LISTENING IN ON INVESTORS' THOUGHTS AND CONVERSATIONS

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One of the most established theories in social psychology suggests that when people consider whether to share a particular content with another person, they tend to be careful about what public image sharing such content might create. We find evidence that such impression-management considerations are also important among investors. Utilizing server-log data from one of the biggest investment-related websites in the United States, as well as experimental data, we find that investors more frequently share articles more suitable for impression management, even if such articles less accurately predict returns and even if such articles are infrequently read by sharers themselves.

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1. Introduction

People constantly share news and recommendations among themselves, for instance, which restaurants to go to (Anderson and Magruder, 2012), which television programs to watch (Seiler, Yao, and Wang, 2017), or which doctors to visit (Luca and Vats, 2013). A large literature finds that people also turn to each other for financial advice and investment ideas (e.g., Shiller and Pound, 1989; Hong, Kubik, and Stein, 2004; Brown, Ivković, Smith, and Weisbenner, 2008; Kaustia and Knüpfer, 2012; Lerner and Malmendier, 2013; Shue, 2013; Hvide and Östberg, 2015; Pool, Stoffman, and Yonker, 2015; Heimer, 2016; Fracassi, 2017; Hwang, Liberti, and Sturgess, 2019).

Through their social interactions, individuals can acquire value-relevant information and make more informed decisions (Maturana and Nickerson, 2019; Haliassos, Jansson, and Karabulut, 2020). However, information acquired from social interactions can also be misleading, as propagators of information may not share all they know or feel; they may also distort information (Hirshleifer, 2015, 2020). Such social transmission biases can cause receivers to misperceive reality and make suboptimal decisions. To provide an example, investors may be eager to share their investment successes, but not be very forthcoming about their investment failures (Kaustia and Knüpfer, 2012; Heimer and Simon, 2017; Escobar and Pedraza, 2019; Lane, Lim, and Uzzi, 2020). Should receivers not account for such communication decisions (Enke, 2020), they may erroneously infer that outperforming the market is easy and flock to active investment strategies (Han, Hirshleifer, and Walden, 2019).

Despite the intuitive appeal of the above argument, beyond the notion that senders prefer to talk about their successes, we still know relatively little about social transmission biases. Presumably, investors spend much of their time exploring news and opinions. Of the overall content that investors consume, what types of content do they choose to share? Do investors explain these selections based on the perceived value relevance of the content or do they prioritize other considerations that, in turn, could lead to the propagation of less informative content?

In this study, we propose one important "other consideration." One of the most established theories in social psychology is that, when considering what types of content to share, people primarily contemplate what impressions their sharing might create among receivers and whether those impressions are consistent with who they are or desire to be. People share certain content to signify status or profess connoisseurship; people also share to project a certain image (e.g., Goffman, 1978; Baumeister, 1982; Leary and Kowalski, 1990; Berger and Schwartz, 2011; Berger and Milkman, 2012; Lovett, Peres, and Shachar, 2013; Packard and Wooten, 2013; Berger, 2014; Gilovich, Keltner, Chen, and Nisbett, 2019). In the literature, this concept is referred to as "self-presentation" or "impression management."

We presume that investors are not immune to impression-management considerations and we propose that when deciding what content to share, investors do not always prioritize the value relevance of the content per se. Instead, they frequently pay greater attention to what impressions they may make by sharing a particular piece of content and whether such impressions agree with their actual or desired self.

Not prioritizing the value relevance of the content can cause a wedge between the content that investors base their own decisions on and the content that they end up sharing. It can also lead to the propagation of less informative content. If receivers do not sufficiently account for such possibility, they may overweigh the investment ideas that they receive, generate mispricing, and experience poor investment performances.

We test our proposition in two empirical settings. In our first setting, we use aggregated server log data from Seeking Alpha (hereafter, SA; http://seekingalpha.com). SA is one of the biggest investment-related websites in the United States, hosting close to 1 million stock-opinion articles and attracting over 15 million unique visitors per month. We obtain data on how often each article published on the SA website from August 2012 through March 2013 was viewed ("number of page views"), how many times a reader scrolled to the bottom of each article ("number of read-to-ends"), and how often an article was shared via email ("number of shares"). In our second setting, we conduct experiments on 540 actual investors, a significant number of whom have net investable assets greater than $300,000.

To preview our findings, our analyses of SA's server-log data reveal that "accurate" SA articles, that is, articles whose tone is subsequently confirmed by the corresponding firm's stock market performance, are substantially more frequently read to the end. This result is consistent with prior studies, which suggest that users of SA-type platforms are informed and can separate accurate articles from inaccurate ones (Chen, De, Hu, and Hwang, 2014; Avery, Chevalier, and Zeckhauser, 2016; Jame, Johnston, Markov, and Wolfe, 2016).[1] Accurate articles do not receive more shares, however. In fact, it is the inaccurate articles that are shared more frequently.

We find the observed discrepancy between the articles that are read and the articles that are shared descriptively interesting. The discrepancy is also consistent with the notion that impression-management considerations can cause a wedge between content consumed and content shared, with the latter generally being less informative. The evidence is only tangential at best, however, as there are other economic and psychological motives that could play a role in generating our finding above.

To provide more specific evidence for our proposition, we develop and test the following prediction: Prior studies suggest that opinions couched in numbers are viewed as more thoughtful, intelligent, and credible (Koetsenruijter, 2011; Berger and Milkman, 2012; Huang, Nekrasov, and Teoh, 2018).

We posit that appearing thoughtful, intelligent, and credible is desirable to investors and that, correspondingly, quantitative articles are better suited for impression management than qualitative articles. If impression management is a priority to investors, then we expect that investors more frequently share quantitative articles, even if investors were to perceive more value in, and thus more frequently consumed, articles that are of qualitative nature.

Consistent with this prediction, we find that while qualitative SA articles more accurately predict abnormal returns and are more frequently read to the end, it is the quantitative articles that generate more shares and thus become a predominant part of investors' conversations.

Our second setting provides additional, experimental evidence that impression-management considerations are important to investors and motivate them to share quantitative content. In our

[1] Other recent studies providing evidence that retail investors, the primary clientele of SA, are informed include Kaniel, Saar, and Titman (2008); Kaniel, Liu, Saar, and Titman (2012); Kelley and Tetlock (2013, 2017); Barrot, Kaniel, and Sraer (2016); and Boehmer, Jones, Zhang, and Zhang (2020).

experiments, we issue the same quantitative SA article to all participants. However, for randomly selected participants, we upward manipulate their desire to manage their impressions and we subsequently track whether they more frequently choose to share the quantitative article with a peer. In the first experiment, we strengthen impression-management considerations by altering the target audience from "a very close friend" to "a co-worker." Existing studies suggest that people have a stronger desire to project a certain image to their co-workers than to their very close friends (Dubois, Bonezzi, and De Angelis, 2016). In the second experiment, we strengthen impression-management considerations by reminding participants of a situation in which they did not feel as knowledgeable as they would have liked. Existing literature suggests that perceived deficiencies-in-the-self strongly enhance impression-management considerations (Wicklund and Gollwitzer, 1981, 1982; Rucker and Galinsky, 2008; Gao, Wheeler, and Shiv, 2009; Mead, Baumeister, Stillman, Rawn, and Vohs, 2011).

Consistent with impression-management considerations being important to investors and inciting them to share quantitative content, we find that investors substantially more frequently choose to share the quantitative article with a co-worker than with a very close friend; investors forced to write about a perceived deficiency-in-the-self also substantially more frequently choose to share the quantitative article than investors in the control group. Interestingly, the differences in the level of sharing are noticeably bigger among investors whose net investable assets are greater than $300,000.

As a placebo test, we repeat our two experiments using a qualitative article, that is, an article we deem less suitable for impression management. We observe no differences in the level of sharing of the qualitative article.

We conclude our paper with an examination of possible asset pricing implications. Our results above suggest that impression-management considerations are important to investors and lead to the dissemination of less informative content. To the degree that receivers do not sufficiently account for impression-management considerations, they may overweigh the signals that they receive. If investors are more likely to buy a stock than short sell (Barber and Odean, 2008), then stocks that are mentioned more frequently in investors' conversations may become overpriced and, subsequently, earn abnormally low returns.

Consistent with this line of thinking, we find that "viral" stocks, that is, stocks whose SA articles receive a disproportionately high number of shares, initially, experience high returns. This high initial performance subsequently reverses. The initial price run-up and subsequent correction is substantially stronger for stocks likely to be short-sale constrained.

In the end, our study makes the following contribution. Given evidence that investors derive much of their information through social interactions (e.g., Shiller and Pound, 1989; Hong, Kubik, and Stein, 2004; Brown, Ivković, Smith, and Weisbenner, 2008; Kaustia and Knüpfer, 2012; Hvide and Östberg, 2015; Pool, Stoffman, and Yonker, 2015; Heimer, 2016), there is good reason to determine whether information acquired from social interactions leads to better or worse investment decisions, and, if the latter, what factors cause information acquired from social interactions to be misleading.

Owing to the richness of our data, we believe our study is the first to observe both (1) what types of content investors read and (2) what types of content investors subsequently decide to share with their peers. We use our data to document that the stories that investors choose to consume are strikingly different from those they choose to share with others. We provide evidence that the content that investors keep to themselves is significantly more informative than the content they end up sharing.

We point to one important psychological motive that, at least partially, explains this finding. In their social interactions, investors are meticulous about what image they project by sharing a particular content and whether such image mirrors their actual or desired self. Stories well suited for impression management are not always value relevant. This creates a wedge between content consumed and content shared, with the latter generally being less informative. While the impression management concept is one of the building blocks in social psychology, to the best of our knowledge, our study is the first to show its relevance in the financial setting.

The implications are clear: Just as hearing only the success stories may cause investors to erroneously presume that outperforming the stock market is easy and flock to active investment strategies, listening to stories without fully considering the sender's motives may cause investors to put too much weight on certain stories, triggering excess buying activity, and generating both temporary mispricing and poor investment performances.

2. Current Literature and Our Hypotheses

In this section, we outline the literature on impression management. We subsequently build on this literature to develop our hypotheses.

