeking Alpha articles cost between $240-2,400 per year: https://seekingalpha.com/subscriptions

[3] On Seeking Alpha, one can read investment advice articles, view earnings call transcripts, monitor stocks and bonds, and discuss investment strategies

the question of whether traditional analysts would change expectations on a focal stock based on SA sentiment of all other firms in the traditional analysts' portfolio an interesting one to study.

We expect that traditional analysts will monitor social media channels. Social media has been shown to be relevant for returns, and thus, could contain incremental information above what is commonly accessible to analysts when making forecasts and recommendations. Bartov et al. (2018) show that Twitter predicts earning surprise and earnings announcement return. Huang et al. (2020) find that information on Glassdoor.com predict earnings announcement return. Cookson et al. (2024) document evidence of StockTwits predicting next-day returns. Other studies have shown that social media subsumes some of the information content provided by analysts, suggesting if analysts want forecasts to be as impactful as possible, they should be aware of social media such as Estimize (Jame et al. 2016) and SA (Drake et al. 2023). However, to the best of our knowledge, there is an absence of studies examining the directional effect of traditional analysts paying attention to SA. That is, will they move closer to the outlook of semi-professional information intermediaries (Drake et al. 2017) or further away.

RQ1*: There is a relationship between Seeking Alpha other portfolio sentiment and forecast error/forecast optimism.*

In social psychology, Herr et al. (1983) and Herr (1986) note that the degree with which individuals move closer, referred to as assimilation effect, or further away, referred to as contrast effect, from a piece of information is contingent on the extent of category overlap between the judgement to be made and the anchoring information. The higher the degree of overlap and the less extreme the defining characteristics of the anchoring information, then the more likely that individuals will shift expectations toward the anchoring information. After attempting to strip away all prior information,

the most accessible heuristic that analysts have to evaluate information from SA is this level of familiarity of SA as an information type compared to Estimize or to peer traditional analyst forecasts.

Our prediction is we will see a different effect than that reported by Kumar et al. (2022). Traditional analysts are very familiar with the process, information content, and format of peer analyst recommendations. As such, they are able to distill the incremental information needed to form separate and informed judgements by benchmarking to peers' forecast errors. Indeed, evidence in Bowers (2015) shows that contrast effects are stronger when analysts can place a stock more comfortably within industry boundaries. We expect Estimize to have a similar effect on traditional analysts' judgements, as they are similar to traditional analyst forecast in form and content. In contrast, Seeking Alpha (SA) provides financial advice but presents this information in a less familiar context. Consequently, analysts may adjust their estimates closer to social media sentiment. This is because they recognize the relevance of social media information to their estimates and forecasts (Kim & Youm, 2017) but lack the familiarity needed to isolate the incremental relevant information from the general sentiment. This situation is similar to the findings of Fich and Xu (2023), who observed assimilation effects in investors' valuations of M&A deals. M&A deals are generally more ambiguous than typical valuation activities due to the complexities involved, such as potential synergies (Shleifer and Vishny 2003).

RQ2*: The relationship between Seeking Alpha other portfolio sentiment and forecast error/forecast optimism is stronger when there is greater ambiguity about the focal firm.*

3. Baseline regression model

We test the effect of peer SA analysts' sentiment on traditional sell-side analysts' earnings forecasts using the following regression model:

$$ForecastError_{i,j,t} / ForecastOptimism_{i,j,t} = \beta_0 + \beta_1 SAOtherSentiment_{i,j,t-1} + \beta_j Controls_{i,j,t-1} + Fixed\ Effects + \varepsilon_{i,j,t-1} \quad (1)$$

We measure the forecast error of sell-side analyst *i* for firm *j* (*ForecastError*) as the difference between his or her first EPS forecast of quarter *t* after the earnings announcement date of quarter *t*-1 and the actual EPS of quarter *t*, scaled by the stock price two days before the earnings announcement date of quarter *t*. Similarly, we measure forecast optimism (*ForecastOptimism*) as the difference between the analyst's first EPS forecast for quarter *t* after the earnings announcement date of quarter *t*-1 and the consensus EPS forecast of quarter *t*, scaled by stock price. These two measures benchmark analysts' EPS forecasts against different references, enhancing the robustness of the empirical tests. Consistent with prior literature, we exclude firm-quarter observations where the quarter-end stock price is below $1.

The testing variable, *SAOtherSentiment*, is calculated as the average sentiment score of articles published by SA analysts (peer analysts) covering *other* firms in the portfolio of analyst *i* in the previous quarter. This measure deliberately excludes the sentiment score of peer analysts from the prior quarter for the focal firm (firm *j*) to avoid any mechanical correlation with the forecast error or optimism of the focal analyst (analyst *i*), which could arise from shared knowledge about the focal firm. By excluding sentiment related to the focal firm, *SAOtherSentiment* effectively serves as a proxy for the broader sentiment context in which the focal analyst operates.

We follow Kumar et al. (2022) and include several control variables and fixed effects. We first control for the average forecast error of peer sell-side analysts on other firms in the portfolio of analyst *i* in the previous quarter (*PeerForecastError*), as an analyst's forecasts are also affected by the previous forecasts and outcomes of the "traditional" sell-side analysts who follow the same firms in the focal

analyst's portfolio. We also control for the focal analyst's previous forecast error on the focal firm (*OwnPreviousForecastError*) and his or her previous average forecast error on other firms in his or her portfolio (*OwnOtherForecastError*), in order to capture the systematic bias that the analyst may have been consistently over-estimating or under-estimating future EPS of the firms he or she covers (Hillary and Hsu 2013).

To account for any unobservable covariates that may systematically influence analysts' forecast errors, we include earnings announcement fixed effects, which control for all common firm- and quarter-specific factors that could affect the forecast errors of analysts following a particular firm. By incorporating these fixed effects, it ensures that we are comparing the forecast errors of all analysts making forecasts for the same firm-quarter against each other (Kumar et al. 2022), thereby isolating the portion of forecast errors attributable to firm- and quarter-specific information. Additionally, we include firm-analyst fixed effects to control for each analyst's systematic forecast error on the firm, which may arise from the analyst's interpretation of firm-specific information.[4] We follow Kumar et al. (2022) and cluster standard errors by earnings announcement.

4. Sample and Data

4.1 Seeking Alpha articles

Using the Natural Language Processing (NLP) methodology outlined in Klevak et al. (2019), we code sentences in an SA article in two steps. The main characteristics of this NLP methodology are

[4] Note that the analyst-firm systematic bias may also arise from the analyst's own psychological bias, which could arise from the context in which the analyst operates, including assimilation or contrast effects. If this is the case, controlling for firm-analyst fixed effects could reduce the likelihood of detecting significant effects of the sentiment of peer SeekingAlpha analysts on the focal analyst's forecast error.

that it recognizes semantic patterns to derive the positive or negative sentiment and that it codes sentiment based on the business events it identifies within phrases and sentences.

