Are social media analysts disrupting the information content of sell-side analysts' reports?

Michael S. Drake
Brigham Young University
mikedrake@byu.edu

James R. Moon, Jr.*
Georgia Institute of Technology
robbie.moon@scheller.gatech.edu

Brady J. Twedt
University of Oregon
btwedt@uoregon.edu

James D. Warren
University of Georgia
james.warren26@uga.edu

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* Corresponding Author

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Abstract

We examine the impact of "social media analysts," individuals posting equity research online via social media investment platforms, on the value-relevance of the forecasts of professional sell-side equity analysts. Using data from Seeking Alpha, we find that the market reaction to the news in a sell-side analyst forecast is substantially reduced when preceded by the report of a social media analyst. Cross-sectional analyses suggest that this result is more pronounced for social media analysts with greater expertise, for those that provide more detailed analyses, and for firms with more retail investors. Additionally, social media analyst reports pre-empt the information content of sell-side analyst forecasts when the tenor of the two information sources is similar. Collectively, our results suggest that equity research posted online by social media analysts is disrupting the information content of sell-side equity research and speak to the evolving role of social media in capital markets.

1. Introduction

We examine how company-specific research made available online via social media investment platforms influences the information content of professional sell-side analyst forecasts.[1] Extant research is just beginning to examine how social media content is influencing the information environment of firms, and it is unclear whether firm-specific research posted by individuals on social media (hereafter "social media analysts") is impacting the relevance of information produced by the professional sell-side analysts that have been a prominent feature of capital markets for decades. An improved understanding is important because the number of social media analysts is likely to continue to rise, while the number of sell-side analysts has been steadily falling (see Figures 1 and 2, as well as Morris 2017). The decline in sell-side research department resources and headcounts is nontrivial and has led some to argue that sell-side equity research is not merely a disrupted industry, but a dying industry (Armstrong 2018, Lee 2019, Pumfrey 2019), suggesting the potential for a growing role for social media in the equity research landscape.

Social media analysts have clear incentives to produce high-quality useful information in order to attract, retain, and grow their readership. Recent research suggests that the reports of social media analysts are associated with significant price changes, which suggests that they are credible and provide valuable information to market participants (Chen et al. 2014; Campbell et al. 2019). In contrast to the more restricted dissemination of sell-side analyst reports, social media reports are generally freely available online, which makes them especially accessible and useful to less sophisticated investors (Farrell et al. 2018; Gomez et al. 2019). In addition, social media analysts

[1] Given our research objective, we focus on *investment*-related social media platforms (and Seeking Alpha in particular). We do not use the term "crowdsourced" because, unlike venues such as Estimize or Glassdoor, the research, opinions, and analyses we examine are not aggregated (or "crowdsourced") in any way.

are not subject to some of the incentives that sell-side analysts face to issue biased reports to generate trading commissions or to support investment banking deals for their brokerage houses (Cowen et al. 2006; Mayew 2008). Finally, extant research finds that social media analysts often have "skin in the game" (i.e., they have an investment position in the stock) and that the disclosure of their position increases the informativeness—and therefore presumably the quality—of their analysis (Campbell et al. 2019). Together, these factors lead to our prediction that the reports of social media analysts are associated with a reduction in the value-relevance of subsequent research provided by sell-side analysts.

However, several factors suggest that social media equity research may have little to no bearing on the value-relevance of sell-side analyst reports. First, the financial sophistication of social media analysts is more difficult to evaluate than that of sell-side analysts. While research suggests that social media analysts are, on average, credible, the hiring and training practices of sell-side analysts' employers ensure a considerable level of financial expertise, which is further enhanced by the technical resources and tools provided by their brokerage. It is unlikely that such resources are available to the average social media analyst, which could result in social media analysts producing a different set of information than that produced by sell-side analysts. Second, social media analysts are not subject to the same level of compliance and oversight from employers and regulators as are sell-side analysts. Third, labor market concerns and reputational costs are likely less significant for social media analysts than they are for their professional sell-side counterparts because social media analysts generally make their living in other ways (Jackson 2005). Finally, although research suggests that sell-side analysts' reports primarily benefit the same group of investors targeted by social media analysts (Amiram et al. 2016), the shift in the focus of sell-side analysts towards personalized, "high-touch" services geared towards institutional clients may result in forecasts that represent a different type of information than that published on social media platforms. Thus, whether the reports of social media analysts are associated with a reduction in the value-relevance of sell-side analyst reports is an open question.

We test our prediction by examining whether the posting of a social media analyst report in the days just prior to the issuance of a sell-side analyst earnings forecast reduces the market reaction to the sell-side analyst forecast. For social media analyst reports, we use firm-specific research and analysis posted on Seeking Alpha. This investment platform is one of the most trafficked social media websites focusing on stock news, with tens of thousands of users visiting the site daily for investment-related content, including stock recommendations, conference call transcripts, earnings announcement calendars, and opinions on recent company disclosures.[2] Further, because it was founded in 2004, Seeking Alpha is among the first investment-related social media platforms and therefore provides a relatively longer time-series of data to examine.

Our sample consists of approximately half a million sell-side analyst forecast revisions during the 2006 to 2017 period. These sell-side analyst forecasts are preceded by over 200,000 Seeking Alpha reports issued by nearly 13,000 unique social media analysts. We find that nearly 20 percent of sell-side analysts' earnings forecasts are preceded by at least one posting of a social media analyst report on Seeking Alpha during the prior seven days. We also find that social media analyst reports do not tend to cluster in advance of sell-side analyst forecasts; when there is a social media report in this window, there is generally only one published report. Because analysts of all types often produce research following the release of earnings news, we conduct our tests using a restricted sample of forecasts issued outside of periods when firms disclose earnings or earnings guidance, but we also present results using the full, unrestricted sample of forecasts as well.

[2] As of January 2019, Seeking Alpha reports an average of 42 million unique site visits per month spread across 13.2 million unique users (Seeking Alpha 2019).

Do the reports of social media analysts reduce the value-relevance of sell-side analyst forecasts? Our evidence suggests that they do. Specifically, we find that the positive association between the news in the sell-side analyst forecast and the immediate abnormal price reaction is significantly reduced (by approximately 34 to 41 percent) when at least one social media analyst posts an equity research article in the seven days prior to the forecast. We find that the magnitude of this effect is similar to that observed when the sell-side analyst forecast is preceded by another sell-side forecast. We find similar evidence using abnormal trading volume: the positive association between the absolute value of the news in the sell-side analyst forecast and abnormal trading volume is significantly reduced in the presence of a prior social media analyst report. These results are robust to a broad set of factors that may determine both the presence of a social media analyst report and the informativeness of the forecast, including general firm characteristics (e.g., size, book-to-market, share turnover, etc.), past market performance, and business press coverage. They are also generally robust to different fixed effect structures (e.g., firm, analyst, analyst-firm), changes to measurement windows, dropping forecasts issued around any firm-initiated press release, and estimating the regressions at the analyst-firm level.