2.1 Literature on Impression Management

One of the key theories in social psychology is that when people interact with one another and contemplate what content to share, they primarily consider how the message might be received by others and what the probable social consequences are, ranging from approval and respect to dislike and ridicule. As Gilovich, Keltner, Chen and Nisbett (2019) describe "*a basic truth: our social self is often a dramatic performance in which we try to project a public self consistent with our hopes and aspirations. This public self is one that we actively create in our social interactions and that is shaped by the perceptions of other people and the perceptions we want others to have of us (Baumeister, 1982; Mead, 1934; Schlenker, 1980; Shrauger & Schoeneman, 1979).*

The public self is concerned with self-presentation – presenting the person we would like others to believe we are. Another term for this concept is 'impression management'" (page 92).

Impression management may be traced back to our evolution (Baek, Scholz, and Falk, 2020). As humans live in communities, to survive and thrive, they are required to socially affiliate with one another and create impressions of power and competence (Lakin and Chartrand, 2003; Lakin, Jefferis, Cheng, and Chartrand, 2003).

The stories that are best suited for impression management may occasionally be the same stories that people heavily base their own beliefs and decisions on. But impression-management considerations can also cause people to transmit content that they personally do not deem important. For instance, individuals may share stories about a secret bar, even when not fond of it, to signify that they are hip, unique, and interesting (e.g., Goffman, 1978; Baumeister, 1982; Leary and Kowalski, 1990; Berger and Schwartz, 2011; Berger and Milkman, 2012; Lovett, Peres, and Shachar, 2013; Packard and Wooten, 2013; Berger, 2014).

2.2 Hypotheses

In our paper, we propose that investors are not immune to impression-management considerations. Moreover, similar to the literature on impression management, we propose that the stories best suited for impression management are not always the stories that investors most heavily base their own beliefs and decisions on. If senders are informed, not prioritizing the value relevance and, instead, focusing on impression management, naturally, leads to the dissemination of less informative content.

This line of thinking yields our first hypothesis, Hypothesis 1: *The content that informed investors share with their peers is less informative than the content that they consume.*

Evidence consistent with Hypothesis 1 could be in line with other economic or psychological motives that govern investors' sharing behavior. To provide more specific evidence that impression-management considerations are important to investors and cause them to transmit less informative content, we study the consumption and transmission of quantitative content.

Some SA articles rely heavily on numbers as they, for instance, discuss the most recent financial statements. Other articles are less reliant on numbers and discuss softer aspects of firms, such as new product- or service lines. Figure 1 presents examples for both article types.

Opinions couched in numbers are often viewed as more thoughtful and convincing (Koetsenruijter, 2011). Quantification also increases concreteness and credibility (Huang, Nekrasov, and Hong, 2018). Berger and Milkman (2012) find that science-related stories are shared more frequently, compared with non-science stories.

We posit that appearing thoughtful, intelligent, and credible is desirable to investors. Quantitative articles are thus better suited for impression management than qualitative articles. We therefore predict in our second hypothesis, Hypothesis 2, that: *Investors more frequently share content that is couched in numbers even if such content is less informative and even if investors, themselves, more frequently read content that is less reliant on numbers.*

If, upon receiving stock recommendations, receivers do not sufficiently account for impression-management considerations and, in addition, more frequently buy stocks, rather than short sell (Barber and Odean, 2008),[2] then stocks that are more frequently mentioned in investors' conversations may become overpriced and subsequently earn abnormally low returns.

Our final hypothesis, Hypothesis 3, states: *The stocks more frequently mentioned in investors' conversations, initially, experience high returns. These high returns subsequently revert. The initial price run-up and subsequent correction is more pronounced among stocks likely to be short-sale constrained.*

We test the first two hypotheses using server-log data and experimental data, as discussed in Sections 3 and 4, respectively. We discuss our test of Hypothesis 3 in Section 5.

3. Impression Management and Investors' Sharing Behavior: Evidence from Server-Log Data

3.1 Server-Log Data

We obtain aggregated server log data for the SA website directly from SA. SA is a leading investments-related website in the United States. Anyone can submit a stock opinion article for possible publication on the SA website. These submissions are curated by a team of SA editors. If deemed of adequate quality and published on the SA website, articles generate income for the corresponding authors through the number of page views the articles generate.[3] SA reports that as of January 2021, the website had published close to 1 million articles authored by 17,247 contributors.[4] From January through March 2019, the SA website attracted over 15 million unique visitors a month, who, on average, spent seven minutes per visit.[5] SA

[2] If propagators of information are more likely to send buy recommendations than sell recommendations, as our evidence in Online Appendix Table A3.4 suggests, then, to arrive at the prediction that investor conversations can lead to overpricing, we no longer require the second assumption that, upon receiving a stock recommendation, investors more frequently buy, rather than short.

[3] The compensation scheme has evolved since 2013. Details on the current compensation scheme can be found here: https://seekingalpha.com/pages/article_payments (accessed January 6, 2021).

[4] https://seekingalpha.com/listing/contributors_stats and https://seekingalpha.com/listing/articles_stats (accessed January 6, 2021).

[5] https://static.seekingalpha.com/uploads/2019/7/22/sa_media_kit_07_2019_generic.pdf (accessed January 6, 2021)

reports that, over the same period, its audience was 83% male; had an average age of 46 years; had an average household income of $321,302; and 65% of them traded at least once a month.[5]

Our server log data cover the period from August 1, 2012 through March 31, 2013. Our data are at the article level; we do not have data at the individual user level. For each *article ID*, which is an identifier set by SA to uniquely identify an SA article, we have data on how often readers viewed an article, how often they scrolled to the bottom of the article, and how often the article was shared via email.[6]

We augment our server log data with additional article-level data, which we scrape directly from the SA website. For each article, we scrape the *article ID*, title, full article text, date of publication, author's name, and stock ticker. Our final sample comprises 16,446 single-stock opinion articles.

3.2 Variables and Descriptive Statistics

3.2.1 Dependent Variables

We use our server-log data to construct three dependent variables. Our first dependent variable is the natural logarithm of one plus the number of page views, *ln (1 + # Page Views)*. We view our first dependent variable as a measure of "cursory" article consumption. Our second dependent variable is the natural logarithm of one plus the number of times an article is read to the end, *ln (1 + # Read-to-Ends)*. We view our second dependent variable as a proxy for "actual, full" article consumption, albeit an upward-biased one, as we cannot rule out that some investors scroll to the bottom of the page without reading the article.

Our third dependent variable is the natural logarithm of one plus the number of times an article is shared via email, *ln (1 + # Shares)*. To share an article, an investor is required to type in the email address of the recipient(s). The type of sharing we consider in this study is thus distinct from the "mass-sharing" among loosely connected individuals, which we typically associate with social media outlets, such as Twitter or Facebook.

[6] Our data are as of March 2014. As 95.9% of article-reads in our sample occur in the first month of article publication, any observed difference in article-reads and shares should not represent differences in time since article publication.

We take the natural logarithms of *#Page Views*, *# Read-to-Ends,* and *# Shares,* as all three variables are highly right-skewed.

3.2.2 Independent Variables

a. Article Accuracy

Following Chen, De, Hu, and Hwang (2014), our measure of article accuracy equals one if an article's tone is above the median and the corresponding stock earns positive abnormal returns over the ensuing month, or, if an article's tone is below the median and the corresponding stock earns negative abnormal returns; our measure equals zero otherwise. Following Chen et al., when computing cumulative abnormal returns, we skip the first two days of article publication and compute abnormal returns as the difference between raw returns and returns on a value-weighted portfolio of firms with similar size, book-to-market ratio, and past return (Daniel, Grinblatt, Titman, and Wermers, 1997), hereafter referred to as DGTW-adjusted returns.

We compute an article's tone as the number of positive words in the article minus the number of negative words, scaled by the total number of words. We account for negation. As has become the norm for textual analysis in the finance field, we use the lists of positive and negative words, as in Loughran and McDonald (2011).

Earlier research involving textual analysis in finance considers the negative word list only when gauging the sentiment of a text (e.g., Tetlock, 2007; Loughran and McDonald, 2011). Recent work adopts a more nuanced view and proposes that the effect of positive words on sentiment depends on the medium (e.g., Loughran and McDonald, 2020). Other studies suggest that researchers always consider both the negative- and the positive word lists (Garcia, Hu, and Rohrer, 2020).

In this study, we consider both positive and negative words because in 27% of our sample articles, authors disclose whether they hold a long or short position regarding the stock in question. We find that a measure of tone, which considers both positive and negative words, correlates more strongly with whether the author holds a long or short position than a measure based on the fraction of negative words alone, suggesting that, at least in our setting, considering positive words helps better represent the author's ultimate view on the stock in question. We note that, when we consider negative words only, our results are very similar to those presented in this study (results available upon request).

b. Reliance on Numbers

We gauge the quantitative nature of an article based on its reliance on numbers versus words. *Reliance on Numbers* is the ratio of the total occurrences of numbers in an SA article to the total number of words.

c. Control Variables

In our regression analyses, we include the following controls, all of which are described in Table 1: *Length, Editors' Pick, Presentation, Long Score, Short Score, ln (1 + Analyst Coverage),* and *ln (1 + DJNS Coverage)*.[7]

3.2.3 Descriptive Statistics

We present descriptive statistics in Table 1.[8] Perhaps the most interesting descriptive statistic is that, on average, for every read-to-end, we observe (only) 0.003 shares (= 5.46/2029.77). While this ratio may appear low, it is hardly unusual. For instance, Twitter reports that for every tweet that is read by a user, we observe only 0.0007 re-tweets.[9]

Importantly, the above fraction suggests that very few page views and read-to-ends originate from individuals who receive emails about the articles. Instead, almost all page views and read-to-ends originate from investors who encounter these articles through their own individual searches.

[7] We thank Andrew Chen and Tom Zimmermann for graciously sharing their anomaly data with us, which we use to construct *Long Score* and *Short Score*.
[8] We report a correlation matrix of our variables in Online Appendix Table A1.
[9] https://blog.twitter.com/en_us/a/2014/new-tweet-activity-dashboard-offers-richer-analytics.html (accessed January 6, 2021)

3.3 Empirical Design and Findings

To assess whether investors view accurate articles more frequently, we estimate the following regression specification at the article level:

$$ln\ (1 + \#\ Page\ Views_i) = \alpha + \beta\ Article\ Accuracy_i + X_{i,j}\ \delta + \varepsilon_i, \tag{1}$$

where j is the stock discussed in article i, and $X_{i,j}$ includes our article- and firm-level controls.[10] *T*-statistics in this and the ensuing regression specifications are based on standard errors adjusted for heteroscedasticity and clustered by day of article publication.