We adapt the natural language processing (NLP) methodology outlined in Klevak et al. (2019) to encode the sentiment embedded in an SA article. This NLP methodology primarily features the recognition of semantic patterns to derive positive or negative sentiments and codes sentiment based on the business events identified within phrases and sentences. We capture the sentiment embedded in a sentence in two steps. In the first step, the processor scans the entire article sentence by sentence, identifying and coding parts of each sentence 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 processor utilizes about 3,000 rules to recognize and categorize business events as positive or negative. These rules also differentiate parts of speech such as nouns, adjectives, verbs, and adverbs, with a sentence. The 3,000 rules are classified over 50 distinct event categories, such as product announcements, mergers and acquisitions, and workforce. Appendix II provides examples of the types of positive and negative business events coded from SA articles in the sample and explanations of how the NLP processor identifies the polarity of business events.

In the second coding step, the NLP processor scans the entire article again to capture any words and phrases that may represent general sentiment. Our NLP methodology includes sets of rules that categorize financial results, earnings guidance, and words from the Loughran and McDonald (2011) financial dictionary. For example, sentiment mentions not associated with specific business events could include phrases like “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, an SA document score, coded using NLP that approximates a human reader's sentiment, is created and referred to as *ReaderSentiment*. This score is calculated as the standardized net sentiment of the document. Specifically, we subtract the negative mentions from the positive mentions and standardize them by the total mentions (both positive and negative). Positive mentions are calculated as an aggregate of positive business event mentions and positive general sentiment mentions, with business event mentions weighted more heavily than positive general sentiment mentions. Negative mentions are aggregated similarly, using negative business event mentions and general sentiment mentions. *ReaderSentiment* can range from -1 and +1, where a positive article would have a score in the range (0,1], a negative article would have a score in the range [-1,0), and a neutral article would have a score of 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.

The SA sentiment measure we create, *ReaderSentiment*, compares favorably to sentiment measures used in previous studies by offering event-based classification and measuring directional sentiment. Chen et al. (2014) report only negative sentiment extracted from articles using the Loughran and McDonald (2011) word list. In contrast, *ReaderSentiment* is calculated using both positive and negative mentions in SA articles. Furthermore, *ReaderSentiment* captures mentions in the Loughran and McDonald (2011) word list but extends beyond it with thousands of rules that measure positive and negative business events, as well as sentiment relevant to the economic context. We employ NLP to more precisely capture the business events and economic context discussed in SA articles. In

Appendix II, we also show how the NLP sentiment compares with Loughran and McDonald (2011) word-based sentiment for two SA articles written during our sample period.

We compile all SA articles written since the establishment of the site in 2004 through October 1, 2018. In total, 350,095 articles are included, covering 5,635 companies. An article may be coded as relating to multiple companies if it is a comparison piece or industry analysis. We then average *ReaderSentiment* for all articles published by SA analysts (peer analysts) covering other firms in the portfolio of analyst i in the previous quarter. The average is the main testing variable, *SAOtherSentiment*. Analyst variables are collected from I/B/E/S. Detailed variable descriptions are included in Appendix I. In total, we have 233,102 observations at the analyst-firm-quarter level.

Table 1 Panel A shows the descriptive statistics of all variables used in the baseline regression model (Model (1)). The average SA sentiment for other firms in the focal analysts' portfolio, *SAOtherSentiment*, is positive, which suggests SA sentiment tracks in the same direction as focal analysts' forecast errors, *OwnPreviousForecastError* and *OwnOtherForecastError* and peer analysts' forecast errors, *PeerForecastError* in quarter t-1. *OwnPreviousForecastError*, *OwnOtherForecastError*, and *PeerForecastError* are all positive on average. However, in quarter t, the measures of analyst forecast error and bias, *ForecastError* and *ForecastOptimism*, respectively, are on average negative.

5. Empirical Results

5.1. Baseline regression results

Table 1, Panel B, and Panel C present the baseline results for the relationship between *SAOtherSentiment* in the prior quarter and the forecast error and forecast optimism, respectively, for

the current quarter. Contrary to the findings of Kumar et al. (2022) that focal analysts learn from the forecast errors of traditional peer analysts and adjust their subsequent forecasts in the opposite direction of these errors, focal analysts do not appear to make forecasts in the opposite direction of the sentiment derived from SA information of other firms in their portfolio. On the contrary, the significantly positive coefficients on *SAOtherSentiment* in both panels (coeff. = 0.024, t = 5.96; coeff. = 0.022, t = 5.37) indicate an incremental effect, with focal analysts' forecast errors correlated with the same direction as the SA sentiment of portfolio firms. Column 4 of Panels B and C indicates that this positive relationship persists even after controlling for other factors influencing focal analysts' forecast error and optimism: peer analysts' evaluations of other firms in the portfolios of the focal analysts (Kumar et al., 2022), focal analysts' own prior biases on the focal firm, and focal analysts' own prior biases on other firms in their portfolios. The signs of coefficients on these variables are also consistent with those documented in Kumar et al. (2022). In terms of economic significance, a one standard-deviation increase in *SAOtherSentiment* leads to a 12% increase in forecast error (0.209*0.024/0.039) and a 7% increase in forecast optimism (0.209*0.022/0.069). Figure 2 corroborates the results in a graphical format. After ranking *SAOtherSentiment* into deciles, we observe that higher *SAOtherSentiment* values are associated with more positive forecast errors and greater optimism.

The positive and significant coefficients on *SAOtherSentiment* are consistent with an assimilation effect of peer social media analysts' sentiment on traditional analysts forecast behaviors. This corroborates with findings in the social psychology literature (Herr et al., 1983; Herr, 1986; Herr 1989) and supports the behavioral implications of analysts' decision-making processes as suggested by Bowers (2015). When analysts are less familiar with the information-production processes of these social media analysts on SA but recognize the validity and usefulness of their sentiment information,

they are more likely to benchmark toward the sentiment, demonstrating an assimilation effect. We consider the mechanism underlying the positive relationship between SA sentiment and analyst forecast error and optimism to be different from that proposed by Kumar et al. (2022). In our case, analysts are not reversing peers' errors because it is difficult for them to identify the specific factors contributing to a peer social media analyst's error. Given this lesser degree of familiarity, analysts instead anchor their judgments, perhaps even unconsciously, on the prevailing market sentiment—the 'talk of the street'—as reflected in social media sentiment.