Next, we conduct cross-sectional analyses to more deeply examine our inference that the muted market reactions to sell-side analyst forecasts are driven by the research activity of social media analysts. We develop three specific predictions based on variation in the biographies of social media analysts on Seeking Alpha, the amount of detail they provide in their reports, and the investor base of the firms about which they write. First, we predict that variation in the credibility of social media analysts will lead to differential investor assessments of their expertise, where expertise is measured based on their investor following and tenure (or length of time they have contributed to Seeking Alpha). We expect this in turn will influence the impact of their reports on the value-relevance of sell-side analyst forecasts. Second, we predict that the disruption effect of social media analysts is concentrated in those reports that are more detailed, where report detail is determined based on the length and number of numbers contained in the report. Third, we predict that the attenuation effect of social media analysts on the relevance of sell-side analysts' forecasts is concentrated in firms with relatively lower proportions of institutional holdings, consistent with less sophisticated retail investors being the primary consumers of social media analyst reports. We find evidence consistent with all three of these predictions.[3]

We conclude with two sets of additional analyses that explore the mechanism(s) through which social media analysts reduce the value-relevance of sell-side research. We first examine whether social media analysts pre-empt sell-side analysts by providing content that is similar in tenor and thus "moves up" the pricing of the sell-side analyst forecast news. We then consider the possibility that social media analysts prompt noise trading, reducing the efficiency of the sell-side forecast price response.

In the first set of tests, we find that the tone of social media analyst reports predicts the news in sell-side analyst forecasts.[4] This suggests that, on average, the information produced by social media analysts is similar in tenor to that subsequently disseminated by sell-side analysts. We then test whether social media analyst reports will pre-empt more of the information content of the subsequent sell-side analyst forecast when the tenor of the two reports agrees (i.e., both are positive or both are negative). We find that price reactions in the days *before* the sell-side forecast are more positively associated with the news in the upcoming forecast (i.e., greater pre-emption)

[3] In one final cross-sectional test, we evaluate whether our results are primarily attributable to social media analysts who cite professional investment-related experience, perhaps as a sell-side analyst, in their biographies. We do not find evidence consistent with this conjecture.

[4] Social media analyst reports lack the homogeneity of their sell-side counterparts. Specifically, they often do not provide numeric forecasts, and when there is a forecast, it is not easily extracted and compiled (i.e., different types, horizons, benchmarks, etc.). Thus, we use the tone of their reports to determine whether they contain positive or negative information about the firm, and compare this to the sign of the forecast news produced by the sell-side analyst.

when the reports agree in tenor than when they disagree.

In the second set of tests, we examine whether social media analyst reports are associated with greater market under-reactions to sell-side analyst forecasts when the two reports disagree in tenor than when they agree. This prediction is motivated in part by Drake et al.'s (2017) finding that information posted online by nonprofessional information intermediaries can trigger correlated noise trading, and this may result in under-reaction to subsequently released forecasts. Using both returns drift and an intraperiod timeliness measure, we find no evidence that supports this prediction.

This study makes several novel contributions to the literature. We contribute to the literature on the role of sell-side analysts in capital markets, and how that role is evolving over time (Lang and Lundholm 1996; Frankel et al. 2006; Drake et al. 2019). Recent research provides evidence that crowdsourced earnings forecasts can be incrementally useful to investors beyond those of professional sell-side analysts (Jame et al. 2016) and potentially discipline sell-side analysts, resulting in less biased forecasts (Jame et al. 2017). We contribute to this literature by providing the first direct evidence that equity research posted online via social media platforms reduces the informativeness of sell-side analyst reports. This evidence is important because the amount of information investors obtain through social media sources is likely to continue to increase over time, while sell-side equity research department budgets and headcounts are likely to continue to decrease. Thus, social media analysts may be able to fill any research void left behind by sell-side analysts.

We also contribute to the emerging literature on the role of social media in capital markets, and investment platforms such as Seeking Alpha in particular. These studies demonstrate that social media analysts provide valuable information to the market in that their reports predict future stock returns (Chen et al. 2014); improve firm liquidity, particularly among retail investors (Farrell et al. 2018) and during earnings announcements (Gomez et al. 2019); and are associated with significant price changes, especially when the social media analyst holds a position in the stock (Campbell et al. 2019). Blankespoor et al. (2019; p. 5) note that "research on social media as an intermediary is nascent" and call for research on the influence of social media on other information intermediaries. Similarly, Miller and Skinner (2015; p. 228) argue that social media is "an important new strand of the literature given its increasing use by a large cross section of society and the potential for users to create and disseminate their own content". We contribute to this emerging literature by demonstrating that the reports of social media analysts actually preempt and substantially reduce the value-relevance of the reports of professional sell-side equity analysts, preeminent intermediaries that investors have long relied on for company-specific analysis.

2. Prior Literature and Motivation

Sell-side equity analysts have played an important role in capital markets for decades. Their research helps establish the market's expectations of earnings, supports specific trading recommendations, and provides investors with important information regarding key investment debates surrounding stocks. Their forecasts and opinions are featured prominently in the business press and news media (Rees et al. 2015). Perhaps not surprisingly, hundreds of published studies examine their activities and impact on markets, and this research provides consistent support for the idea that their reports move markets (Gleason and Lee 2003; Frankel et al. 2006; Beyer et al. 2010; Li et al. 2015).[5] This research helps us understand the various incentives sell-side analysts face to curry favor with management, generate trading commissions, and promote investment banking transactions, and how these incentives negatively impact the objectivity of their

[5] See Ramnath et al. (2008), Bradshaw (2011), and Bradshaw et al. (2016) for detailed reviews of this literature.

recommendations and forecasts (Lin and McNichols 1998; Jackson 2005; Mayew 2008). These compromising incentives notwithstanding, sell-side analysts have been generally regarded as the primary source of equity investment research for investors for nearly half a century.

In recent years, the sell-side equity research landscape has shifted for reasons related to changes in regulation and in the market's supply of and demand for information (Drake et al. 2019). Regulation such as the Global Settlement reduced opportunities for equity research departments to support and promote investment banking transactions for their brokerages. This has led sell-side analysts to focus more of their efforts on monetizing their research through trading commissions (Kadan et al. 2009; Groysberg and Healy 2013). To do this, analysts now devote more of their time to the needs of their high-commission institutional clients (e.g., hedge funds) by providing them with more specialized, high-touch research services (e.g., broker-hosted conferences, proprietary forecasting models, etc.; see Green et al. 2014 and Brown et al. 2015). As Alpha Magazine reported, hedge funds "hate written product, and would rather spend two hours on the phone with the analyst."[6] As a result of these changes, budgets and headcounts of equity research departments have been steadily falling in recent years (Groysberg and Healy 2013, Ch. 4), and Figure 1 confirms this trend in our data.[7] Additionally, McKinsey recently estimated that equity research budgets at the top ten sell-side brokerages would soon decline by an *additional* 30 percent (Morris 2017).