Our second regression specification assesses whether investors more frequently finish reading articles that are accurate:

$$ln\ (1 + \#\ Read\text{-}to\text{-}Ends_i) = \alpha + \beta\ Article\ Accuracy_i + X_{i,j}\ \delta + \varepsilon_i. \tag{2}$$

We estimate regression equation (2) first including $ln\ (1 + \#\ Page\ Views_i)$ as an additional control and then without $ln\ (1 + \#\ Page\ Views_i)$ as an additional control. The former shows what features promote that an article is read to the end, on the condition that the article is being viewed. The latter sheds light on what features lead to more frequent read-to-ends, unconditionally.

Upon deciding whether to view an article, and then whether to read it to the end, an investor has a final decision to make: whether to share the article with others (Investors can only share an article after scrolling to the bottom.).

To gauge to what degree an article's accuracy determines its level of sharing, we re-estimate regression equation (2) but replace the dependent variable with $ln\ (1 + \#\ Shares_i)$:

$$ln\ (1 + \#\ Shares_i) = \alpha + \beta\ Article\ Accuracy_i + X_{i,j}\ \delta + \varepsilon_i. \tag{3}$$

We estimate regression equation (3) both while including and then excluding $ln\ (1 + \#\ Read\text{-}to\text{-}Ends_i)$ as an additional control.

We report our results in Table 2. As shown in the first three columns, we find that accurate articles receive 3.6% more frequent page views (*t*-statistic = 2.72) and 4.1% more frequent read-to-ends (*t*-statistic

[10] We do not include $Presentation_i$ in regression equation (1), as investors do not observe how well-presented an article is prior to reading it.

= 2.95). Our finding is consistent with prior studies, which suggest that actual- and possible users of SA-type platforms are informed and may be able to separate accurate SA articles from the inaccurate ones (Kaniel, Saar, and Titman, 2008; Kaniel, Liu, Saar, and Titman, 2012; Kelley and Tetlock, 2013; 2017; Chen, De, Hu, and Hwang, 2014; Avery, Chevalier, and Zeckhauser, 2016; Barrot, Kaniel, and Sraer, 2016; Jame, Johnston, Markov, and Wolfe, 2016; Boehmer, Jones, Zhang, and Zhang, 2020).

The estimates for our control variables largely agree with expectations. Similar to Umar (2019), we find that articles with longer titles are less likely to be viewed. Additionally, investors are less likely to finish reading articles with long texts. Editors' Pick articles as well as articles on stocks that are currently receiving extensive media coverage are viewed more frequently. Articles on stocks that already have existing investment recommendations in the form of analyst reports are less frequently viewed and read to the end.

The above results shed light on how investors behave by themselves. Next, we consider how investors behave and interact with one another. While our previous result suggests that investors are more likely to view and read investment ideas to the end if they are accurate, the results in columns (4) and (5) suggest that investors tend to keep such investment ideas mostly to themselves. It is the inaccurate investment ideas that receive the greater number of shares and, consequently, become predominant in investors' conversations. Put differently, while the estimates for *Article Accuracy* in columns (1) through (3) are positive, in columns (4) and (5), the estimates turn strongly negative. The estimate for *Article Accuracy* reported in column (4) suggests that, if investors finish reading two articles that are seemingly identical except for their levels of accuracy, the inaccurate article receives 5.7% more frequent article shares (*t*-statistic = -6.18). The estimate for *Article Accuracy* reported in column (5) suggests that inaccurate articles receive 3.3% more frequent shares (*t*-statistic = -2.53), unconditionally. That is, inaccurate articles receive substantially more shares even though they are significantly less likely to be viewed and read to the end in the first place.

In Online Appendix Table A2, we present results based on a different empirical design. We build on Chen, De, Hu, and Hwang (2014), who provide evidence that the average SA article has investment value, in that the overall tone revealed in an SA article positively predicts the corresponding firm's subsequent stock market performance. We estimate a regression of cumulative abnormal returns on an article's tone, the natural logarithm of one plus the number of read-to-ends, the natural logarithm of one plus the number of shares, and the article's tone interacted with these two variables. The estimates for the interaction terms indicate whether articles that have greater investment value are those with the more frequent read-to-ends or those with the more frequent shares.

We find that irrespective of the return horizon, the estimates for the interactions between article tone and *ln (1 + # Read-to-Ends)* are all positive and statistically significant, suggesting that the articles that investors more frequently read to the end have greater investment value. In stark contrast, the estimates for the interaction term with *ln (1 + # Shares)* are all negative. That is, while the tone in the articles with the more frequent read-to-ends more accurately predicts abnormal returns, the tone in the articles with the more frequent shares does not. These results are, again, consistent with Hypothesis 1 that individuals keep the more useful investment advice to themselves.

To test Hypothesis 2, we re-estimate regression equations (2) and (3) but replace *Article Accuracy* with *Reliance on Numbers*. We do not re-estimate regression (1) as SA-article titles rarely contain numbers.

Our results from regression equation (2) are tabulated in the first two columns of Table 3. We find that investors prefer to read articles that are less reliant on numbers. The estimates for *Reliance on Numbers* in columns (1) and (2) are -1.212 (*t*-statistic = -7.55) and -1.833 (*t*-statistic = -4.50), respectively. The estimate for *Reliance on Numbers* in column (1) suggests that on the condition that an article is being viewed, a one-standard-deviation increase in its reliance on numbers leads to 4.8% less frequent read-to-ends. That is, if there are two articles that are both viewed and that are seemingly identical except for their reliance on numbers, the quantitative article is substantially less likely to be read to the end. The economic significance is even stronger for the unconditional result. Here, a one-standard-deviation increase in reliance on numbers leads to 7.3% less frequent read-to-ends (column (2)).

Do the qualitative articles that SA investors more frequently choose to read to the end also more accurately predict returns? To answer this question, we estimate regressions of cumulative abnormal returns on an article's tone, *Reliance on Numbers*, and the article's tone interacted with *Reliance on Numbers*. Consistent with qualitative articles having greater investment value and as tabulated in Online Appendix Table A2, we find that the estimates for the interactions between article tone and *Reliance on Numbers* are all negative.

Turning to our results from regression equation (3), tabulated in columns (3) and (4) of Table 3, we find that the sign of the estimates for *Reliance on Numbers* flips from negative to positive. The estimates for *Reliance on Numbers* in columns (3) and (4) are 1.689 (t-statistic = 6.12) and 0.607 (t-statistic = 3.13), respectively, and suggest that a one-standard-deviation increase in *Reliance on Numbers* leads to 6.8% more frequent article shares, on the condition that an article is being read to the end, and 2.4% more frequent shares, unconditionally.

Overall, similar to the results in Table 2, the results in Table 3 show that the content investors consume and the content they end up sharing with others can be strikingly different. Consistent with Hypothesis 2, our results suggest that while investors predominantly fill their heads with stories emphasizing softer aspects of firms, they keep such content mostly to themselves; instead, they share the few stories in their arsenal that are couched in numbers.

3.4 Sensitivity Analyses

We conduct a host of sensitivity analyses. First, we consider the binary relationship between *Reliance on Numbers* and the level of article consumption and then the level of article sharing. As reported in Online Appendix Table A3.1, the results are similar to those presented in Table 3.

As *Long Score* and *Short Score* include just about any firm characteristic, we do not separately control for firm characteristics in our regression equations. In Online Appendix Table A3.2, we report estimates obtained from regressions, which exclude *Long Score* and *Short Score,* and instead, include firm characteristics as separate control variables. The firm characteristics we consider are past one-month stock returns, previous month's stock return volatility, the natural logarithm of previous month's turnover, and the natural logarithm of market capitalization as of the previous month. In short, we continue to make similar observations.

In our main analyses, we do not include author-fixed effects as our hypothesis speaks to variations in the reliance on numbers irrespective of whether such variations occur across authors or within authors. One possible concern with our approach is that authors that have a tendency to compose quantitative (or qualitative) articles may differ along other author characteristics, and it may be that those other, unobserved author characteristics are what generate our findings. To gauge the relevance of this concern, we re-estimate our regression equations with author-fixed effects. As reported in Online Appendix Table A3.3, we find that the results are largely unchanged.

Finally, we consider the possibility that articles with a greater reliance on numbers differ along other textual attributes and that it is those other attributes that generate our results. We consider the article tone as well as the extent to which such tone differs from the average tone of articles on the corresponding stock over the previous month. The results in Online Appendix Table A3.4 show that the inclusion of these textual attributes has almost no impact on our main results.

4. Impression Management and Investors' Sharing Behavior: Evidence from Two Experiments

4.1 Data

To provide causal evidence that impression-management considerations govern investors' sharing decisions, we conduct two online experiments on 540 actual investors. We recruit 230 out of the 540 investors through Prolific (https://www.prolific.co) and the remaining 310 investors through CoreData Research (https://coredataresearch.com).

Prolific is a platform that allows researchers to recruit pre-screened participants for online experiments. We require that participants are U.S. residents, list "*English*" as their first language, and answer "*yes*" to the following two questions: (1) "*Have you ever made investments (either personally or through your employment) in the common stock or shares of a company?*" (2) "*Have you invested in any of the following types of investment in the past? – Stock Market*."