5.2. Robustness tests

5.2.1. Paired analysts test

As discussed in Section 3, the complex fixed effects structure of the baseline regression model helps mitigate concerns that the observed association between the sentiment of peer SA analysts and the focal analyst's forecast error could be driven by firm- and quarter-specific information, or by systematic firm-analyst bias. In this section, we further address these concerns by pairing analysts who follow the same firm in a given quarter and calculating the difference between their respective peer SA analysts' sentiment and forecast errors/optimism. We then apply the following model to conduct the paired analysts test:

$$\Delta ForecastError_{i,k,j,t} / \Delta ForecastOptimism_{i,k,j,t} = \beta_0 + \beta_1 \Delta SAOtherSentiment_{i,k,j,t-1} + \beta_j \Delta Controls_{i,k,j,t-1} + Fixed\ Effects + \varepsilon_{i,k,j,t-1} \quad (2)$$

In a firm-quarter with N analysts following, there would be C_N^2 pairs of analysts. For each pair, the dependent variable, $\Delta ForecastError$ ($\Delta ForecastOptimism$), represents the difference between analyst i's and analyst j's forecast error (optimism). The testing variable, $\Delta SAOtherSentiment$, captures

the difference between the peer SA analysts' sentiment for analyst *i* and analyst *j* in the previous quarter. By focusing on the differences between pairs of analysts following the same firm, this model eliminates any mechanical association among forecast outcomes as a result of firm-specific factors, leaving differences driven solely by variations in the analysts' working contexts unrelated to the focal firm. This approach provides a more robust interpretation of the influence of peer SA analysts' sentiment on analysts' forecast error and optimism. A positive (negative) coefficient on $\Delta SAOtherSentiment_{i,k,j,t-1}$ is consistent with the assimilation (contrast) effect.

Table 2 shows the results with using $\Delta SAOtherSentiment$ as our variable of interest. Similar to the results with *SAOtherSentiment* the coefficient on $\Delta SAOtherSentiment$ is positive and significant across all model specifications, providing further evidence that the focal analyst makes forecasts in the same orientation as his or her peer SA analysts' sentiment in the previous quarter.

5.2.2. Exogenous shocks to peer SeekingAlpha analysts' sentiment

It is possible that the association between peer SA analysts' sentiment and the focal analyst's forecast error/optimism is driven by other unobservable factors systematically correlated with both peer SA analysts' sentiment and the focal analyst's forecast outcomes. For instance, both sets of analysts may rely on the same information sources, which could simultaneously influence peer SA analysts' sentiment and the focal analyst's forecast error or optimism. To address this concern, we employ a seemingly endogenous shock to peer SA analysts' sentiment resulting from the acquisition of firms in the focal analyst's portfolio. Specifically, if one or more firms in the focal analyst's portfolio are acquired and cease to exist in the market, the analysts are forced to stop covering those firms, leading to a reduction or complete loss of connection between the focal analyst and peer SA analysts,

diminishing or eliminating the influence of those peers on the focal analyst. Most importantly, since the decision to acquire the peer firms in the focal analyst's portfolio is made by the acquiring firms, it is unlikely to directly affect the focal analyst's forecast outcomes for the focal firm. Thus, the acquisition affects the focal analyst's forecast outcomes only through its influence on the analyst's portfolio.

To conduct this analysis, we focus on a subsample of firm-quarters where the average sentiment of peer SA analysts' articles changed due to the acquisition of one or more firms in the focal covering analyst's portfolio. We only include cases of 100% acquisitions from the SDC Database, and use the acquisition completion date as the point when analysts cease to cover the acquired firms. To further ensure the validity of our identification strategy, we confirm that no financial statement or stock return information for the acquired firms is available in Compustat or CRSP after the acquisition completion date, verifying that the firms no longer exist as publicly listed entities. Additionally, we check that no SA articles or I/B/E/S analysts' forecasts on these firms are issued after the acquisition completion date. We then calculate the change in the average sentiment of peer SA analysts' articles ($SAOtherSentiment_{After\ -\ Before}$) and use this as the testing variable. The change in the focal analyst's forecast error / optimism serves as the dependent variable. A positive coefficient on the change in peer SA analysts' sentiment indicates an assimilation effect, while a negative coefficient suggests a contrast effect.

Table 3 shows that the coefficients on the variable of interest, $SAOtherSentiment_{After\ -\ Before}$, are significantly positive across all model specifications. Changes in the average peer SeekingAlpha analysts' sentiment as a result of portfolio firms being acquired is positively associated with the changes in the focal analyst's forecast error and forecast optimism. The results alleviate concerns that

the observed relationship between peer social media analysts' sentiment and the focal analyst's forecast error or optimism is driven by unobservable factors systematically correlated with both. This further reinforces the main findings.

5.3. Cross-sectional tests

Our next set of tests examines whether the mechanism through which traditional analysts make forecasts in the same direction as SA analysts' sentiment is driven by their relative unfamiliarity with social media analysts compared to traditional analysts. To investigate this, we partition our sample based on environments characterized by high and low information uncertainty. Information uncertainty is proxied by analyst dispersion, past negative earnings surprises, and past losses. We hypothesize that when the focal firm operates under high information uncertainty, analysts are more likely to assimilate towards SA analysts' sentiment about other firms. This tendency arises because, in such situations, analysts have less confidence and familiarity with accurately forecasting the focal firm. They may place trust in SA analysts to gather relevant information about the industry and peers, leading them to match their estimates more closely with the SA analysts' opinions. Table 4 provides evidence supporting these arguments.

Table 4 Panel A shows that analysts' forecast dispersion on the focal firm in the previous quarter has significant incremental effect on the positive association between *SAOtherSentiment* and forecast error and forecast optimism in the current quarter. This finding supports the notion that analysts align their forecasts with sentiments expressed by SA analysts when they face higher levels of uncertainty and greater difficulty in predicting earnings. Interestingly, the coefficient on *SAOtherSentiment* is insignificant, suggesting analysts are more likely to seek outside opinions when there is a lack of past

consensus about the firm. Table 4 Panel B shows that the positive association between *SAOtherSentiment* and forecast error and forecast optimism in the current quarter is stronger when the focal firm has negative earnings surprise in the previous quarter. This result corresponds with the idea that analysts require additional information to make accurate forecasts when a firm encounters bad news. Consequently, they may seek such information from their peer SA analysts. Table 4 Panel C shows that the positive association between SAOtherSentiment and forecast error and forecast optimism in the current quarter is stronger when the focal firm experienced a loss in the previous quarter. The implications of this finding are similar to those reported in Panel B—analysts facing heightened uncertainty, such as bad news about the firm, turn to their peer analysts on social media for additional insights. Taken together, these cross-sectional tests support the argument that analysts benchmark away from traditional analyst peers, as they are familiar with traditional analysts and their forecasting processes. In such cases, analysts are confident in their own abilities and distance themselves from their peers. Conversely, analysts benchmark towards SA analysts because they are less familiar with SA analysts and perceive that they provide valuable, relevant information. This effect is particularly pronounced in situations where analysts feel uncertain about their ability to accurately forecast firms, such as when information uncertainty is high.