The downward trend in equity research budgets is largely driven by shifts in regulation that alter the demand for and supply of sell-side research. This trend provides an opportunity for

[6] "How Hedge Funds Rate Wall Street Analysts," Alpha Magazine, November 21, 2005. This anecdotal evidence may initially appear inconsistent with the conclusion in Amiram et al. (2016) that sell-side analyst forecasts represent new information only to less sophisticated, retail investors. However, it is likely that the timing of the "high-touch" services provided to institutional clients does not correspond with the timing of analysts' public forecasts. In this case, one could still observe the result in Amiram et al. (2016) even with a shift in focus towards institutional clients.
[7] We address the concern that this trend may be confounding our analyses through various control variables, fixed effect structures, and within analyst-firm analyses, discussed in more detail later.

alternative sources of equity research, such as social media analysts, to step in. As noted by Drake et al. (2017), "virtually any individual with internet access can express opinions about firms and editorialize about company news" (p. 544), and research suggests that these individuals, at least on average, provide value-relevant information. For instance, crowdsourced earnings forecasts on Estimize provide news incremental to that of professional analysts (Jame et al. 2016). Similarly, user sentiment on Twitter predicts future sales and earnings surprises (Tang 2018; Bartov et al. 2018), and company outlook expressed in employer reviews on Glassdoor positively relates to firms' future voluntary and mandatory disclosures (Hales et al. 2018).

In contrast to the trend in the number of sell-side analysts (Figure 1), the number of social media analysts posting on Seeking Alpha has grown significantly in recent years, as shown in Figure 2. Similar to professional sell-side analysts, social media analysts express opinions about companies' outlook based on their own research, and the literature suggests that these opinions are generally credible. For instance, Chen et al. (2014) provide evidence that the views expressed in these reports are predictive of future stock returns and earnings surprises, suggesting that they contain value-relevant information. Campbell et al. (2019) document immediate price responses to Seeking Alpha articles and suggest that investors view social media analysts who have "skin in the game" (i.e., have personal financial positions in the stocks they write about) as more credible than those who do not. Farrell et al. (2018) find that Seeking Alpha reports facilitate informed trading by retail investors and reduce information asymmetry. Gomez et al. (2019) provide evidence that Seeking Alpha coverage of a firm during a fiscal quarter reduces sophisticated investors' information advantage during earnings announcements. Their rationale is that social media analyst reports help to forge a consensus between less and more sophisticated investors.

Collectively, the evidence in these studies suggests that the reports of social media analysts contain value-relevant information. This evidence is also consistent with the incentives of social media analysts to produce value-relevant, high-quality information. Producing useful information is necessary to establish and maintain credibility in order to increase their readership and, eventually, monetize their postings.[8] The reports of social media analysts are also likely to be unaffected by the well-documented biases in sell-side analysts' outputs resulting from investment banking relationships, the generation of trading commissions, and the desire to maintain access to management. In addition, the research of social media analysts is generally freely available (or available at low cost) to any investor with an internet connection, which allows for much broader dissemination and, therefore, a potentially larger market impact than that of the less freely available reports of sell-side analysts.[9]

In combination, the changes in the sell-side equity research landscape and the recent availability of investment research online through social media platforms raise the important question of whether the activities of social media analysts have disrupted the value-relevance of sell-side analyst forecasts. Additionally, sell-side analyst forecasts have historically been most useful to less sophisticated investors (Amiram et al. 2016), the same group that is more likely to rely on the reports of social media analysts (Farrell et al. 2018; Gomez et al. 2019). Thus, we predict that social media reports in the days prior to a sell-side analyst earnings forecast will reduce the value-relevance of that forecast.

However, there are a number of reasons why this disruption effect may not exist. Investors

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[8] According to Chen et al. (2014), contributors on Seeking Alpha earn $10 per one thousand page views. Seeking Alpha also helps authors promote their work on major media outlets and hosts networking events, both of which help contributors build their reputations in the investment community and potentially monetize their skills through other means (Seeking Alpha 2019). In addition, Seeking Alpha recently began hosting a "marketplace" where authors can sponsor their own "paid-for" research platform, which further incentivizes social media analysts to produce high-quality analysis.

[9] Seeking Alpha recently shifted its model to put most research behind a relatively inexpensive paywall, referred to as "essential α," but users may freely access current and recent analysis for stocks in their portfolio maintained in their user account. During our sample period, the Seeking Alpha content we analyze was free to all users.

may perceive social media analysts as lacking the financial sophistication of trained professional sell-side analysts, and this may be compounded by differences in technical resources and tools. As a result, the content of social media analysts reports' may fundamentally differ from the signal provided by an earnings forecast. The lack of compliance and governance mechanisms may also weaken the credibility of their reports.[10] In addition, labor market and reputational concerns are presumably less important for social media analysts compared to professionals. Thus, the question of whether or not the reports of social media analysts reduce the value-relevance of sell-side analyst forecasts is ultimately an open empirical question.

3. Data and Sample

Our sample of social media analyst reports comes from Seeking Alpha. Similar to prior research (e.g., Chen et al. 2014; Campbell et al. 2019), we focus on content beginning with the URL "seekingalpha.com/article," which includes the long-form articles that are similar in many respects to sell-side analyst reports.[11] While content appeared on Seeking Alpha as early as 2004, regular postings about a broad set of stocks did not occur until 2006, so our sample period spans from 2006 to 2017. We use a series of Python scripts to collect a total of 471,089 social media analyst reports published by 12,971 unique social media analysts.

Seeking Alpha uses two types of metadata to identify stocks about which articles are written. If at least one stock is the primary focus of the article, the stock's ticker appears in the "Primary" (or "about_primary_stocks") field in the HTML header information. Stocks that are

[10] While Campbell et al. (2019) generally conclude that Seeking Alpha authors are credible, the site has been targeted as a purveyor of "fake news" that allows some anonymous contributors to profit on misleading articles (Levick 2019), and material posted on Seeking Alpha has been cited during SEC investigations related to market manipulation (Stempel 2017). However, Clarke et al. (2019) investigate the presence of fake news on Seeking Alpha and find that although fake news articles garner greater attention, the market appears to price them correctly. We exploit cross-sectional variation in several measures of Seeking Alpha author credibility in Section 4.2.1.

[11] We do not collect content with "news" URLs, as those typically represent news flashes or dissemination of news published elsewhere.

only referenced, but not extensively discussed, are denoted in the "About" ("about_stocks") field. While articles referencing multiple stocks may provide information relevant to investors, this signal is likely noisy. For instance, social media analysts may contrast two firms, discussing one favorably and the other unfavorably, making it very difficult to identify the true tenor of the article. Therefore, we limit our sample to articles focusing on a single ticker that is identified in the "Primary" stock field.[12] This reduces our sample of social media analyst reports to 280,995, of which 202,476 precede at least one sell-side analyst report and thus appear in our sample.

We obtain one-quarter-ahead earnings forecast revisions by sell-side analysts using IBES. On days when multiple analysts issue a forecast for a given firm, we compute the mean revision across analysts so that our unit of observation becomes, essentially, the "firm-day."[13] We also require stock return data from CRSP, financial statement data from Compustat, institutional ownership data from Thomson, management forecast data from IBES Guidance, and business press data from RavenPack. Finally, we construct two samples using quarterly forecasts issued between 2006 and 2017. The restricted sample consists of 368,714 sell-side analyst forecasts that are issued *outside* of earnings news windows (i.e., not following earnings announcements or management earnings guidance). The unrestricted sample consists of 533,844 sell-side forecasts issued at any time during the fiscal year.