CoreData Research is a market research firm that conducts investor surveys for large financial institutions. Participants recruited through CoreData Research reside in the U.S., are fluent in English, and are above the age of 22. For each participant, CoreData Research provides information regarding the age, gender, and net investable assets. The average age of the participants in our sample is 57, with 66% of the participants being male. As tabulated in Appendix 1, of the 310 investors recruited through CoreData Research, 32% possess net investable assets greater than $300,000, 12% possess net investable assets greater than $500,000, and 4% possess net investable assets greater than $1 million. We have no information regarding the net investable assets of the investors recruited through Prolific. In this study, we assume that all investors recruited through Prolific have net investable assets equal to or below $300,000. Going forward, we refer to investors with net investable assets equal to or below $300,000 as "mass-market investors" and to those with net investable assets above $300,000 as "mass-affluent investors." [11]

4.2 Experimental Design

Our first experiment comprises 280 investors, whom we randomly assign to two groups of 140 investors each. Each group, in turn, comprises 110 mass-market investors and 30 mass-affluent investors.[12]

Online Appendix Figure A1 presents our full online experiment. We first ask all investors to read the same quantitative article; the article recommends that investors buy Tesla; the article's *Reliance on Numbers* is above the median.[13]

At the end of the article, investors in the first group are asked: "*Is this an article you would share with a co-worker?*" Investors in the second group are asked whether they would share the article "*with a very close friend.*" Existing studies suggest that people have stronger desires to manage their impressions while interacting with their co-workers than with their very close friends (Dubois, Bonezzi and De Angelis,

[11] Investors recruited through Prolific receive the equivalent of $16/hour for participating in our experiments. Our agreement with CoreData Research disallows us from disclosing information regarding the amount paid to CoreData Research and the amount paid to the participants recruited through CoreData Research.

[12] Each group comprises 55 investors recruited through Prolific and 85 investors recruited through CoreData Research.

[13] The participants in our experiments only see the article text and do not observe other information typically displayed on the SA website, including information regarding the author, the author disclosure statement, the date the article was published, the number and the content of comments and the number of likes.

2016). If impression-management considerations are important to investors and lead to the sharing of quantitative content, we therefore expect that, compared with those in the second group, investors in the first group more frequently share the quantitative article.

Our second experiment comprises 260 investors, whom we randomly assign to two groups of 130 investors each. Each group, in turn, comprises 110 mass-market investors and 20 mass-affluent investors.[14]

As shown in Online Appendix Figure A1, the investors in the first group are given the following task: "*Please think about a situation where you felt you did not look as knowledgeable in the eyes of your co-workers as you would have liked. Briefly describe the situation in the box below. [minimum of 2 sentences].*" The investors in the second group are given the following task: "*Please think about what a "perfect" office would look like to you. Briefly describe this "perfect" office in the box below. [minimum of 2 sentences].*" Afterwards, as part of a seemingly unrelated second task, all investors read the same quantitative article; the article is the same we use in our first experiment. At the end of the article, investors are asked whether they would share this article with a co-worker.

A large literature finds that people engage in more impression management when they perceive deficiencies-in-their-self (Wicklund and Gollwitzer, 1981, 1982; Rucker and Galinsky, 2008; Gao, Wheeler, and Shiv, 2009; Mead, Baumeister, Stillman, Rawn, and Vohs, 2011; Packard and Wooten, 2013). If writing about a perceived deficiency-in-the-self enhances impression-management considerations, then the greater desire to manage one's impression, induced in the first task for investors in the first group, should spill over into the second task and lead to more frequent sharing of the quantitative article. We thus predict that, compared with those in the second group, investors in the first group more frequently share the quantitative article.

As a placebo test, we repeat the above two experiments using a qualitative article (also displayed in Online Appendix Figure A1). Similar to the quantitative article, the qualitative article recommends that

[14] Each group comprises 60 investors recruited through Prolific and 70 investors recruited through CoreData Research.

investors buy Tesla; the article was published in the same week as the quantitative article; the key difference is that the qualitative article's *Reliance on Numbers* is below the median.

4.3 Findings

We report our findings for the first experiment in Panel A of Table 4. Column (1) shows that while 60.7% of investors would share the quantitative article with a co-worker, only 45.7% of investors would share the article with a very close friend. The difference is 15.0% (*t*-statistic = 2.53). In columns (2) and (3), we report the differences separately for mass-market- and mass-affluent investors, respectively. While for mass-market investors, the difference in the fraction of investors choosing to share the quantitative article with a co-worker versus a very close friend is 12.7%, for mass-affluent investors, the difference is 23.3%.

Panel B in Table 4 reports our findings for the second experiment. We find that 50% of the investors asked to write about a perceived deficiency-in-the-self would share the quantitative article with a co-worker. The corresponding number for investors in the control condition is 39.2%. The difference is 10.8% (*t*-statistic = 1.75). The difference increases from 9.1% for mass-market investors to 20.0% for mass-affluent investors.

Online Appendix Table A4 reports the results from our placebo test. Unlike those for the quantitative article, we observe only small differences in the level of sharing between the treatment group and the control group. The differences for the first and second experiment are 0.0% (*t*-statistic = 0.00) and 1.5% (*t*-statistic = 0.25), respectively.

Overall, the results from our experiments are consistent with Hypothesis 2 and provide causal evidence that impression-management considerations are important to investors and lead to the sharing of quantitative content. Our experimental evidence also shows that this effect substantially strengthens with investors' net investable assets.

5. Asset Pricing Implications

Our final analysis tests Hypothesis 3: Stocks that are more frequently mentioned in investors' conversations, initially, experience high returns. These high returns subsequently revert. The initial price run-up and subsequent correction is more pronounced among stocks likely to be short-sale constrained.

To test this hypothesis, we first compute the level of "virality," $Virality_{SA}$, at the end of each day, for each stock i. $Virality_{SA}$ is the total number of times SA articles about stock i are shared through email, scaled by the total number of times these articles are viewed or read to the end. We scale by the total number of page views or read-to-ends to exclude any effects arising from increased investor attention that is unrelated to sharing.

At the end of each day, we sort all stocks by $Virality_{SA}$. Following the methodology by Jegadeesh and Titman (1993), we then create two portfolios: a low-virality portfolio, which is the equal-weighted portfolio of 10% of the stocks with the lowest level of $Virality_{SA}$, and a high-virality portfolio, which is the equal-weighted portfolio of 10% of the stocks with the highest level of $Virality_{SA}$. We report the average daily raw returns for each of the two portfolios and the corresponding long-short portfolio. We also report the average daily DGTW-adjusted returns for each of the two portfolios and the corresponding long-short portfolio.

In our sample, around 88% of page views and read-to-ends occur in the first week of article publication.[15] As the time-period over which virality may build, we therefore choose the first week of article publication. As the time-period over which overpricing may correct, we choose the ensuing three weeks. In asset pricing terms, our high- and low-virality portfolios are held for either one week or one month, while skipping the first week. *T*-statistics are based on Newey-West standard errors with five lags, which is the equivalent to one calendar week.

Panel A in Table 5 reveals that if $Virality_{SA}$ is calculated as the total number of shares scaled by the total number of page views, in the first week of article publication, stocks with high virality earn daily

[15] This information was provided to us by SA.

DGTW-adjusted returns of +0.13% on average (t-statistic = 3.23). This outperformance reverses over weeks 2 through 4, as high-virality stocks earn average DGTW-adjusted returns of -0.04% a day (t-statistic = -1.92). Compared with low-virality stocks, high-virality stocks have +0.19% (t-statistic = 2.54) higher daily returns in week 1 and -0.08% (t-statistic = -2.21) lower daily returns over weeks 2 through 4. As the portfolio-holding period is three times longer in the "reversal stage," the above numbers imply that whatever cumulative outperformance high-virality stocks accrue in the first week is more than eliminated over the ensuing three weeks.

We make the same observations when calculating $Virality_{SA}$ as the total number of shares scaled by the total number of read-to-ends (Panel B in Table 5). Here, in week 1, high-virality stocks earn daily DGTW-adjusted returns that are 0.24% higher compared with those experienced by low-virality stocks (t-statistic = 3.21). Over weeks 2 through 4, high-virality stocks underperform low-virality stocks by 0.08% (t-statistic = -2.04).

5.1 Sensitivity Analyses

In designing our empirical tests, we have relatively few degrees of freedom, which, perhaps, alleviates concerns that our results are the product of data mining and that the statistical significance of our findings is too low to be relied upon (Harvey, Liu, and Zhu, 2016). Specifically, the construction of our virality measure and the choice of our portfolio holding period are rooted in theory and server-log data, respectively. The manner in which we form portfolios is standard in the literature, at least since Jegadeesh and Titman (1993).

We do have degrees of freedom in how we measure abnormal performances, and, in additional analyses, we consider alternative methods. In Online Appendix Table A5.1, instead of reporting average DGTW-adjusted returns, we present alphas based on both the Fama-French-3-factor model and the Fama-French-5-factor model (Fama and French, 1993, 2015). The results are similar, both economically and statistically, compared to those reported in Table 5. In Online Appendix Table A5.2, we report results from

Fama-MacBeth regressions of returns on an indicator denoting high virality and various firm characteristics. Again, the results are similar to those reported in Table 5.

5.2 The Role of Short-Sale Constraints

A key component of Hypothesis 3 is that our effect is stronger among stocks likely to be short-sale constrained. In Table 6, we separately consider stocks that are likely to be short-sale constrained. We measure short-sale constraints based on the average daily lending fees (from Markit), and consider stocks as likely to be short-sale constrained if their average daily lending fees in the month of article publication are in the top 30% of their distribution at a given point in time.

In line with our hypothesis, our results, tabulated in Table 6, suggest that, when stocks are short-sale constrained, virality creates even greater overpricing, which then reverses over time. For instance, when calculating $Virality_{SA}$ as the total number of shares scaled by the total number of page views (Panel A in Table 6), we find that, in week 1, high-virality stocks that are likely short-sale constrained earn DGTW-adjusted returns of 0.27% a day (t-statistic = 2.11) compared with 0.13% in Table 5. Over weeks 2 through 4, high-virality stocks that are likely short-sale constrained earn DGTW-adjusted returns of -0.16% a day (t-statistic = -2.19) compared with -0.08% in Table 5.

The result we find particularly striking is that among short-sale constrained stocks, the seeming overpricing that develops during week 1 is so high that, over weeks 2 through 4, stocks with high virality experience not only negative DGTW-adjusted returns but also negative raw returns.

We conclude this subsection with two caveats. First, we would like to emphasize that we do not believe that the anomalous returns documented in Tables 5 and 6 are generated by the sharing of SA articles per se. In this study, we merely assume that the sharing behavior of SA readers provides a representative glimpse of the sharing behavior of non-negligible parts of the investor population. That is, we assume that when SA readers tend to share certain ideas, so do non-negligible parts of the investor population.