5.4. Can investors discern the benchmarking forecast bias of analysts?

Finally, we are interested in how the market perceives the assimilation behavior exhibited by analysts. To test this, we examine market returns during the short window around earnings announcements, based on the extent to which analysts incorporate SA analysts' sentiment from other firms in the portfolio. Table 5 shows that *SAOtherSentiment* has no incremental effect on the positive

association between forecast error and optimism and short-term market reactions to these forecasts. This suggests that investors may not be able to discern the forecast bias of analysts caused by their working context. If they could, the market would likely discount analysts' forecasts based on the extent to which their forecasts are influenced by this context, leading to a negative cross-sectional effect of *SAOtherSentiment* on the relationship between forecast error and optimism and short-term market reactions to these forecasts.

6. Conclusion

This study investigates how analysts incorporate information from social media, focusing on SA as a representative platform. The findings reveal that analysts benchmark their forecasts towards the sentiment expressed in SA articles about other firms in their portfolio, proxied by an incremental and significant positive relationship between SA sentiment and both forecast error and forecast optimism. In environments with greater information ambiguity, analysts show an even stronger tendency to adjust their forecasts in the direction of SA sentiment.

The paper makes several contributions to the literature on analyst behavior and social media's role in capital markets. First, it highlights a new decision heuristic—analysts' familiarity with the content and form of information—which shapes their benchmarking practices. Unlike prior studies that focus on industry categorizations, this study emphasizes the impact of the information medium. Second, it demonstrates that analysts are less adept at isolating useful information from noise in social media compared to traditional sources, which influences their benchmarking behaviors. Finally, it expands the understanding of how analysts interact with emerging information sources,

particularly those with unique features, such as SA articles, which blend characteristics of traditional financial intermediary with social media.

This study underscores the complexity of analysts' decision-making processes in an era of rapidly evolving information channels. The findings suggest that social media platforms like SA play a distinct and influential role in shaping analyst forecasts, especially in ambiguous information environments. By shedding light on analysts' reliance on new mediums, this research provides insights into how forecasting behavior adapts to the changing informational landscape. These results have broader implications for assessing the information content and relevance of analyst forecasts and understanding the integration of diverse information sources in financial decision-making.

References

Bartov, E., Faurel, L., & Mohanram, P. S. (2018). Can Twitter help predict firm-level earnings and stock returns?. *The Accounting Review*, 93(3), 25-57.

Bernhardt, D., Wan, C., & Xiao, Z. (2016). The reluctant analyst. *Journal of Accounting Research*, 54(4), 987-1040.

Bowers, A. (2015). Relative comparison and category membership: The case of equity analysts. *Organization Science*, 26(2), 571-583.

Bradley, D., Hanousek Jr, J., Jame, R., & Xiao, Z. (2024). Place your bets? The value of investment research on Reddit's Wallstreetbets. *The Review of Financial Studies*, 37(5), 1409-1459.

Butler, K. C., & Lang, L. H. (1991). The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism. *Journal of Accounting Research*, 150-156.

Campbell, J. L., DeAngelis, M. D., & Moon, J. R. (2019). Skin in the game: Personal stock holdings and investors' response to stock analysis on social media. *Review of Accounting Studies*, 24, 731-779.

Cen, L., Hilary, G., & Wei, K. J. (2013). The role of anchoring bias in the equity market: Evidence from analysts' earnings forecasts and stock returns. *Journal of Financial and Quantitative Analysis,* 48(1), 47-76.

Chen, H., De, P., Hu, Y., & Hwang, B. H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, 27(5), 1367-1403.

Chen, Q., Mayew, W. J., & Yan, H. (2024). Equity analyst social interactions and geographic information transmission. *Review of Accounting Studies*, 29(1), 327-353.

Clarke, J., Chen, H., Du, D., & Hu, Y. J. (2020). Fake news, investor attention, and market reaction. *Information Systems Research*, 32(1), 35-52.

Coleman, B., Merkley, K., & Pacelli, J. (2022). Human versus machine: A comparison of robo-analyst and traditional research analyst investment recommendations. *The Accounting Review*, 97(5), 221-244.

Cookson, J. A., Lu, R., Mullins, W., & Niessner, M. (2024). The social signal. *Journal of Financial Economics*, 158.

Da, Z., & Huang, X. (2020). Harnessing the wisdom of crowds. *Management Science*, 66(5), 1847-1867.

Do, T. P. T., & Zhang, H. (2020). Peer effects among financial analysts. *Contemporary Accounting Research*, 37(1), 358-391.

Drake, M. S., Moon Jr, J. R., Twedt, B. J., & Warren, J. D. (2023). Social media analysts and sell-side analyst research. *Review of Accounting Studies*, 28(2), 385-420.

Drake, M. S., Thornock, J. R., & Twedt, B. J. (2017). The internet as an information intermediary. *Review of Accounting Studies*, 22, 543-576.

Fich, E. M., & Xu, G. (2023). Assimilation Effects in Financial Markets. *Journal of Financial and Quantitative Analysis*, 58(7), 2890-2927.

Francis, J., & Philbrick, D. (1993). Analysts' decisions as products of a multi-task environment. *Journal of Accounting Research*, 31(2), 216-230.

Hartzmark, S. M., & Shue, K. (2018). A tough act to follow: Contrast effects in financial markets. *The Journal of Finance*, 73(4), 1567-1613.

Herr, P. M. (1986). Consequences of priming: Judgment and behavior. *Journal of Personality and Social Psychology*, 51(6), 1106.

Herr, P. M. (1989). Priming price: Prior knowledge and context effects. *Journal of Consumer Research*, 16(1), 67-75.

Herr, P. M., Sherman, S. J., & Fazio, R. H. (1983). On the consequences of priming: Assimilation and contrast effects. *Journal of Experimental Social Psychology*, 19(4), 323-340.

Hilary, G., & Menzly, L. (2006). Does past success lead analysts to become overconfident?. *Management Science*, 52(4), 489-500.

Huang, K., Li, M., & Markov, S. (2020). What do employees know? Evidence from a social media platform. *The Accounting Review*, 95(2), 199-226.

Jame, R., Johnston, R., Markov, S., & Wolfe, M. C. (2016). The value of crowdsourced earnings forecasts. *Journal of Accounting Research*, 54(4), 1077-1110.

Jame, R., Markov, S., & Wolfe, M. C. (2022). Can FinTech competition improve sell-side research quality?. *The Accounting Review*, 97(4), 287-316.

Jia, W., Redigolo, G., Shu, S., & Zhao, J. (2020). Can social media distort price discovery? Evidence from merger rumors. *Journal of Accounting and Economics*, 70(1).

Kim, E. H., & Youm, Y. N. (2017). How do social media affect analyst stock recommendations? Evidence from S&P 500 electric power companies' Twitter accounts. *Strategic Management Journal*, 38(13), 2599-2622.

Kumar, A., Rantala, V., & Xu, R. (2022). Social learning and analyst behavior. *Journal of Financial Economics*, 143(1), 434-461.

Lim, T. (2001). Rationality and analysts' forecast bias. *The Journal of Finance*, 56(1), 369-385.

Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Science*, 62(12), 3412-3427.