4. Empirical Design and Results

4.1 Primary Analyses

We test our primary prediction that the reports of social media analysts reduce the informativeness of sell-side analysts' earnings forecasts by estimating the following model

[12] Articles missing a primary ticker frequently discuss general macroeconomic events or industry trends.
[13] For social media reports and sell-side forecasts issued after 4 pm, we adjust the announcement date to the next trading day so that our return windows (described later) correctly identify the "event" day. We also delete a small number of sell-side forecasts dated *after* the firm's earnings announcement, which likely reflect data errors.

(subscripted values in brackets denote the variable's measurement window where needed):

$$AbRet_{[0,1]} / AbVol_{[0,1]} = \alpha_0 + AF(\beta_0 + \boldsymbol{\beta_1 SMA_{[-7,-1]}} + \beta_2 Size + \beta_3 MB + \beta_4 SMA_{[0,1]} + \beta_5 InstOwn + \beta_6 Turnover + \beta_7 Following + \beta_8 Horizon + \beta_9 AbRet_{[-5,-1]} + \beta_{10} BizPress_{[-14,-8]} + \beta_{11} BizPress_{[-7,-1]} + \beta_{12} BizPress_{[0,1]}) + \alpha_1 SMA_{[-7,-1]} + \alpha_2 Size + \alpha_3 MB + \alpha_4 SMA_{[0,1]} + \alpha_5 InstOwn + \alpha_6 Turnover + \alpha_7 Following + \alpha_8 Horizon + \alpha_9 AbRet_{[-5,-1]} + \alpha_{10} BizPress_{[-14,-8]} + \alpha_{11} BizPress_{[-7,-1]} + \alpha_{12} BizPress_{[0,1]} + e \quad [1]$$

Equation [1] is similar to an earnings-response-coefficient (ERC) model where the terms in parentheses (with β coefficients) capture factors that may affect the value relevance of earnings or, in this case, the value relevance of *forecasted* earnings. The dependent variable in Equation [1] is the two-day market response to the sell-side analyst forecast, measured using either the signed buy-and-hold abnormal return beginning on the trading day on which an analyst forecast is issued, or abnormal volume.[14] Abnormal returns are computed using portfolios based on size, book-to-market, and momentum as in Daniel et al. (1997). We compute *AbVol* as the standardized difference between two-day volume and the firm's average volume over the prior fiscal year.[15] *AF* represents the news conveyed in the sell-side analyst revision, calculated using two alternative methods: (1) the difference between the analyst's forecast and the prior consensus, constructed using the median of the most recent forecast for each analyst covering the firm in the 90 days preceding the analyst's forecast (*News*), or (2) the revision in the forecast for the analyst from his or her own prior forecast (*Rev*). *SMA* is an indicator set equal to one when the forecast is preceded by at least one social media analyst report (zero otherwise). If the reports of social media analysts preempt sell-side analysts' reports, then we should observe a negative coefficient on β_1, the coefficient on the interaction between *SMA* and *AF*.

[14] Variable definitions are provided in Appendix A.

[15] When using *AbVol* as the dependent variable, we slightly alter [1] to account for the unsigned nature of trading volume. Specifically, we use the absolute value of *AF* (|*AF*|), and we drop *Turnover* as a control since *AbVol* already adjusts for expected levels of trading.

We identify control variables that may influence both the likelihood of social media analyst coverage and the informativeness of earnings. We include several broad measures of a firm's information environment including firm size (*Size*), market-to-book (*MB*), institutional ownership (*InstOwn*), and analyst following (*Following*). These factors contribute to the value relevance of earnings information as well as the demand for the reports of social media analysts. We also control for news preceding the forecast, which could prompt research by social media analysts as well as sell-side analysts' forecasts. Specifically, we include the level of business press coverage in the two weeks preceding the forecast ($BizPress_{[-14,-8]}$ and $BizPress_{[-7,-1]}$) and returns leading up to the forecast ($AbRet_{[-5,-1]}$). We also control for share turnover since trading activity likely contributes to social media analysts' decisions to publish articles, as well as how forecasts are incorporated into price. We control for forecast horizon (*Horizon*) to address the relation between forecast timeliness and both value relevance and attention by social media analysts. We also control for both news coverage and social media coverage contemporaneous to the forecast ($SMA_{[0,1]}$ and $BizPress_{[0,1]}$), as we are interested in whether social media coverage pre-empts the news in sell-side analyst forecasts, controlling for any contemporaneous dissemination effects.[16] Finally, we include industry-month-year fixed effects to control for time-varying industry-specific events that potentially impact share price and social media analyst coverage, and we cluster standard errors by industry-month-year to address the cross-sectional correlation in the error term within each industry that is common in returns models (Peterson 2009).[17]

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[16] To the extent that social media analysts' reports increase the likelihood that news about the upcoming analyst forecast is disseminated either on social media ($SMA_{[0,1]}$) or by the business press ($BizPress_{[0,1]}$), these two controls may not be appropriate as they are not predetermined with respect to our variable of interest (Swanquist and Whited 2018). However, if we exclude them, then our results could plausibly be driven by dissemination (since business press and social media coverage surrounding the forecast correlate with coverage prior to the forecast). If we exclude these two variables, our results are qualitatively similar (untabulated).

[17] We examine the robustness of our results to alternative fixed effects structures (i.e., firm or analyst fixed effects) later in this section. Additionally, when testing our predictions using our unrestricted sample, which includes earnings announcement windows, we also control for the firm's earnings surprise (*EarnSurp*).

One potential concern about our design is that the issuance of sell-side analyst forecast revisions and social media analyst reports is non-random. That is, both sell-side and social media analysts could publish research following significant events, such as earnings announcements. We make two design choices to mitigate concerns that significant events unduly influence our inferences. First, sell-side analysts frequently revise their forecasts immediately following the firm's disclosure of earnings news (i.e., earnings announcements and management earnings guidance). Therefore, we conduct our tests using a restricted sample of forecasts that occur *outside* these events.[18] Second, we control for the intensity of the business press's coverage of the firm over various windows before the forecast window in our tests, which is likely correlated with significant firm events.

Descriptive statistics for the variables in Equation [1] are presented in Table 1. We present descriptive statistics for both the restricted sample (excluding earnings announcement and management forecast periods) and the unrestricted sample. We find that both measures of analyst forecast news, *News* and *Rev*, exhibit negative means and medians, consistent with analysts walking down forecasts over the course of a fiscal period. The mean values for $SMA_{[-7,-1]}$ suggest that approximately 17 percent of analyst forecasts are pre-empted by at least one social media analyst report. Interestingly, this value is very similar across the two samples, suggesting that social media analysts do not necessarily publish more research prior to the release of earnings information (and subsequent sell-side forecasts). The slightly negative mean and median values for *AbRet* (which are multiplied by 100) are consistent with the average analyst forecast containing negative news. *AbVol* is standardized, so the mean values exceeding one suggest higher-than-average trading following forecasts. With respect to the control variables, we find that the median

[18] In a robustness test discussed later, we also remove all forecasts issued following the release of any firm-issued press release.

firm has a market cap of 3.7 billion, a market-to-book of approximately 2, and an analyst following of 13. We also find that the average forecast in our sample is associated with 5.6 (1.7) business press articles written about the firm in the week prior to (day of and day after) a sell-side analyst forecast.