Second, we would like to emphasize that our attempt at deriving asset-pricing implications using an 8-month-sample period is ambitious. Our results should thus be interpreted with caution. We conduct two final tests in response to this limitation.

5.3 Additional Evidence Based on Twitter

We repeat our previous analysis on a 6-year sample comprising all tweets regarding publicly traded firms in the United States. Specifically, we write a web scraping program that uses Twitter's Advanced Search function (https://twitter.com/search-advanced)[16] to search for all tweets written in English and containing the "$" sign followed by a ticker of a stock traded in the United States (e.g., $AAPL).[17] In total, our sample comprises 91,262,601 tweets on 10,079 stocks from January 2013 through December 2018. For each of the more than 91 million tweets, we obtain the following information: tweet ID, date and time the tweet was posted, user ID (i.e., screen _name on Twitter), content, number of retweets, number of replies, and number of likes.

At the end of each day, we compute the total number of tweets about each stock *i* as well as how many times those tweets are retweeted. The level of virality, $Virality_{Twitter}$, is the total number of retweets, scaled by the total number of tweets. At the end of each day, we sort all stocks by $Virality_{Twitter}$. Unlike with $Virality_{SA}$, most of the realizations of $Virality_{Twitter}$ are zero.[18] Therefore, rather than considering the returns of stocks in the top- and bottom decile, we contrast the performance of stocks for which $Virality_{Twitter}$ is equal to zero to that of stocks for which $Virality_{Twitter}$ is greater than zero. We report the average daily raw returns for each of the two portfolios and the corresponding long-short portfolio as well as the average daily

[16] We did not collect our data through the free, standard Twitter API because the standard API only covers tweets published over the past 7 days.
[17] Since July 31, 2012 (https://twitter.com/twitter/status/230098997010911233), users can make a ticker symbol "clickable" by adding the "$" symbol (e.g., "$AAPL"). This feature makes it easier to identify tweets that discuss stocks. There is still some noise, however. In our analysis, we exclude thirteen "tickers" from our sample that have more than 1 million tweets per year: ABC, EBAY, DON, ETSY, FOX, GAGA, GOP, JACK, KIM, LFC, PTI, VOX, and WWE. To put the 1 million tweets/year in comparison, AAPL, which is one of the most popular tickers tweeted in our sample, has 284,595 tweets in 2019. We believe the reason these thirteen "tickers" have so many tweets is that users use the "$" symbol not just to denote a stock ticker; all of the thirteen "tickers" are names or part of the names (usernames) of products and celebrities.
[18] The distribution of $Virality_{Twitter}$ is such that $Virality_{Twitter}$ starts becoming greater than zero only after the 74th percentile.

DGTW-adjusted returns. Portfolios are again held for either one week or three weeks (starting from week 2).

The advantage of considering retweets over the sharing of SA articles is that we have a much longer sample period. A potential disadvantage is that, compared with SA articles, tweets may be less informative and less representative of actual investors' viewpoints. In line with this view, Online Appendix Table A6 shows that compared with the tone of tweets, the average tone of articles published on SA much more strongly correlates with contemporaneous abnormal returns.

Table 7 reports our results. We find that in week 1, high-virality stocks earn DGTW-adjusted returns of +0.07% a day (*t*-statistic = 11.12). The initial outperformance reverses in weeks 2 through 4 as high-virality stocks earn daily DGTW-adjusted returns of -0.01% (*t*-statistic = -2.02). Compared with low-virality stocks, high-virality stocks have +0.07% (*t*-statistic = 11.97) higher daily DGTW-adjusted returns in week 1 and -0.01% (*t*-statistic = -2.46) lower daily DGTW-adjusted returns over weeks 2 through 4. The results are similar for raw returns.

Overall, our Twitter analysis produces results similar to those produced when considering SA data. Consistent with tweets less accurately reflecting actual investors' viewpoints, the economic magnitude of the results based on retweets is substantially smaller compared with that of the SA-based results.

5.4 Additional Evidence Based on an Investor Survey

Our final test provides survey-based evidence regarding Hypothesis 3. As shown in Online Appendix Figure A1, at the conclusion of each of our two experiments, we ask all 540 investors the following question (1): "*Over the past 12 months, did a co-worker, friend, or family member mention a stock to you that they thought you might be interested in buying?*" The answer choices are "*Yes*" and "*No*."

All investors who respond "*Yes*" to question (1) are posed two follow-up questions. In question (2), we ask: "*How thoroughly do you think that person researched that stock before mentioning it to you?*" The scales are 1 ("*Rather casually*") to 5 ("*Rather thoroughly*"). In question (3), we ask: "*Did you end up buying the stock?*" The answer choices are "*Yes*" and "*No*."

All investors who respond "*Yes*" to question (3) are asked one final question (4): "*What was or has been your overall return since you bought the stock? If you are not sure, please answer "don't know.""* The answer choices are: "*(1) less than -20%, (2) between -20% and -10.01%, (3) between -10% and -0.01%, (4) between 0% and +10%, (5) between +10.01% and +20%, (6) greater than +20%, (7) don't know.*"

In column (1) of Table 8, we report the responses across all investors. In columns (2) and (3) we report the responses separately for mass-market- and mass-affluent investors, respectively.

Consistent with social interactions playing an important role in the transmission of investment ideas, we find that 43.7% of investors respond "*yes*" to question (1).

Consistent with investors taking signals received through word-of-mouth seriously, responses to questions (2) and (3) show that there are more investors who believe that the sender "rather thoroughly" researched the corresponding stock than there are investors who believe that the sender "rather casually" researched the stock; 33.9% of investors report to have bought the underlying stock.

The responses from mass-affluent investors are similar to those from mass-market investors. While a smaller portion of mass-affluent investors reports to have received an investment idea through word-of-mouth (34.0% for mass-affluent investors compared with 45.9% for mass-market investors), more of these investors indicate that they acted on the idea and ended up buying the underlying stock (41.2% for mass-affluent investors compared with 32.7% for mass-market investors).

For question (4), 23.8% of the investors who bought the underlying stock indicate that they experienced negative raw returns. To put this observation in perspective, as of the survey-completion date, the returns of the S&P 500 Index over the previous 1, 6, and 12 month(s) were 6.1%, 24.4%, and 18.2%, respectively. In other words, a substantial portion of the investors in our sample would have been better off not buying the corresponding stock and holding cash. A substantially greater fraction of investors would have been significantly better off investing in a fund tracking the S&P 500 Index. The results are even more pronounced for mass-affluent investors. Here, 35.6% of the investors indicate that they experienced negative raw returns since buying the stock.

Overall, our results are consistent with the proposition that social transmission biases can lead to the propagation of noise and, if taken at face value, can generate poor investment performances.

6. Conclusion

In this study, we argue and provide evidence that the content investors choose to share is governed not only by the content's perceived value relevance but also by self-presentation purposes. Self-presentation purposes can cause even well-informed investors to inadvertently propagate noise and lead to both price dislocations and poor investment decisions.

Given how much people rely on information transmitted through social interactions, we believe that it is important to understand (1) what types of content propagate in financial markets through social interactions, (2) whether such transmissions are better seen as social transmission biases or as mechanisms to aggregate information efficiently, and (3) the overall implications of these factors for investor trading and asset prices.

Our study provides some initial answers to these questions by applying one of the building blocks in social psychology, the impression management concept, to the financial setting. There are likely economic considerations as well as other psychological motives that govern investors' sharing decisions. Berger (2014) and Gilovich, Keltner, Chen, and Nisbett (2019) provide an overview of the psychological motives.

After decades of examining a long list of individual-person-level psychological biases, behavioral finance has eventually found its "*center of gravity … in a small number of ideas … - extrapolation, overconfidence, and gain-loss utility*" (p. 78, Barberis, 2018). We believe that pursuing a similar research agenda in social finance and examining which of the various social-psychology motives are the most relevant in financial markets represents an exciting avenue for future research.

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Appendix 1
Descriptive Statistics of Online-Experiment Participants

Below, we present the number of participants across our two online experiments by participants' net investable assets. We recruit 230 participants through Prolific (https://www.prolific.co/) and 310 participants through CoreData (https://www.coredataresearch.com/). We require that participants recruited through Prolific reside in the United States, list "*English*" as their first language, and report "*yes*" to the following two questions: (1) "*Have you ever made investments (either personal or through your employment) in the common stock or shares of a company?*" (2) "*Have you invested in any of the following types of investment in the past? – Stock Market.*" Participants recruited through CoreData reside in the United States, are fluent in English, and are above the age of 22; the average age is 57; 66% of participants are male. We have no data on the net investable assets for participants recruited through Prolific and thus place them all in the "*unknown*" category.

Net Investable Assets …	Prolific (1)	CoreData (2)
… unknown	230	
… less than $100,000		166
… $100,000 to $300,000		44
… $300,001 to $500,000		62
… $501,000 to $1,000,000		26
… more than $1,000,000		12
∑	230	310

Figure 1

This figure displays two SA articles. The first article is of a more "qualitative" nature (its realization of *Reliance on Numbers* is below the median). The second article is of a more "quantitative" nature (its realization of *Reliance on Numbers* is above the median).

First Article:

Berkshire Hathaway: Buffett's 'Secret' Investment Shouldn't Be The Only Reason To Invest

Dec. 15, 2020 11:46 PM by: The Value Portfolio

Summary

- Warren Buffett's "secret" investment by itself is no reason to invest in Berkshire Hathaway.
- The company has a long impressive history of generating exciting investment opportunities for shareholders.
- In 2008, the company generated massive shareholder returns by taking advantage of the downturn to capture unique investments. BNSF, BOA, etc. generated tens of billions of dollars in shareholder value.
- The real risk of Berkshire Hathaway is trusting the company to be stewards of capital, but the company has done well so far.

The news rumors have been circulating over the past month about Warren Buffett (NYSE: BRK.A) (NYSE: BRK.B) building up a "secret" position. Recent articles have come up on Seeking Alpha purporting to discuss the secret investment. Of interest to us was one which specifically said that an exciting secret investment would be the reason to invest.