Merkley, K. J., Pacelli, J., Piorkowski, M., & Williams, B. (2024). Crypto-influencers. *Review of Accounting Studies*, 29(3), 2254-2297.

Millo, Y., Spence, C., & Valentine, J. (2023). The field of investment advice: The social forces that govern equity analysts. *The Accounting Review*, 98(7), 457-477.

Shleifer, A., & Vishny, R. W. (2003). Stock market driven acquisitions. *Journal of Financial Economics*, 70(3), 295-311.

Schafhäutle, S. G., & Veenman, D. (2024). Crowdsourced forecasts and the market reaction to earnings announcement news. *The Accounting Review*, 99(2), 421-456.

Wänke, M., Bless, H., & Schwarz, N. (1998). Context effects in product line extensions: Context is not destiny. *Journal of Consumer Psychology*, 7(4), 299-322.

Figure 1. Theoretical framework

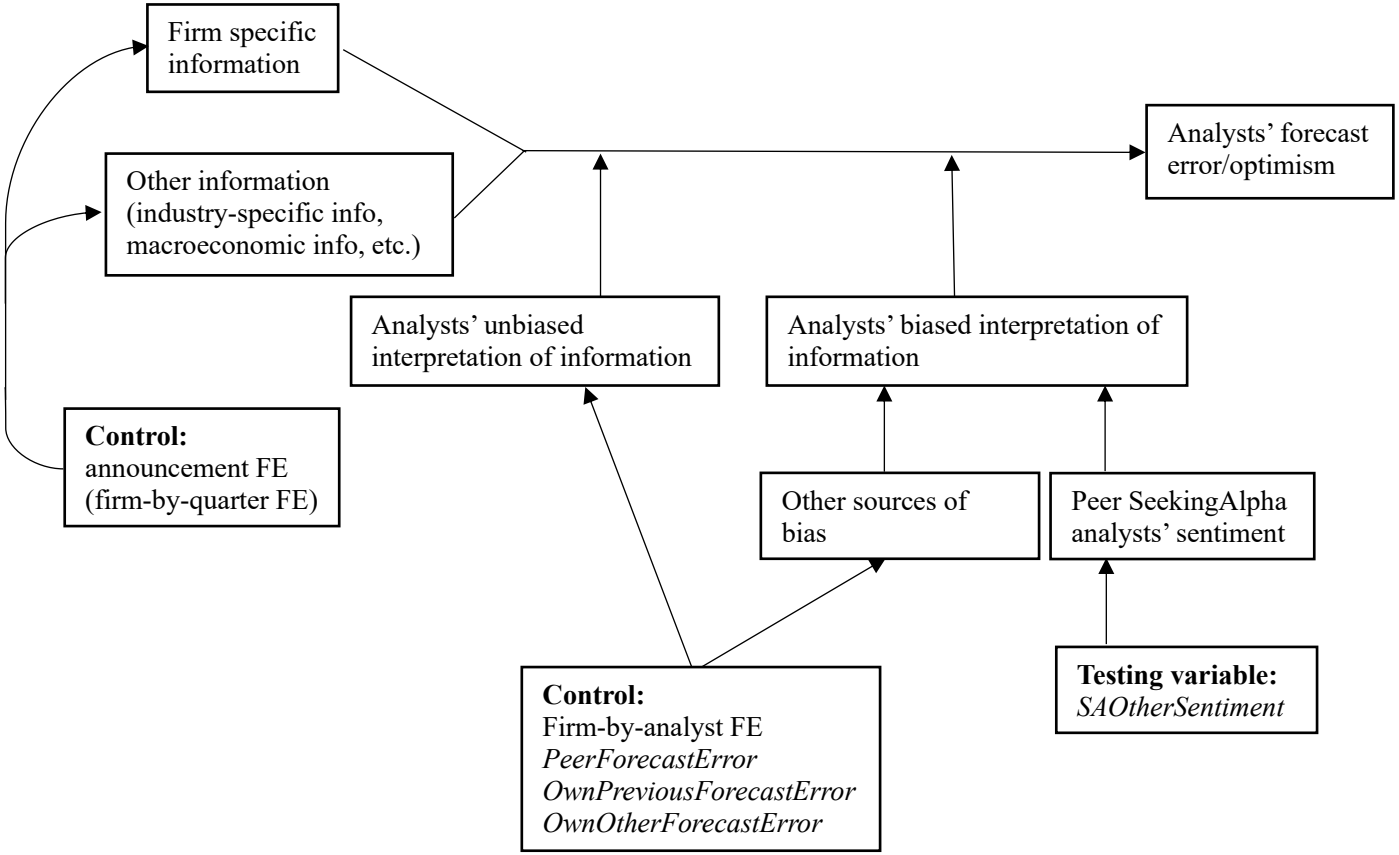
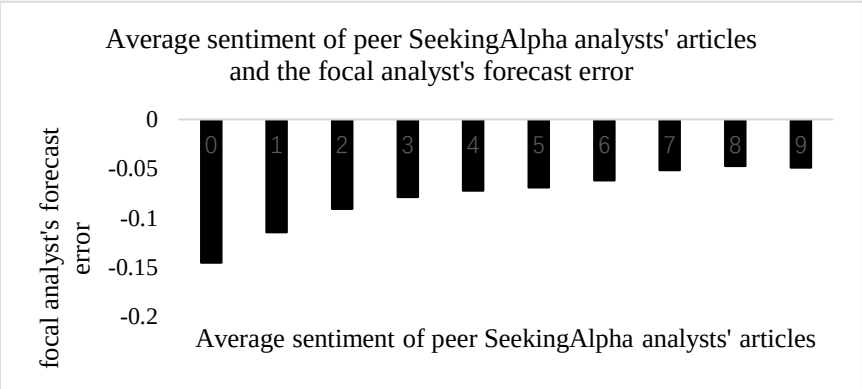


Figure 2. Context effect on the focal analyst's forecast error and forecast optimism



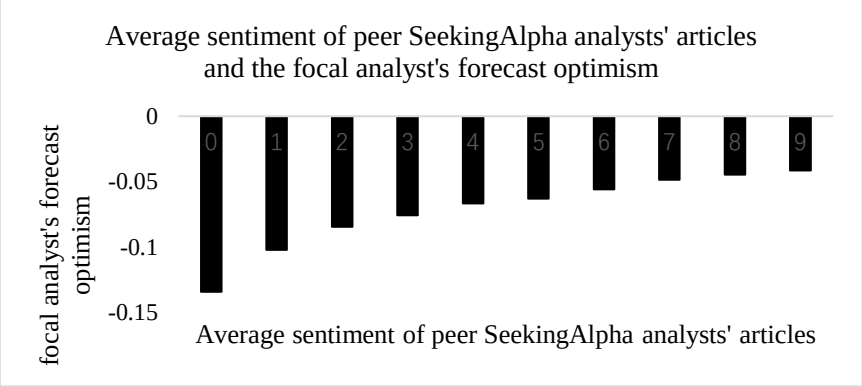


Table 1. Baseline regression results

Panel A. Descriptive statistics

	N	Mean	S. D.	P25	P50	P75
ForecastError	233,102	-0.039	1.263	-0.188	-0.046	0.046
ForecastOptimism	233,102	-0.069	0.404	-0.140	-0.020	0.043
SAOtherSentiment	233,102	0.200	0.209	0.098	0.210	0.320
PeerForecastError	233,102	0.003	0.808	0.000	0.002	0.005
OwnPreviousForecastError	233,102	0.002	0.021	-0.002	0.000	0.003
OwnOtherForecastError	233,102	0.003	1.581	0.000	0.002	0.005