Table 2 presents Pearson (Spearman) correlations above (below) the diagonal. For brevity, we report correlations only for our restricted sample. As expected, our two measures of forecast news, *News* and *Rev*, exhibit positive correlations between 0.54 and 0.60. While the correlation is large, there appears to be sufficient variation across the two to indicate that each variable captures a different aspect of forecast news. *AbRet* exhibits significantly positive correlations with both news measures, consistent with investors responding to analyst forecasts. Interestingly, *AbVol* exhibits small, negative correlations with forecast news, likely because investors trade on both positive and negative forecast information. Importantly, *SMA* exhibits economically insignificant correlations (0.01) with our measures of forecast news, suggesting that the presence of a social media report does not influence analysts' forecasts. *SMA* correlates positively with several indicators of firm size (i.e., *Size, Following,* and *MB*) and with business press coverage (*BizPress*). The highest correlation (0.63) among our variables is between *Size* and *Following*, suggesting that multicollinearity is unlikely to be a concern.

In Table 3, we present the results from estimating Equation [1] using *AbRet* as the dependent variable. Columns 1 and 2 (3 and 4) present results using *News* (*Rev*) to measure analyst forecast news (*AF*). Columns 1 and 3 report results using the restricted sample of forecasts issued outside of earnings news periods, while columns 2 and 4 report results using the unrestricted sample. Note that all variables not naturally centered on zero are demeaned for the estimation, which allows us to interpret the main effect of each variable as its effect at the average levels of the other variables. We observe a highly significant coefficient on *AF*, consistent with share price moving in the same direction as forecast news. In columns 2 and 4, we also observe a highly significant coefficient on *EarnSurp* using the unrestricted sample, which suggests that earnings news similarly moves prices.

Our primary prediction is that the presence of research published by social media analysts in the days prior to a sell-side analyst forecast reduces its value relevance. The coefficient of interest for this prediction is the interaction between *AF* and *SMA*, which is bolded in Table 3. Consistent with our prediction, we find a highly significant negative interaction in all four specifications. To assess the economic significance of this effect, we compare the magnitude of the interaction terms to the coefficient on the main effect of analyst forecast news (*AF*). For the restricted samples, our estimates suggest that the presence of a social media analyst report in the week preceding an analyst forecast reduces the informativeness of that forecast by between 34 and 41 percent.[19] We observe similar effect sizes in columns 2 and 4 when we use the unrestricted sample of forecasts. In untabulated tests, we re-estimate Equation [1] and include a variable identifying whether the sell-side forecast of interest is preceded by another sell-side forecast. This allows us to compare the effects of social media analysts to that of sell-side analyst "herding" (e.g., Cooper, Day, and Lewis 2001). Depending on the specification, we find that the reports of social media analysts reduce the informativeness of sell-side forecasts either at a similar level to, or slightly more than, the forecasts of other professional analysts. Thus, reports by social media analysts appear to have a meaningful impact on the usefulness of sell-side analysts' forecasts that is comparable to professional information intermediaries.

We find that other factors consistently impact the relation between forecast news and

[19] Specifically, -0.068 divided by 0.164 equals 0.415, and -0.079 divided by 0.230 equals 0.343.

returns. For example, we observe consistently positive coefficients on the interaction between *AF* and *InstOwn*, and negative coefficients on the interaction between *AF* and *Turnover*. Additionally, consistent with the business press playing a significant role in earnings news dissemination (e.g., Twedt 2016; Blankespoor et al. 2018), we observe a significantly positive coefficient on the interaction between *AF* and $BizPress_{[0,1]}$.

Table 4 repeats the analysis reported in Table 3 using abnormal trading volume (*AbVol*). We apply the same basic design as in Equation [1], but with a few modifications because of the unsigned nature of the dependent variable. First, we use the absolute value of *AF* (|*AF*|), and we drop *Turnover* as a control since our measure of *AbVol* already adjusts for normal levels of trading for a given firm. We also use the absolute value of abnormal returns ($|AbRet_{[-5,-1]}|$) in the days leading up to the forecast to control for the magnitude of news announced during this period. For samples that include earnings announcement windows, we include the absolute value of *EarnSurp* (|*EarnSurp*|) to control for the magnitude of the earnings surprise.

Consistent with our prediction and the results in Table 3, the results in Table 4 suggest that trading is muted when the analyst forecast is preempted by a report from a social media analyst on Seeking Alpha. More specifically, we find a highly significant negative coefficient on the interaction between |*AF*| and *SMA*. In fact, the combination of |*AF*| and |*AF*| × *SMA* yields an effect size insignificantly different than zero, suggesting that sell-side analyst forecasts following analysis on social media induce no abnormal trading activity.

We conduct a number of untabulated tests to assess the robustness of these primary results. First, we re-estimate the model using a variety of alternate fixed effects structures, including firm and year fixed effects, sell-side analyst plus industry-month-year fixed effects, and sell-side-analyst-firm fixed effects. Second, we change the social media analyst report measurement window from seven days (in our primary test) to either five days or three days leading up to the sell-side analyst forecast. Third, we use a reduced sample where we exclude any sell-side analyst forecast where the firm issued a press release during the five-day window around the analyst forecast (recall that we already exclude observations around earnings announcements and management guidance). We use a comprehensive sample of firm-initiated press releases provided by RavenPack to conduct this test, which helps ensure that a significant corporate news event is not confounding the analyses as a correlated omitted variable.[20] Fourth, we use a reduced sample where we exclude sell-side analyst forecasts that are preceded by more than three social media analyst reports. Across all of these alternative methods and research design choices, we find that our primary inferences remain unaffected.

While we include an extensive array of controls to address the possibility that analyst forecast news and the reports of social media analysts are non-random, it is difficult to control for the relevance of a given analyst for a specific firm, or their average forecast response coefficient. In other words, our results could be affected by "low-quality" sell-side analysts regularly issuing forecasts following analysis on Seeking Alpha. While the analyst-firm fixed effects discussed above address this concern to some extent, we also estimate a simplified version of Equation [1] for each analyst-firm combination in our sample. This approach controls for the relevance of each specific analyst covering a given firm. For each analyst-firm combination with at least 10 observations, we regress *AbRet* on *AF*, *SMA*, and the interaction between *SMA* and *AF.* We then restrict the results to instances where the coefficient on *AF* is positive (suggesting that forecasts by that analyst for that firm are generally informative) and compute Fama-MacBeth (1973) t-

[20] In addition, we note that our prediction is that social media analyst reports will *reduce* the information content of sell-side analyst forecasts. If social media analysts selectively publish reports following significant firm events that make analyst reports appear more useful, this should lead to a larger, rather than smaller, observed market reaction to the subsequently published sell-side analyst forecast.

statistics for the interaction between *SMA* and *AF*. In untabulated analysis, we continue to find a significantly negative average interaction across these firm-analyst specific regressions for three of our four primary specifications.