While I acknowledge that many investors invest in Berkshire for diversification benefits, that's not me. If Berkshire announced a major deal in the coming months, however, I will reassess the growth profile of the company to determine whether return expectations and risk characteristics match my investment objectives and risk profile.

However, as we'll see throughout this article, a "secret" investment from Berkshire Hathaway shouldn't be the reason to invest. Rather Berkshire Hathaway has a long history of generating massive shareholder returns from unique opportunities. As we'll see throughout this article, the BNSF, Bank of America (NYSE:BAC), and Goldman Sachs (NYSE:GS) are examples of how the company did this previously and we expect will be able to do this going forward.

Unique History of Opportunities

Berkshire Hathaway has an impressive cash position and a unique history of receiving new opportunities due to its cash position. No better time indicates this than 2008. The company made numerous investments during this time period, investments that it could only make because of its massive cash position.

Some investments the company made during the 2008 collapse and subsequent year include Bank of America, Goldman Sachs, BNSF, Wrigley's, USG, and many others. Most importantly, through the collapse and subsequent years, the company deployed more than $60 billion, showing its ability to rapidly deploy its cash pile as opportunities presented themselves.

The company's most significant investment from the time period was BNSF, the company's largest ever acquisition. The company purchased $34 billion in stock and assumed $10 billion in debt. Based on Union Pacific's (NYSE: UNP) current valuation, with BNSF a comparably sized company, that investment is now worth well over $100 billion.

At the same time, Warren Buffett dove straight into the heart of the collapse. The company bought $5 billion in Bank of America preferred shares at a 5% coupon. He then exchanged them for warrants for 700 million shares of Bank of America. Those shares are worth roughly $20 billion today, highlighting the massive returns.

Other investments in the banking industry include $5 billion in Goldman Sachs preferred stock, which generated a multi-billion dollar profit. The company also purchased General Electric preferred equity. In the bond markets, the company was active. It helped Mars acquire Wrigley buying bonds of the company at an 11.45% coupon. It issued Harley-Davidson $300 million in bonds at a 15% coupon.

Most importantly, it managed to aggressively deploy a $50 billion cash pile down towards Warren Buffett's minimum of ~$20 billion. With market cycles continuously underway, and Warren Buffett having near $150 billion cash pile, we see no reason why he won't be able to easily do the same during the next collapse.

In fact, as the energy markets have struggled over the past few years, he's taken advantage by investing, as we'll see next.

Major 2020 Investments

At the same time, on top of being a cash flow giant, Berkshire Hathaway has taken advantage of 2020 to make some major investments.

Warren Buffett made a massive investment in Occidental Petroleum (NYSE:OXY) in 2019 through preferred shares, but in 2020 it's continued to receive common shares. The company has been selling this common stock as it has received it. However, it didn't leave the energy industry, buying Dominion Energy's (NYSE:D) natural gas assets in a $10-billion deal in mid-2020.

The company has also made other investments like Scripps dividends with preferred equity. It's made some interesting equity investments throughout the year; however, the key takeaway is through one of the most volatile years the company has continued to find and capture unique investment opportunities for growth.

Figure 1. Continued.

More importantly, it shows Berkshire Hathaway's ability to continue doing what it always has done, find opportunities. A useful indication of the company's commitment to this is its investment in energy assets in the middle of the downturn.

Berkshire Hathaway Secret Investment

Now we enter into discussion about Berkshire Hathaway's secret investment. Specifically, the company asked for special treatment on its 13F to avoid revealing an investment to the market. The investment, based on discrepancies in the company's reported value, is likely to be worth at least billions so far and could continue growing for the long run.

The company has previously utilized this treatment for both its IBM and Phillips 66 investment, both of which turned into massive investments. We're not sure what this investment would be. However, Berkshire Hathaway has a history of investing in undervalued investments at unique times, and we expect it to be energy.

Why? Because the energy markets have collapsed in 2020, just like financials did in 2008 and 2011. The company has a history of bottom feeding at opportune times and we see no reason why its current investment would be any different.

Berkshire Hathaway Shareholder Return Opportunity

Long-term, we see Berkshire Hathaway as an undervalued company that has the ability to generate strong shareholder returns.

The first component of Berkshire Hathaway's valuation is the company's equity and cash position. The company has nearly $260 billion in equity, almost $120 billion of which is its massive position in Apple (NASDAQ: AAPL). The company has numerous other large positions like Bank of America, Coca-Cola (NYSE:KO), and American Express (NYSE:AXP).

Added to this, the company also has a massive cash position of nearly $150 billion. Putting these together is roughly $400 billion in valuation. For a company with a $530 billion valuation, this means the market isn't putting much value on the rest of the company. That's important because these other businesses generate roughly $20 billion in annualized earnings.

These investments come from a variety of businesses, and rather than being worth $130 billion, they're likely worth closer to $400 billion separately. This adjustment to the company's value can alone generate significant returns. Berkshire Hathaway alone definitely believes this, they've been aggressively pursuing share buybacks.

In addition to moving towards a fair value, the company's other source of value is its continued history and ability to fairly deploy its capital.

Risk

Many people call Berkshire Hathaway's risk the chance of subpar returns due to its massive cash pile, but we feel that in the current time that's actually quite limited.

First, the market is historically very overvalued at the current time. Especially with the tech focus, it feels a lot like 1999. There's massive value to having cash available at times when the market is overvalued. It means the company has plenty of room to make quality investments when the market drops. Cash isn't always bad.

The real risk of investing in Berkshire Hathaway is investors are trusting Warren Buffett to be stewards of their capital. Whether or not that pans out remains to be seen, and it's a risk worth noting, but historically it's worked out quite well.

Conclusion

A recent Seeking Alpha article argued that Warren Buffett's secret investment might be a reason to invest. Specifically, the article looked to see Warren Buffett deploying Berkshire Hathaway's massive cash pile into a worthwhile investment opportunity. However, Berkshire Hathaway has a long history of finding opportunistic investments.

Berkshire Hathaway through 2008 and subsequent years did an incredibly good job of finding unique opportunities. We expect that it'll be able to continue doing this going forward and that's the real reason to invest in Berkshire Hathaway for the long run. The company has the ability to drive long run shareholder returns.

Disclosure: I am/we are long BRK.A, BRK.B. I wrote this article myself, and it expresses my own opinions. I am not receiving compensation for it (other than from Seeking Alpha). I have no business relationship with any company whose stock is mentioned in this article.

Figure 1. Continued.

Second Article:

Berkshire Hathaway: Intrinsic Value Estimate Exceeds $300 Per Class B Share

Dec. 9, 2020 12:55 PM by: Left Shark Investing

Summary

- Estimate investment portfolio has appreciated by just under $30 billion since 3Q.
- Non-insurance operating companies, led by BNSF and BHE, could generate record profits in 2021.
- Berkshire consolidating apparent discount to intrinsic value with large-scale repurchases.

Introduction

With an estimated near $30 billion in investment gains since the end of 3Q, Berkshire's (NYSE:BRK.A)(NYSE:BRK.B) cash and investments should now exceed $400 billion after deducting taxes due on unrealized gains. I estimate that Berkshire's non-insurance operating companies will earn a record $20 billion in 2021 and value them at $336 billion *after* subtracting holding company debt. As such, I believe Berkshire's intrinsic value is now ~$740 billion ($315 per Class B share), or ~$200 billion greater than the current market capitalization. Adding to this positive dynamic, Berkshire has been repurchasing shares at a substantial clip, further consolidating the apparent value proposition for remaining stakeholders.

Valuation Summary	Estimated Value ($ Billions)
Investments + Cash (Net of deferred taxes)	406.2
Operating Companies (Net of holdco. debt)	335.7
Intrinsic value estimate	741.9
Class B equivalent shares outstanding (billions)	2.34
Intrinsic value per Class B share	$ 316.51

Investments & Cash

Investments + cash (Estimated)	Value ($ billions)
Domestic equities (incl. KHC)	261.0
OXY Pref.	10.0
BYD Company Limited	5.0
Japan Trading Companies	6.5
Total Pre-tax	282.5
Estimated deferred taxes	(41.2)
Total After-tax	241.2
Cash + T-bills	145.7
Fixed maturity	19.3
Total	406.2

Equities

Including preferred and foreign holdings, Berkshire equity investments have an estimated current fair market value of $282 billion. Since the end of the 3rd quarter, Berkshire's investment portfolio has appreciated by an estimated near $30 billion. Interestingly, although Berkshire is often characterized as a financial stock, its equity allocation in the technology sector is by far the largest (anchored by the AAPL position) and exceeds its financials company exposure by nearly 2:1.

From Berkshire's equity portfolio, I deduct $41 billion, representing the estimated cash taxes that would come due if Berkshire sold the holdings and realized gains.

Cash

Figure 1. Continued.

As of 3Q 2020, Berkshire had consolidated cash and equivalents of $145.7 billion.

Fixed Maturity

At of the end of the 3rd quarter, Berkshire's investments in fixed maturity securities were $19.3 billion.

Operating Companies

Non-insurance operating companies	Estimated 21 Earnings ($ billions)	Multiple	Value ($ billions)
BNSF	6.4	20	127.2
BHE	3.3	20	66.1
Manufacturing, service and retail	9.8	16	156.0
Non-KHC equity method earnings	0.5	16	8.6
Total	20.0	18	357.9
Holdco. Debt			(22.2)
Total value			335.7

BNSF

I estimate that BNSF will earn approximately 6.4 billion next year. My estimate is driven by $24 billion in revenue at a 60% operating ratio, slightly over $1 billion in interest expense and a 24% tax rate. Note that Berkshire's operating ratio has improved dramatically, from a historical range of around 65% to marginally below 60% last quarter.

Note that BNSF's operating income over the last two quarters has essentially mirrored that of Union Pacific (NYSE:UNP). Union Pacific currently has a $138 billion market capitalization. Here I assign a $127 billion valuation although BNSF is larger by both revenue and carloads (with slightly lower margins). I believe a 20x multiple is appropriate as BNSF has near infinite replacement costs and a secular tailwind from continued intermodal growth.

Interestingly, despite the recession, BNSF carloads are now positive on a year-over-year basis for the 4th quarter, paced by extremely strong performance in intermodal.