Panel B. Context effect on earnings forecast error

	DV = $ForecastError_{i, j, t}$			
	Coeff. (t-stat.)	Coeff. (t-stat.)	Coeff. (t-stat.)	Coeff. (t-stat.)
Variable	(1)	(2)	(3)	(4)
Constant	-0.062***	-0.062***	-0.066***	-0.066***
	(-79.17)	(-72.07)	(-72.20)	(-71.94)
$\boldsymbol{SAOtherSentiment_{i, j, t-1}}$	**0.024*** **	**0.023*** **	**0.024*** **	**0.024*** **
	(5.96)	**(5.94)**	**(6.01)**	**(6.03)**
$PeerForecastError_{i, j, t-1}$		-0.031	-0.021	-0.254**
		(-0.30)	(-0.21)	(-1.99)
$OwnPreviousForecastError_{i, j, t-1}$			2.582***	2.577***
			(13.06)	(13.04)
$OwnOtherForecastError_{i, j, t-1}$				0.329***
				(2.92)
N	233,102	233,102	233,102	233,102
Adj. R-squared	0.839	0.839	0.840	0.840
Earnings Announcement Fixed Effects	Yes	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes	Yes

Panel C. Context effect on earnings forecast optimism

	DV = $ForecastOptimism_{i, j, t}$			
	Coeff. (t-stat.)	Coeff. (t-stat.)	Coeff. (t-stat.)	Coeff. (t-stat.)
Variable	(1)	(2)	(3)	(4)
Constant	-0.076***	-0.076***	-0.080***	-0.081***
	(-92.47)	(-83.55)	(-83.71)	(-83.36)
$\boldsymbol{SAOtherSentiment_{i, j, t-1}}$	**0.022*** **	**0.022*** **	**0.022*** **	**0.022*** **
	(5.37)	**(5.36)**	**(5.43)**	**(5.46)**
$PeerForecastError_{i, j, t-1}$		-0.003	0.009	-0.222*
		(-0.02)	(0.08)	(-1.66)
$OwnPreviousForecastError_{i, j, t-1}$			3.044***	3.039***
			(14.88)	(14.86)
$OwnOtherForecastError_{i, j, t-1}$				0.326***
				(2.83)
N	233,102	233,102	233,102	233,102
Adj. R-squared	0.621	0.621	0.624	0.624
Earnings Announcement Fixed Effects	Yes	Yes	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes	Yes	Yes

Table 2. Paired analysts test

	DV = $\Delta ForecastError_{i,k,j,t}$	DV = $\Delta ForecastOptimism_{i,k,j,t}$
	Coeff.	Coeff.
	(t-stat.)	(t-stat.)
Variable	(1)	(2)
Constant	0.001	0.001
	(0.66)	(0.30)
$\Delta \boldsymbol{SAOtherSentiment_{i,k,j,t-1}}$	**0.017*** **	**0.015*** **
	(3.19)	**(2.61)**
$\Delta PeerForecastError_{i,k,j,t-1}$	-0.332***	-0.306***
	(-3.13)	(-2.78)
$\Delta OwnPreviousForecastError_{i,k,j,t-1}$	3.559***	4.192***
	(17.80)	(19.89)
$\Delta OwnOtherForecastError_{i,k,j,t-1}$	0.526***	0.542***
	(6.09)	(6.08)
N	905,386	905,386
Adj. R-squared	0.206	0.207
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst *i*-Analyst *k* Fixed Effects	Yes	Yes

Table 3. Exogenous shocks to peer SeekingAlpha analysts' sentiment

	DV = $ForecastError_{After - Before}$	DV = $ForecastOptimism_{After - Before}$
	Coeff.	Coeff.
	(t-stat.)	(t-stat.)
Variable	(1)	(2)
Constant	0.007***	-0.012***
	(34.51)	(-57.30)
$\boldsymbol{SAOtherSentiment_{After - Before}}$	**0.080*** **	**0.050*** **
	(4.24)	**(2.95)**
$PeerForecastError_{After - Before}$	-0.196	-0.156
	(-0.54)	(-0.48)
$OwnPreviousForecastError_{After - Before}$	4.194***	1.174*
	(6.34)	(1.93)
$OwnOtherForecastError_{After - Before}$	0.291	0.161
	(0.85)	(0.58)
N	37,603	37,603
Adj. R-squared	0.711	0.598
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes

Table 4. Cross-sectional tests

Panel A. Analyst forecast dispersion

	$ForecastError_{i, j, t}$	$ForecastOptimism_{i, j, t}$
	Coeff.	Coeff.
	(t-stat.)	(t-stat.)
Variable	(1)	(2)
Constant	-0.067***	-0.080***
	(-65.91)	(-74.65)
$\boldsymbol{SAOtherSentiment_{i, j, t-1} * Dispersion_{j, t-1}}$	0.326***	0.405***
	(2.87)	(3.19)
$SAOtherSentiment_{i, j, t-1}$	0.004	-0.002
	(0.68)	(-0.29)
$PeerForecastError_{i, j, t-1}$	-0.271**	-0.238*
	(-2.14)	(-1.78)
$OwnPreviousForecastError_{i, j, t-1}$	2.492***	2.989***
	(12.62)	(14.58)
$OwnOtherForecastError_{i, j, t-1}$	0.374***	0.359***
	(3.34)	(3.13)
N	229,311	229,311
Adj. R-squared	0.839	0.623
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes

Panel B. Negative earnings surprise

	$ForecastError_{i, j, t}$	$ForecastOptimism_{i, j, t}$
	Coeff.	Coeff.
	(t-stat.)	(t-stat.)
Variable	(1)	(2)
Constant	-0.066***	-0.080***
	(-71.50)	(-82.67)
$\boldsymbol{SAOtherSentiment_{i, j, t-1} * NegativeSurprise_{j, t-1}}$	0.016*	0.021**
	(1.83)	(2.24)
$SAOtherSentiment_{i, j, t-1}$	0.019***	0.017***
	(4.32)	(3.69)
$PeerForecastError_{i, j, t-1}$	-0.254**	-0.214
	(-1.97)	(-1.59)
$OwnPreviousForecastError_{i, j, t-1}$	2.576***	3.045***
	(12.92)	(14.77)
$OwnOtherForecastError_{i, j, t-1}$	0.332***	0.325***
	(2.93)	(2.80)
N	230,022	230,022
Adj. R-squared	0.839	0.624
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes

Panel C. Loss firm-years

	ForecastError$_{i, j, t}$	*ForecastOptimism*$_{i, j, t}$
	Coeff.	Coeff.
	(t-stat.)	(t-stat.)
Variable	(1)	(2)
Constant	-0.067***	-0.081***
	(-72.02)	(-82.45)
SAOtherSentiment$_{i, j, t-1}$ **** Loss***$_{j, t-1}$	0.042***	0.040**
	(2.73)	(2.52)
SAOtherSentiment$_{i, j, t-1}$	0.017***	0.015***
	(4.46)	(3.96)
PeerForecastError$_{i, j, t-1}$	-0.232*	-0.201
	(-1.82)	(-1.50)
OwnPreviousForecastError$_{i, j, t-1}$	2.610***	3.098***
	(13.15)	(15.15)
OwnOtherForecastError$_{i, j, t-1}$	0.325***	0.330***
	(2.89)	(2.86)
N	231,759	231,759
Adj. R-squared	0.840	0.624
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes

Table 5. Market reactions

	Return - R_f (-2,2)	*Return - R_f (-2,2)*
	Coeff.	Coeff.
	(t-stat.)	(t-stat.)
Variable	(1)	(2)
Constant	0.226***	0.177***
	(12.89)	(10.24)
SAOtherSentiment$_{i, j, t-1}$ * ForecastError$_{i, j, t}$	0.166	
	(0.67)	
ForecastError$_{i, j, t}$	0.855***	
	(10.36)	
SAOtherSentiment$_{i, j, t-1}$ * ForecastOptimism$_{i, j, t}$		-0.001
		(-0.01)
ForecastOptimism$_{i, j, t}$		0.177**
		(2.53)
SAOtherSentiment$_{i, j, t-1}$	-0.172**	-0.167**
	(-2.23)	(-2.17)
Market-Rf (-2,2)	1.125***	1.125***
	(53.36)	(53.18)
SMB (-2,2)	0.375***	0.376***
	(10.09)	(10.09)
HML (-2,2)	-0.028	-0.028
	(-0.66)	(-0.65)
RMW (-2,2)	-0.009	-0.011
	(-0.16)	(-0.18)
CMA (-2,2)	0.102	0.101
	(1.50)	(1.47)
MOM (-2,2)	-0.122***	-0.121***
	(-4.77)	(-4.73)
N	233,102	233,102
Adj. R-squared	0.838	0.837
Earnings Announcement Fixed Effects	Yes	Yes
Firm-Analyst Fixed Effects	Yes	Yes

Appendix I
Variable Definitions

Variable	Description
Dependent variables	
ForecastError	The difference between the focal analyst's first EPS forecast of quarter *t* after the earnings announcement date of quarter *t*-1 and the actual EPS of quarter *t*, scaled by the stock price two days before the earnings announcement date of quarter *t*.
ForecastOptimism	The difference between the focal analyst's first EPS forecast of quarter *t* after the earnings announcement date of quarter *t*-1 and the consensus EPS forecast of quarter *t*, scaled by the stock price two days before the earnings announcement date of quarter *t*.
Δ*ForecastError*	The difference in *ForecastError* between each two analysts that cover a firm-quarter.
Δ*ForecastOptimism*	The difference in *ForecastOptimism* between each two analysts that cover a firm-quarter.
$ForecastError_{After - Before}$	The change in *ForecastError* from before to after one or more firms in the focal analyst's portfolio are acquired and cease to exist in the market.
$ForecastOptimism_{After - Before}$	The change in *ForecastOptimism* from before to after one or more firms in the focal analyst's portfolio are acquired and cease to exist in the market.
Return - R_f *(-2,2)*	The five-day raw return minus the five-day treasury bill rate centered at the focal analyst's EPS announcement date.
Testing variables	
SAOtherSentiment	The average sentiment score of articles published by SA analysts (peer analysts) covering *other* firms in the portfolio of the focal analyst in the previous quarter.
Δ*SAOtherSentiment*	The difference in *SAOtherSentiment* between each two analysts that cover a firm-quarter.
$SAOtherSentiment_{After - Before}$	The change in *SAOtherSentiment* from before to after one or more firms in the focal analyst's portfolio are acquired and cease to exist in the market.
Dispersion	The standard error of EPS forecasts made by all analysts covering a firm in the previous quarter.
NegativeSurprise	An indicator variable equal to one the firm's actual EPS in the previous quarter is smaller than the consensus EPS forecast, and zero otherwise.
Loss	An indicator variable equal to one the firm has negative net income in the previous quarter, and zero otherwise.
Control variables	
PeerForecastError	The average forecast error of peer sell-side analysts on *other* firms in the portfolio of the focal analyst in the previous quarter
OwnPreviousForecastError	The focal analyst's previous forecast error on the focal firm, calculated as the focal analyst's first EPS forecast of quarter *t*-1 after the earnings announcement date of quarter *t*-2 and the actual EPS of quarter *t*-1, scaled by the stock price two days before the

	earnings announcement date of quarter *t*-1.
OwnOtherForecastError	The focal analyst's average forecast error on other firms in his or her portfolio in the previous quarter.
Δ*PeerForecastError*	The difference in *PeerForecastError* between each two analysts that cover a firm-quarter.
Δ*OwnPreviousForecastError*	The difference in *OwnPreviousForecastError* between each two analysts that cover a firm-quarter.
Δ*OwnOtherForecastError*	The difference in *SAOtherSentiment* between each two analysts that cover a firm-quarter.
$PeerForecastError_{After - Before}$	The change in *PeerForecastError* from before to after one or more firms in the focal analyst's portfolio are acquired and cease to exist in the market.
$OwnPreviousForecastError_{After- Before}$	The change in *OwnPreviousForecastError* from before to after one or more firms in the focal analyst's portfolio are acquired and cease to exist in the market.
$OwnOtherForecastError_{After - Before}$	The change in *OwnOtherForecastError* from before to after one or more firms in the focal analyst's portfolio are acquired and cease to exist in the market.
Market-R_f *(-2,2)*	The five-day excess return on the market centered at the focal analyst's EPS forecast announcement date, where excess return is calculated as the market return minus the treasury bill rate.
SMB (-2,2)	The five-day Fama-French size factor centered at the focal analyst's EPS forecast announcement date.
HML (-2,2)	The five-day Fama-French value factor centered at the focal analyst's EPS forecast announcement date.
RMW (-2,2)	The five-day Fama-French operating profitability factor centered at the focal analyst's EPS forecast announcement date.
CMA (-2,2)	The five-day Fama-French investment factor centered at the focal analyst's EPS forecast announcement date.
MOM (-2,2)	The five-day momentum factor centered at the focal analyst's EPS forecast announcement date.