4.2 Cross-Sectional Analyses

The results discussed thus far provide consistent evidence that the reports of social media analysts reduce the informativeness of sell-side analyst forecasts. We now conduct several cross-sectional tests to provide additional support for our inference that this muted market reaction to sell-side analysts' forecasts is indeed being driven by the research activities of social media analysts.[21] We do this by first considering two characteristics reflecting social media analyst expertise and two characteristics reflecting the detail of their reports. We then examine whether our results vary depending on the firm's level of institutional ownership. Finally, we evaluate whether our results are attributable to social media analysts who cite professional investment-related experience, perhaps as a sell-side analyst, in their biographies.

4.2.1 Social Media Analyst Expertise

There is likely substantial variation in the expertise and credibility of social media analysts. This variation may in turn impact investors' perceptions of their reports and the influence they have on the value-relevance of sell-side analyst forecasts. Recognizing that investors desire information on who publishes content on the site, Seeking Alpha hosts a biography page for each social media analyst. These biographies include a number of quantitative attributes, as well as a short textual biography provided by each contributor. We expect that readers use this information to evaluate the credibility of social media analysts. Accordingly, we exploit two novel features of this biographical information to examine whether the relation between social media analysts and

[21] For brevity, we report results for these tests using *AbRet* as the dependent variable. Results are generally similar using *AbVol*.

the attenuation of the response to sell-side research varies with social media analyst expertise.

Specifically, we focus on two proxies for SMA expertise that we derive from their biographical information. First, we examine whether the disruption effect of social media analyst reports on the market reaction to sell-side analyst forecasts is stronger when social media analysts have a larger investor following, which we assume indicates greater perceived expertise (or quality) and larger dissemination of their reports. Second, we use social media analyst tenure, or the length of time they have contributed to Seeking Alpha, to capture overall experience as another measure of expertise (Clement 1999). To examine whether investors perceive greater credibility along each of these dimensions of SMA expertise, we construct two new variables. For these tests, *SMAhigh* is an indicator variable set equal to one if the sell-side analyst forecast is preceded by a social media analyst report posted on Seeking Alpha by an analyst with "high expertise," and to zero otherwise.[22] *SMAlow* is an indicator variable set equal to one for the reports of "low-expertise" social media analysts, and to zero otherwise. Both high and low variables are set to zero for observations without any Seeking Alpha content preceding the sell-side forecast. We then modify Equation [1] by replacing the general *SMA* indicator variable with these two measures and interact both with *AF*. The model is specified as follows:

[22] We use median splits to partition our sample into high and low groupings. For tenure, we do this as of the date of the article (results hold if we partition across the full sample). For following, because we do not have a time-series of biographical information (we use data collected between April and July 2019), we rely on median cuts across the unrestricted sample. With respect to following, we recognize the potential for this to skew the "high-expertise" sample towards either older articles (if authors writing earlier in our sample have larger followings) or more recent articles (if overall readership in more recent years boosts following for authors of these articles). We examine these possibilities and find that our partitions are relatively consistent from 2008 onward, though authors do exhibit lower followings in 2006 and 2007. We conduct an untabulated robustness test after removing these two years, and we find results consistent with those reported.

$$
\begin{aligned}
AbRet_{[0,1]} = \alpha_0 + AF(&\beta_0 + \boldsymbol{\beta_1 SMAhigh_{[-7,-1]}} + \boldsymbol{\beta_2 SMAlow_{[-7,-1]}} + \beta_3 Size + \beta_4 MB \\
&+ \beta_5 SMA_{[0,1]} + \beta_6 InstOwn + \beta_7 Turnover + \beta_8 Following + \beta_9 Horizon \\
&+ \beta_{10} AbRet_{[-5,-1]} + \beta_{11} BizPress_{[-14,-8]} + \beta_{12} BizPress_{[-7,-1]} + \beta_{13} BizPress_{[0,1]}) \\
&+ \alpha_1 SMAhigh_{[-7,-1]} + \alpha_2 SMAlow_{[-7,-1]} + \alpha_3 Size + \alpha_4 MB + \alpha_5 SMA_{[0,1]} \\
&+ \alpha_6 InstOwn + \alpha_7 Turnover + \alpha_8 Following + \alpha_9 Horizon + \alpha_{10} AbRet_{[-5,-1]} \\
&+ \alpha_{11} BizPress_{[-14,-8]} + \alpha_{12} BizPress_{[-7,-1]} + \alpha_{13} BizPress_{[0,1]} + e \qquad [2]
\end{aligned}
$$

If the reports of social media analysts with greater expertise cause a greater reduction in the value relevance of sell-side analyst forecasts, then we expect the coefficient β_1 to be more negative than β_2 (i.e., $\beta_1 < \beta_2$). We provide the Equation [2] estimation results in Table 5. Columns 1 through 4 (5 through 8) use social media analyst following (tenure) to measure expertise. Columns 1, 2, 5, and 6 report results using *News* to measure *AF*, and columns 3, 4, 7, and 8 report results using *Rev*. As in earlier tables, we report results for both the restricted (odd columns) and unrestricted (even columns) samples.

In Table 5, columns 1 through 4, we observe a negative and significant interaction effect only when the social media analyst has above-median investor following; the interaction effects are insignificantly different from zero for social media analysts with below-median investor following. An F-test confirms that the coefficient on *AF×SMAhigh* is significantly more negative than the coefficient on *AF×SMAlow* in three of four specifications. This suggests that the disruption effect of social media analysts is concentrated in those analysts with relatively larger followings. Columns 5 through 8 of Table 5 produce similar inferences using social media analyst tenure as a proxy for expertise. In three of four specifications the interaction effects are only significant for social media analysts with above-median experience. In addition, two of the F-tests are significant. This evidence indicates that the preemption effect of social media analysts is focused primarily in those with greater expertise.

4.2.2 Social Media Analyst Report Detail

We next examine whether variation in the level of detail provided in the social media analyst report has a moderating influence on the disruption effect. Our expectation is that reports that provide more qualitative (number of words) or quantitative (more numbers) information are more likely to disrupt the usefulness of sell-side analyst reports.

To test this prediction, we re-estimate Equation [2], but where *SMAhigh* is now an indicator variable set equal to one if the sell-side analyst forecast is preceded by a social media analyst report with "high detail," and to zero otherwise. Similarly, *SMAlow* is now an indicator variable set equal to one for "low detail" social media analyst reports, and to zero otherwise. High and low detail are determined based on above/below median sorts of the number of words and the number of numbers contained in the report. If social media analyst reports with greater detail cause a greater attenuation in the value relevance of sell-side analyst forecasts, then the coefficient β_1 should be more negative than β_2 (i.e., $\beta_1 < \beta_2$).

We provide the results in Table 6. Columns 1 through 4 (5 through 8) use report word count (number of numbers) to measure detail. Columns 1, 2, 5, and 6 report results using *News* to measure *AF*, and columns 3, 4, 7, and 8 report results using *Rev*. As predicted, columns 1 through 4 report a negative and significant interaction effect only when the social media analyst report has above-median number of words; the interaction effects are insignificantly different from zero for below median reports. An F-test indicates that the coefficient on *AF×SMAhigh* is significantly more negative than the coefficient on *AF×SMAlow* in three of four specifications. We find similar, though weaker, evidence in Columns 5 through 8, which report results using the number of numbers to measure report detail. Thus, similar to our results with respect to expertise, these findings suggest that the reduction in the value-relevance of sell-side analysts' forecasts occurs primarily for reports providing greater detail to readers.