BHE

I estimate that BHE will earn $3.3 billion in 2021, or 7% higher than my 2020 estimate. 88% of BHE operating income comes from rate-regulated assets, so earnings growth should largely be a function of assets placed into service. Additionally, there should be some benefit from the acquisition of the Dominion assets.

BHE has spent over $29 billion on renewables, and wind and solar now account for 36% of generation capacity. In 2015, that figure was 25%.

I believe a 20x multiple is appropriate given the predictable nature of earnings, large investments in renewables, valuations of comparable publicly traded utilities, and low bond yields.

Manufacturing, Service and Retail

I estimate Manufacturing, Service and Retail will earn around $9.8 billion in 2021. I expect improved performance later in the year from Precision Castparts as aerospace build rates recover. In the meantime, Berkshire has significant exposure to housing end markets which helps offset the lost aerospace business. For reference, this division in aggregate earned $9.4 billion in 2019.

I assign a below market multiple of 16x to the earnings. This reflects the cyclicality in many of their end markets. However, given the disparate nature of these business, finding a direct market comparable is difficult.

Non-KHC Equity Method Earnings

These businesses earned .5 billion in 2019 to which I apply a 16x multiple for valuation. Again, they are a disparate group of partially owned businesses, and the earnings are small enough within the context of Berkshire that the "correct" multiple is relatively inconsequential in the overall valuation.

Holding Company Debt

I deduct $22 billion in debt from Berkshire Hathaway Inc. The interest expense of this debt is included in "Other" earnings. Interest expense at individual subsidiaries is deducted from earnings at the subsidiary level.

Insurance and Float

When valuing Berkshire, I neither capitalize underwriting earnings nor deduct float balances - currently $135 billion. As Berkshire typically generates significant underwriting income, the value of assets purchased with float dollars accrues entirely to the benefit of shareholders. Perhaps Buffett explains it better:

Figure 1. Continued.

"So how does our attractive float affect the calculations of intrinsic value? When Berkshire's book value is calculated, the full amount of our float is deducted as a liability, just as if we had to pay it out tomorrow and were unable to replenish it. But that's an incorrect way to look at float, which should instead be viewed as a revolving fund. If float is both costless and long-enduring, which I believe Berkshire's will be, the true value of this liability is *dramatically* less than the accounting liability." 2012 Annual Letter.

I would argue that if Berkshire generates average underwriting profits and operates in perpetuity, then float, although an accounting liability, has a positive net present value and should be counted as an asset. We will keep it simple here where float and underwriting profits net to zero.

Concluding Thoughts

In a market where valuations appear stretched on many traditional metrics, Berkshire appears to trade at a significant discount. Buffett seems to realize this discount, repurchasing a record $9.3 billion in shares during the 3rd quarter, ~2% of the outstanding shares and ~2x of what they repurchased in all of 2019. Given the substantial estimated discount to intrinsic value, these repurchases create value for ongoing shareholders.

Disclosure: I am/we are long BRK.B. I wrote this article myself, and it expresses my own opinions. I am not receiving compensation for it (other than from Seeking Alpha). I have no business relationship with any company whose stock is mentioned in this article.

Table 1
Descriptive Statistics

In this table, we present summary statistics for our main variables at the article level. The sample includes 16,446 opinion articles written on a single stock published on Seeking Alpha from August 2012 through March 2013. *# Page Views* is the number of page views of an article. *# Read-to-Ends* is the number of times SA users scroll to the bottom of an article. *# Shares* is the number of times an article is shared via email. *Article Accuracy* equals one if an article's "tone" is above the median and the cumulative DGTW-adjusted stock return over one month following article publication (while skipping the first two trading days) is positive, or, if an article's "tone" is below the median and the cumulative DGTW-adjusted stock return is negative, and zero otherwise. "Tone" is the number of positive words minus the number of negative words divided by the total number of words in an article. *Reliance on Numbers* is the ratio of the total occurrences of numbers to the total number of words in an article. *Length* is the number of words used in a title or an article. *Editors' Pick* equals one if an article is selected as an "Editors' Pick," and zero otherwise. *Presentation* is constructed as follows: Our server log data contain scores that SA editors assigned internally to each article based on how "actionable," "convincing," or "well-presented" they perceived the article to be. Scores range from 1 through 5, with 1 being the lowest and 5 being the highest. *Presentation* is the sum of the above three scores. We provide more details in Online Appendix Figure A2. *Long Score* (*Short Score*) compute for how many out of 172 anomalies a stock resides in the long (short) leg. Short- and long-leg stocks are generally stocks in the top and bottom deciles (or quintiles) with respect to a given firm characteristic. Some firm characteristics are indicator variables, and there is either only a long leg or only a short leg. For the full list of 172 anomalies and a description of each anomaly variable, please see Chen and Zimmermann (2019). *Analyst Coverage* is the number of analysts covering the stock in question. *DJNS Coverage* is the number of DJNS articles about a given stock over the previous month.

Variable	N	Mean	Std. Dev.	25th Percentile	50th Percentile	75th Percentile
Article-Level Variables						
# Page Views	16,446	4512.94	4581.09	1765.00	3284.50	5732.00
# Read-to-Ends	16,446	2029.77	1982.82	758.00	1467.00	2638.00
# Shares	16,446	5.46	8.51	1.00	3.00	7.00
Article Accuracy	16,446	0.51	0.50	0.00	1.00	1.00
Reliance on Numbers	16,446	0.04	0.04	0.02	0.03	0.05
$Length_{Title}$	16,446	8.19	2.71	6.00	8.00	10.00
Length	16,446	1000.38	621.13	620.00	866.00	1187.00
Editors' Pick	16,446	0.08	0.28	0.00	0.00	0.00
Presentation	16,446	9.55	0.79	9.00	9.00	10.00
Stock-Level Variables						
Long Score	16,446	10.43	5.52	6.00	10.00	14.00
Short Score	16,446	14.96	8.34	9.00	13.00	19.00
Analyst Coverage	16,446	5.01	9.44	0.00	0.00	6.00
DJNS Coverage	16,446	39.89	46.65	8.00	24.00	57.00

Table 2
The Consumption and Sharing of Accurate Stock-Opinion Articles

In this table, we present coefficient estimates from regressions of measures of article-consumption- and article-sharing levels on characteristics of the corresponding article's content. The sample includes 16,446 opinion articles written on a single stock published on Seeking Alpha from August 2012 through March 2013. The dependent variable in column (1) is the natural logarithm of one plus the number of page views that an article receives. The dependent variable in columns (2) and (3) is the natural logarithm of one plus the number of read-to-ends, and the dependent variable in columns (4) and (5) is the natural logarithm of one plus the number of times an article is shared via email. All variables are defined in Table 1. We do not report the intercept. *T*-statistics are reported in parentheses and are based on standard errors adjusted for heteroscedasticity and clustered by day of article publication. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	What Makes an Article More Likely to be …				
	Viewed?	Read to the End?		Shared?	
	(1)	(2)	(3)	(4)	(5)
Article Accuracy	0.035***	0.005	0.040***	-0.055***	-0.032**
	(2.72)	(1.26)	(2.95)	(-6.18)	(-2.53)
Length $_{Title}$	-0.010***				
	(-3.89)				
Length		-0.199***	0.011	0.337***	0.343***
		(-29.99)	(0.72)	(28.56)	(24.89)
Editors' Pick	0.525***	-0.170***	0.089***	0.341***	0.393***
	(22.46)	(-11.85)	(2.60)	(12.93)	(11.62)
Presentation		0.001	0.108***	0.056***	0.119***
		(0.16)	(9.51)	(5.98)	(10.28)
Long Score	0.013***	0.001***	0.015***	-0.011***	-0.003**
	(9.93)	(2.85)	(10.86)	(-9.85)	(-1.98)
Short Score	0.026***	0.001***	0.027***	0.000	0.016***
	(30.52)	(5.18)	(31.04)	(0.08)	(17.04)
ln (1 + Analyst Coverage)	-0.075***	-0.006	-0.076***	-0.040***	-0.084***
	(-9.12)	(-1.63)	(-8.00)	(-6.87)	(-11.91)
ln (1 + DJNS Coverage)	0.066***	-0.003***	0.066***	-0.008**	0.030***
	(15.14)	(-2.34)	(14.30)	(-2.21)	(6.87)
ln (1+ # Page Views)		1.018***			
		(270.67)			
ln (1 + # Read-to-Ends)				0.585***	
				(79.10)	
# Obs.	16,446	16,446	16,446	16,446	16,446
R^2	0.138	0.920	0.122	0.455	0.147

Table 3
The Consumption and Sharing of Quantitative Stock-Opinion Articles

In this table, we present coefficient estimates from regressions of measures of article-consumption- and article sharing-levels on characteristics of the corresponding article's content. The sample includes 16,446 opinion articles written on a single stock published on Seeking Alpha from August 2012 through March 2013. The dependent variable in columns (1) and (2) is the natural logarithm of one plus the number of read-to-ends; the dependent variable in columns (3) and (4) is the natural logarithm of one plus the number of times an article is shared via email. All variables are defined in Table 1. We do not report the intercept. *T*-statistics are reported in parentheses and are based on standard errors adjusted for heteroscedasticity and clustered by day of article publication. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	What Makes an Article More Likely to be …			
	Read to the End?		Shared?	
	(1)	(2)	(3)	(4)
Reliance on Numbers	-1.212***	-1.833***	1.689***	0.607***
	(-7.55)	(-4.50)	(6.12)	(3.13)
Length	-0.209***	-0.005	0.351***	0.348***
	(-35.86)	(-0.35)	(30.14)	(25.06)
Editors' Pick	-0.140***	0.135***	0.298***	0.377***
	(-10.72)	(3.89)	(11.26)	(11.01)
Presentation	0.003	0.111***	0.052***	0.118***
	(0.77)	(9.81)	(5.59)	(10.20)
Long Score	0.001***	0.014***	-0.011***	-0.003*
	(2.59)	(10.82)	(-9.81)	(-1.94)
Short Score	0.001***	0.026***	0.001	0.016***
	(3.61)	(30.02)	(0.76)	(17.25)
ln (1 + Analyst Coverage)	-0.004	-0.073***	-0.042***	-0.085***
	(-1.11)	(-7.84)	(-7.27)	(-12.07)
ln (1 + DJNS Coverage)	-0.003**	0.065***	-0.008**	0.030***
	(-2.54)	(14.32)	(-2.22)	(7.01)
ln (1+ # Page Views)	1.016***			
	(273.20)			
ln (1 + # Read-to-Ends)			0.590***	
			(79.13)	
# Obs.	16,446	16,446	16,446	16,446
R^2	0.923	0.128	0.460	0.147