Appendix II
NLP Methodology

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.	Positive
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.	Negative
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.	Positive
Workforce	These **include headcount reductions**, reengineering our products and processes, improving efficiencies and raw material pricing…	Negative
Supply and Demand	The company is growing its fleet to service the **increasing demands** for air travel in the region.	Positive

Outlined above are some examples of how the NLP processor captures the sentiment of business events. In the first example, there is a semantic 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, ensuring that phrases like "forced acquisition" are not incorrectly classified as positive events. Another advantage of NLP is its ability to handle additional modifiers between keywords in the rules, allowing for more varied word combinations in a

sentence to be correctly categorized with the appropriate event type and sentiment. In the mergers and acquisitions example, the company name “Alibaba” appears between “potential” and “acquisition”. Despite this, the NLP schema correctly associates “potential” with “acquisition”, rather than with “spin-off” mentioned earlier or “likelihood” mentioned later in the sentence. Thus, the NLP processor accurately recognizes the completion of the rule and increases the count for positive merger and acquisition events. Similarly, in the third example, numerous words appear between the verb “secure” and the noun “contract”. The NLP processor identifies that “long-term”, “fuel-cell” and “supply” are modifiers of “contract”, leading it to increase the count for positive contract events.

The second example illustrates the advantage of NLP over a word-based approach in capturing sentiment polarity more precisely. The keywords in this rule are the noun “default” and the adjective “rising”. The rule also includes synonyms of “rising” such as “increasing”, but the overall context remains the same—the adjective must indicate an increase in “default”. In a word-based approach, “default” is typically classified as a negative-sentiment word (Loughran and McDonald 2011). However, if “default” is preceded by a word like “reduced”, as in “reduced defaults”, the sentiment should shift from negative to positive. NLP enables these types of refined classifications. In the rule mentioned above, the NLP processor checks for a modifier that signifies an increase before the noun “default”. Only if it detects an adjective related to “increase” does it increase the counter for a negative default event.

The following articles provide two examples of how NLP extracts sentiment from SA articles. The first example, published on August 16, 2013, 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 soon reverse. Moreover, within this

industry, the author considers Mattel the leader. Mattel not only learned from the successes of competitor MGA Entertainment and launched its own line of unconventional dolls, but it is also the manufacturer of the top three doll brands by market share at the time of writing. MGA Entertainment owns the fourth- and fifth-ranked brands. This article seems to praise Mattel's positives more than criticize its negatives, which is closely captured by the *READER SENTIMENT* score of 0.6875. In contrast, the Loughran and McDonald word list tone rates the article as -0.091, a net negative score. The second example, published on August 20, 2015, offers a brief analysis of a firm that was closely watched 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 according to the article, it will not be able to manage its growth while maintaining quality control. The author is also pessimistic due to insider selling shortly after the 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 aligns with Loughran and McDonald (2016, 2011), which suggest 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).

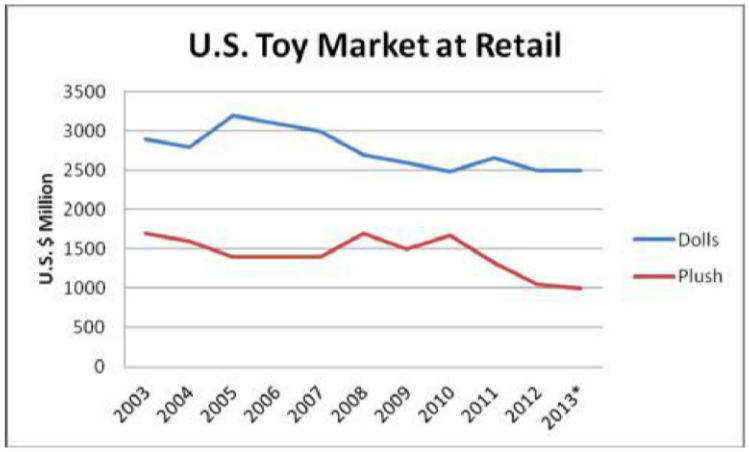
Why Mattel Continues To Dominate The Dolls Category

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.

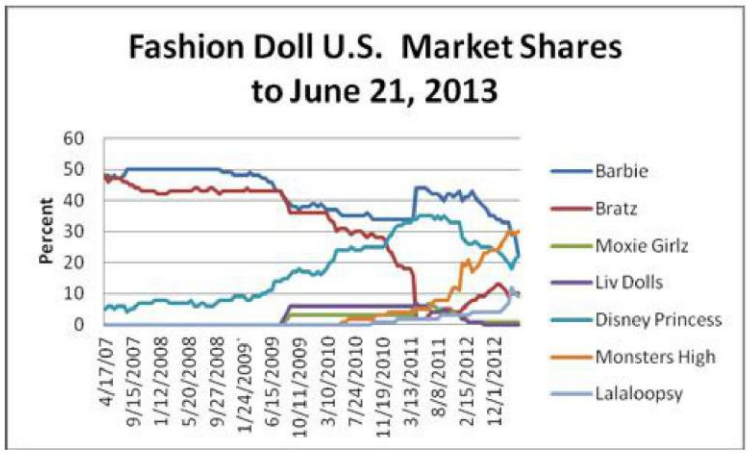
The most important segment of the Doll category is fashion dolls, and as far back as we can remember, Mattel's (NASDAQ:MAT) Barbie has reigned supreme there. Only once was she challenged -- between 2004 and 2007 when MGA Entertainment's Bratz nearly got to a 50% market share in the U.S. fashion doll 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..

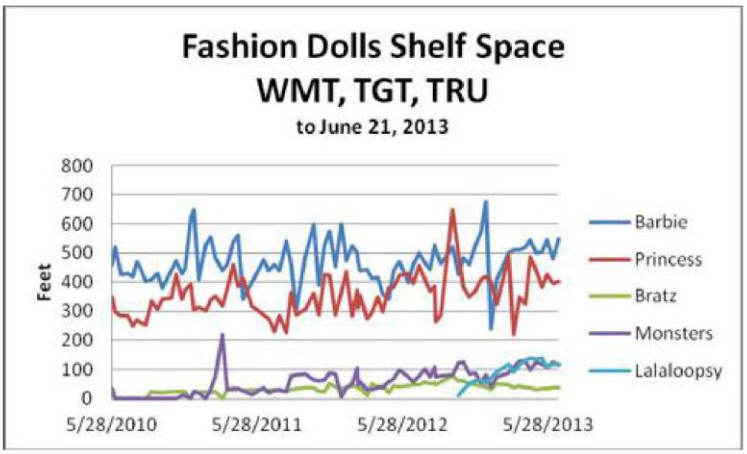
Throughout all this, Mattel's Disney Princess (DIS) sailed like a stately ship through these choppy waters, holding onto its No 2 or No. 3 position regardless of the ups and downs of all the other brands competing for the top spot. The Princess trend is experiencing a mild resurgence due to the very 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

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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

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