4.2.3 Investor Base

Next, we focus on the firm's investor base. Because the reports of social media analysts are more likely to be consumed by less sophisticated individual investors (Farrell et al. 2018), we predict that the effect of social media analysts on the relevance of sell-side research will be concentrated in firms with relatively lower proportions of institutional holdings. We test this prediction by partitioning our sample at the median level of institutional holdings and re-estimate equation [1]. We report these results in Table 7. Columns 1 through 4 of Table 7 report results using *News* to measure *AF*, and columns 5 through 8 report results using *Rev*. Odd (even) columns in Table 7 report results for the low (high) institutional ownership samples. We again present results for both the restricted and unrestricted samples. Consistent with our prediction, we observe that the interaction between *AF* and *SMA* is significantly negative in the low-ownership partitions only. Additionally, the difference in coefficients is highly significant in all specifications. These results suggest that the disruptive role of social media analysts is concentrated in firms with a relatively less sophisticated investor base.

4.2.4 Social Media Analyst Professional Experience

In our final cross-sectional test, we address a potential concern with Seeking Alpha, and social media in general, that it is difficult to understand the background of the individuals writing the reports. It may be that some of the most relevant research on Seeking Alpha is posted by a professional moonlighting as a social media analyst. While it is difficult to fully identify this behavior, we attempt to identify social media analysts who cite professional investment-related experience in their biographies.

Specifically, we assume that the text in the biography of a professional social media analyst would cite experience working as a professional analyst in an investment bank, a brokerage, or a hedge fund. Seeking Alpha biographies reveal a wide variation in language used, so we use an unsupervised machine-learning approach called k-means clustering to partition the biographies into groups. We describe the details of this procedure in Appendix B. Model diagnostics suggest that the data are best described by 20 different clusters. Two of these clusters appear to reflect either missing or generic biographies, so we exclude these and code the remaining biographies as likely reflecting either professional or individual investors. Table B1 in Appendix B provides the words found in each of these clusters and our classifications. Similar to our use of *SMAhigh* and *SMAlow*, we define two variables, *SMAProf* and *SMANonprof,* to capture the publication of reports written by potentially professional and nonprofessional social media analysts, respectively, preceding a sell-side forecast.

Table 8 provides the results based on the clustered biographies. Here, we generally observe stronger effects for articles written by the social media analysts we classify as nonprofessional investors, though we recognize that these classifications are highly subjective and noisy. In addition, we note that the difference in coefficients is never statistically significant.[23] In sum, these results are inconsistent with our primary results being attributed primarily to professional analysts posting on Seeking Alpha.

5. Additional Analyses

In this section, we conduct three additional sets of tests to further examine the relation between the reports of social media analysts and the pricing of sell-side analyst forecasts. We begin by evaluating whether the research reports published by these two types of intermediaries agree in tenor, on average. We then further explore how social media analysts impact price formation by

[23] We recognize that classifications are subjective, and we view this test as suggesting that neither professionals nor individuals solely drive our main results. In addition, one cluster (cluster 10 described in Table B1) accounts for roughly 30 percent of our sample. We categorized this cluster as individual since it includes words like "investor" and "individual," though words like "years" or "business" suggest that it may capture some professional contributors as well. We estimated results after either excluding this cluster or classifying it as professional. While the significance of individual coefficients changes, the difference between *AF x SMAProf* and *AF x SMANonProf* is never significant.

investigating whether their reports pre-empt the information content of sell-side analyst reports by "moving up" the pricing of their forecasts. Finally, we consider whether the reports of social media analysts delay the pricing of sell-side analysts' forecasts. We note that these tests *require* the presence of a social media report in the seven-day period before a sell-side analyst forecast, so our sample is reduced to observations preceded by Seeking Alpha reports for these tests.

5.1 Social Media Analyst Report Tone and Sell-Side Analyst Forecast News

We start by examining the association between the tenor of the reports published by the two types of analysts using the following model. As mentioned earlier, social media analysts on Seeking Alpha do not consistently provide numeric forecasts, and even those provided reflect different metrics, horizons, etc. Therefore, we rely on lexical tone (or sentiment) to capture the tenor of social media analyst reports (positive versus negative). For sell-side analyst forecasts, we rely on the numeric forecast news (*AF*) to capture their tenor. We estimate the following model:

$$AF = \alpha_0 + \alpha_1 SMATone_{[-7,-1]} + \alpha_2 Size + \alpha_3 MB + \alpha_4 InstOwn + \alpha_5 Following + \alpha_6 Horizon + \alpha_7 BizPressSentiment_{[-14,-8]} + \alpha_8 BizPressSentiment_{[-7,-1]} + e \quad [3]$$

The dependent variable, *AF*, is the news contained in the analyst forecast, defined as either *News* or *Rev*, as in earlier tests. To measure the tenor of social media analysts' reports, we compute textual tone (*SMATone*) using the Loughran and McDonald (2011) financial sentiment dictionary.[24] Specifically, we define *SMATone* as positive words minus negative words divided by the sum of positive and negative words. We predict a positive association between $SMATone_{[-7,-1]}$ and *AF* because we expect that, on average, both social media analysts and sell-side analysts will agree on the direction of the firm's future prospects.

In Equation [3], we again control for firm and information environment characteristics that likely influence both the tenor of social media analysts' coverage and sell-side analyst forecast

[24] This dictionary is available at https://sraf.nd.edu/textual-analysis/resources/.

news. Specifically, we include *Size*, *MB*, *InstOwn*, and *Following* to control for general information environment characteristics. We also include *Horizon* since the proximity to a firm's earnings announcement likely affects the news environment of the firm. We also include the sentiment of the business press (*BizPressSentiment*) as computed by RavenPack measured over two windows leading up to the forecast. Finally, we include industry-month-year fixed effects, and we cluster standard errors by firm and calendar month to address serial and cross-sectional correlation in the error term.[25]

We present the results from estimating Equation [3] in Table 9. As expected, we find a positive and significant coefficient on $SMATone_{[-7,-1]}$, which suggests that the sign of the news contained in the reports of social media analysts and those of sell-side analysts generally track one another. With respect to controls, the tone of media coverage is positively associated with upcoming analyst forecast news, as the coefficients on $BizPressSentiment_{[-7,-1]}$ are consistently positive. Firms with higher market-to-book ratios also experience more positive forecast revisions, on average, and in columns 2 and 4, analysts appear to adjust their earnings estimates in a manner directionally consistent with prior earnings surprises.