Table 4
Effect of Impression-Management Considerations on the Sharing of Quantitative Articles

In this table, we present responses from two online experiments. In our first experiment, 280 investors are randomly assigned to two groups of 140 investors each. Each group, in turn, comprises 110 investors with reported/estimated net investable assets below or equal to $300,000 and 30 investors with reported net investable assets above $300,000. All investors are asked to read the same quantitative article (shown in Online Appendix Figure A1). At the end of the article, investors in the first group are asked whether they would share this article with a co-worker. Investors in the second group are asked whether they would share this article with a very close friend. In column (1) we report, for each of the two groups, the fraction of investors that would share the quantitative article; we also report the difference in the fractions across the two groups. In columns (2) and (3) we report the corresponding numbers separately for investors with net investable assets below or equal to and above $300,000, respectively. In our second experiment, a different set of 260 investors is randomly split into two groups of 130 investors each. Each group, in turn, comprises 110 investors with reported/estimated net investable assets below or equal to $300,000 and 20 investors with reported net investable assets above $300,000. The investors in the first group are given the following task: "*Please think about a situation where you felt you did not look as knowledgeable in the eyes of your co-workers as you would have liked. Briefly describe the situation in the box below. [minimum of 2 sentences].*" The investors in the second group are given the following task: "*Please think about what a "perfect" office would look like to you. Briefly describe this "perfect" office in the box below. [minimum of 2 sentences].*" All investors are subsequently asked to read the same quantitative article as in the first experiment. At the end of the article, investors are asked whether they would share this article with a co-worker. We again report the fractions of investors responding they would share the quantitative article as well as the differences in the fractions. *T*-statistics are reported in parentheses and are based on standard errors adjusted for heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

		Investors with Net Investable Assets	
Fraction of investors responding they would share the quantitative article …	All Investors (1)	≤ $300,000 (2)	> $300,000 (3)
Panel A: Experiment 1			
(a) … with a co-worker	60.7%	59.1%	66.7%
(b) … with a very close friend	45.7%	46.4%	43.3%
(a) – (b)	15.0%**	12.7%*	23.3%*
	(2.53)	(1.90)	(1.84)
Panel B: Experiment 2			
(c) … with a co-worker after writing about a "perceived deficiency-in-the-self"	50.0%	52.7%	35.0%
(d) … with a co-worker after writing about a neutral topic	39.2%	43.6%	15.0%
(c) – (d)	10.8%*	9.1%	20.0%
	(1.75)	(1.35)	(1.46)

Table 5
Virality and Stock Returns

This table reports the daily average raw returns or daily average DGTW-adjusted returns for portfolios formed by the level of virality a stock receives. The sample is based on 16,446 opinion articles written on a single stock published on Seeking Alpha from August 2012 through March 2013. For each stock, at the end of each day, we compute the level of virality as the total number of times SA articles about the corresponding stock were shared through email, scaled by the total number of times SA articles were viewed (Panel A) or read to the end (Panel B). Each day, we rank stocks based on their level of virality. "Low Virality" is the equal-weighted portfolio of 10% of the stocks with the lowest level of virality. "High Virality" is the equal-weighted portfolio of 10% of the stocks with the highest level of virality. Portfolios are held either for one week or for three weeks (starting from week 2). *T*-statistics are based on Newest-West standard errors (five lags) and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Week 1		Weeks 2 through 4	
	Raw Returns	DGTW-Adjusted Returns	Raw Returns	DGTW-Adjusted Returns
Panel A: Virality = # Shares / # Page Views				
Low Virality	0.04%	-0.06%	0.15%**	0.04%
	(0.45)	(-0.82)	(2.18)	(1.31)
High Virality	0.24%***	0.13%***	0.05%	-0.04%*
	(3.00)	(3.23)	(0.83)	(-1.92)
High minus Low	0.20%***	0.19%**	-0.10%**	-0.08%**
	(2.75)	(2.54)	(-2.43)	(-2.21)
# Obs.	169	169	181	181
Panel B: Virality = # Shares / # Read-to-Ends				
Low Virality	0.01%	-0.09%	0.15%**	0.04%
	(0.09)	(-1.17)	(2.22)	(1.45)
High Virality	0.26%***	0.16%***	0.07%	-0.03%
	(3.38)	(3.74)	(1.09)	(-1.41)
High minus Low	0.26%***	0.24%***	-0.09%**	-0.08%**
	(3.40)	(3.21)	(-2.13)	(-2.04)
# Obs.	169	169	181	181

Table 6
Virality and Stock Returns among Stocks Likely to be Short-Sale Constrained

This table replicates Table 5 for stocks whose average daily lending fees in the month of article publication are in the top 30% of their distribution at a given point in time.

	Week 1		Weeks 2 through 4	
	Raw Returns	DGTW-Adjusted Returns	Raw Returns	DGTW-Adjusted Returns
Panel A: Virality = # Shares / # Page Views				
Low Virality	-0.00%	-0.11%	0.20%	0.08%
	(-0.00)	(-0.45)	(1.72)	(0.97)
High Virality	0.38%**	0.27%**	-0.06%	-0.16%**
	(2.38)	(2.11)	(-0.55)	(-2.19)
High minus Low	0.38%	0.38%	-0.26%**	-0.24%**
	(1.45)	(1.45)	(-2.29)	(-2.22)
# Obs.	166	166	179	179
Panel B: Virality = # Shares / # Read-to-Ends				
Low Virality	-0.01%	-0.12%	0.20%	0.09%
	(-0.03)	(-0.51)	(1.89)	(1.16)
High Virality	0.31%**	0.22%	-0.02%	-0.13%*
	(1.99)	(1.63)	(-0.20)	(-1.81)
High minus Low	0.32%	0.34%	-0.22%**	-0.22%**
	(1.20)	(1.29)	(-2.01)	(-2.09)
# Obs.	166	166	179	179

Table 7
Virality and Stock Returns: Evidence Based on Tweets and Retweets

This table reports the daily average raw returns or daily average DGTW-adjusted returns for portfolios formed by the level of virality a stock receives. The sample is based on 91,262,601 tweets covering 10,079 stocks from January 2013 through December 2018. For each stock, at the end of each day, we compute the level of virality as the total number of retweets of tweets mentioning the corresponding stock, scaled by the total number of tweets. Each day, we rank stocks based on their level of virality. "Low Virality" is the equal-weighted portfolio of stocks for which virality equals zero. "High Virality" is the equal-weighted portfolio of stocks for which virality is greater than zero. Portfolios are held either for one week or for three weeks (starting from week 2). *T*-statistics are based on Newest-West standard errors (five lags) and are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Week 1		Weeks 2 through 4	
	Raw Returns	DGTW-Adjusted Returns	Raw Returns	DGTW-Adjusted Returns
Low Virality	0.04%*	-0.00%	0.04%*	0.00%
	(1.67)	(-1.37)	(1.79)	(0.77)
High Virality	0.12%***	0.07%***	0.03%	-0.01%**
	(4.25)	(11.12)	(1.20)	(-2.02)
High minus Low	0.07%***	0.07%***	-0.01%**	-0.01%**
	(12.08)	(11.97)	(-2.26)	(-2.46)
# Obs.	1,511	1,511	1,507	1,507

Table 8
Virality and Stock Returns: Evidence Based on an Investor Survey

In this table, we present responses from an investor survey. At the conclusion of the two experiments described in Table 4, we ask all 540 investors the following question (1): "*Over the past 12 months, did a co-worker, friend, or family member mention a stock to you that they thought you might be interested in buying?*" All investors who respond "*Yes*" to question (1) are asked two follow-up questions (2): "*How thoroughly do you think that person researched that stock before mentioning it to you?*" and (3): "*Did you end up buying the stock*?" All investors who respond "*Yes*" to question (3) are asked a final question (4): "*What was or has been your overall return since you bought the stock? If you are not sure, please answer, "don't know.'*"" In column (1), we report the responses across all investors. In columns (2) and (3), we report the responses separately for investors with net investable assets below or equal to and above $300,000, respectively.

		Investors with Net Investable Assets	
	All Investors	≤ $300,000	> $300,000
	(1)	(2)	(3)
Fraction of investors responding ____ to the following question:			
(1) "*Over the past 12 months, did a co-worker, friend or family member mention a stock to you that they thought you might be interested in buying?*"			
- … "*yes*" …	43.7%	45.9%	34.0%
Fraction of investors responding "*yes*" to question (1) and responding ____ to the following question:			
(2) "*How thoroughly do you think that person researched that stock before mentioning it to you*?"			
- … "*1 (Rather Casually)*" …	8.1%	8.4%	5.9%
- … "*2*" …	25.0%	26.7%	14.7%
- … "*3*" …	23.7%	22.8%	29.4%
- … "*4*" …	27.5%	26.2%	35.3%
- … "*5 (Rather Thoroughly)*" …	15.7%	15.8%	14.7%
Fraction of investors responding "*yes*" to question (1) and responding _____ to the following question:			
(3) "*Did you end up buying the stock*?"			
- … "*yes*" …	33.9%	32.7%	41.2%
Fraction of investors responding "*yes*" to question (3) and responding ____ to the following question:			
(4) "*What was or has been your overall return since you bought the stock? If you are not sure, please answer "don't know.'*""			
- … "*don't know*" …	11.3%	10.6%	14.3%
- … "*less than -20%*" …	2.5%	1.5%	7.1%
- … "*between -20% and -10.01%*" …	11.3%	9.1%	21.4%
- … "*between -10% and -0.01%*" …	10.0%	10.6%	7.1%
- … "*between 0% and +10%*" …	41.3%	45.5%	21.4%
- … "*between +10.01% and +20%*" …	15.0%	12.1%	28.6%
- … "*greater than +20%*" …	8.8%	10.6%	0.0%