5.2 Social Media Analysts and the Pre-Emption of Sell-Side Analyst Forecast News

The results presented in Tables 3 through 8 reveal that the investor response to sell-side analysts' forecasts is attenuated when social media analysts issue reports in the seven days prior to the forecast. The results presented in Table 9 imply that the news in the reports of social media analysts potentially captures some of the information contained in upcoming sell-side analyst forecasts. Taken together, these results suggest that the equity analysis published by social media

[25] We cluster by firm (in addition to time period) because serial correlation in the error term is likely a concern when the dependent variable is analyst forecast news (due to walk-downs, for example). Serial correlation is unlikely to affect short-window abnormal returns.

analysts could pre-empt the information subsequently released by sell-side analysts. We expect that any preemption effect will be stronger when the tenor of the social media report is consistent in direction (i.e., positive versus negative) with that of the sell-side analyst forecast than when it is inconsistent. To test this prediction, we develop a model that is similar in spirit to the short-window future earnings response coefficient (FERC) model developed in Drake et al. (2012). This model and sample allow us to examine whether stock prices move in the direction of *future* analyst forecasts to a greater degree when social media analysts publish analysis that agrees (in tenor) with the upcoming forecast than when they do not. We specify the model as follows:

$$AbRet_{[-5,-1]} = \alpha_0 + AF(\beta_0 + \boldsymbol{\beta_1 Agree} + \beta_2 Size + \beta_3 MB + \beta_4 SMA_{[0,1]} + \beta_5 InstOwn + \beta_6 Turnover + \beta_7 Following + \beta_8 Horizon + \beta_9 BizPress_{[-14,-8]} + \beta_{10} BizPress_{[-7,-1]} + \beta_{11} BizPress_{[0,1]}) + \alpha_1 SMA_{[-7,-1]} + \alpha_2 Size + \alpha_3 MB + \alpha_4 SMA_{[0,1]} + \alpha_5 InstOwn + \alpha_6 Turnover + \alpha_7 Following + \alpha_8 Horizon + \alpha_{10} BizPress_{[-14,-8]} + \alpha_{11} BizPress_{[-7,-1]} + \alpha_{12} BizPress_{[0,1]} + e \quad [4]$$

As in Equation [1], the β terms in parentheses in Equation [4] capture the determinants of the FERC, or the degree to which the disclosure news, in this case the sell-side analyst forecast, that occurs at a later date is preemptively incorporated into price. We expect that when social media analysts agree with sell-side analysts, more of the analyst forecast news *(AF*) is impounded into price in the week prior to the forecast. This effect is captured by the interaction between *AF* and *Agree*, an indicator variable equal to one if the sign of *SMATone* agrees with the sign of the forecast news (and zero otherwise). We predict a positive coefficient on this interaction. The remaining variables in Equation [4] are similar to those in Equation [1], except that we remove $AbRet_{[-5,-1]}$ from the control variables as it is the dependent variable in this specification. In Equation [4], we again include industry-month-year fixed effects and cluster standard errors on this same dimension.

We present the estimation results for Equation [4] in Table 10. We find that the coefficient on *AF* is significantly positive in all four regressions, which suggests that sell-side analyst forecast news is partially impounded into price in the week leading up to the forecast announcement. As predicted, we find that the analyst forecast FERC is significantly stronger when preceded by social media analysis that agrees (in tenor) with the forecast. We also find that this effect is economically significant. Recall that we de-mean all variables, so the main effects can be interpreted as the marginal effect of that variable at the average level of the interacted terms. Thus, we find that when we use *News* to measure *AF*, the FERC more than doubles, moving from 0.15 to 0.36 in the restricted sample. When we use *Rev*, the FERC increases by nearly 80%. These findings indicate that the reports of social media analysts can pre-empt a substantial portion of the news of subsequently released sell-side analyst forecasts.

With respect to other factors in the model, we find that business press coverage in the week prior to the forecast appears to play a similar role in moving up the market response to forecast news, as the coefficient between *AF* and $BizPress_{[-7,-1]}$ is consistently positive. Other measures exhibit mixed effects on the FERC. Earlier forecasts (larger values for *Horizon*) tend to have larger FERCs when we use *Rev* to measure *AF*, though not when we use *News*. We also find some evidence that the FERC declines with *Turnover.*

5.3 Post-forecast Price Formation

Our final set of tests examine whether the presence of social media analysis in the seven days prior to a sell-side analyst forecast adversely affects the price formation process following the forecast issuance. Specifically, we consider whether the tenor of social media analysis interacts with analyst forecast news, exacerbating drift or reducing the efficiency of price formation. This test is motivated by the idea that information posted online by nonprofessional information intermediaries can potentially trigger correlated noise trading, and we explore whether this may result in systematic under-reaction to subsequently released sell-side analyst forecasts in our setting. To test this possibility, we estimate the following model.

$$
\begin{aligned}
AbRet_{[+2,+k]} \text{ or } IPT_{[0,+k]} = {} & \alpha_0 + \alpha_1 PosAF + \alpha_2 PosSMA + \alpha_3 PosAF \times PosSMA + \alpha_4 Size \\
& + \alpha_5 MB + \alpha_6 SMA_{[0,1]} + \alpha_7 InstOwn + \alpha_8 Turnover + \alpha_9 Following \\
& + \alpha_{10} Horizon + \alpha_{11} AbRet_{[-5,-1]} + \alpha_{12} BizPress_{[-14,-8]} + \alpha_{13}\, BizPress_{[-7,-1]} \\
& + \alpha_{14}\, BizPress_{[0,1]} + e \qquad [5]
\end{aligned}
$$

We measure post-forecast drift (*AbRet*) between (1) two and six days following the forecast and (2) two and 12 days following the forecast. For intraperiod timeliness (*IPT*), we use measurement windows of (1) zero to six days and (2) zero to 12 days relative to the forecast. Evidence of drift in returns post-forecast would be consistent with a lack of an efficient immediate incorporation of forecast news into price (Gleason and Lee 2003). Similarly, the short-window IPT measure captures the overall efficiency of the price formation process with respect to an information event, and a reduction in IPT would be consistent with an adverse effect on price formation (Twedt 2016). Our variables of interest are two indicator variables, *PosAF* and *PosSA*, set equal to one when the sell-side analyst forecast news and social media analyst tone are positive, respectively, and to zero otherwise. For brevity, we consider only the measures of *PosAF* derived from *News*, but the results are similar if we instead use *Rev* to capture forecast news.

We present the results from estimating Equation [5] in Table 11. Again, we include industry-month-year fixed effects, and we cluster standard errors by the same dimension. Column 1 (2) of Table 11 presents results using *AbRet* measured between two and six (two and 12) days, and column 3 (4) presents results using IPT measured between day zero and 6 (day zero and 12). We find no evidence that social media analysis has adverse effects on post-forecast price formation, as we fail to observe any significant associations between either *posAF* or *posSA* and either post-forecast price drift or intra-period timeliness.

6. Conclusion

This study provides novel evidence that equity research posted online by social media analysts pre-empts and substantially reduces the value-relevance of the reports of professional sell-side analysts. This result is more pronounced for social media analysts with greater expertise, for those that provide more detailed analyses, and for firms with more retail investors. We also find that the market reaction to sell-side analyst forecasts is partially pre-empted when the forecast is preceded by a social media analyst report that agrees, in tenor, with the forecast news.

These findings help us better understand how social media is impacting capital markets in general, and the role of information intermediaries in particular. Numerous supply and demand factors including budget cuts and new regulation are changing the sell-side equity research landscape. At the same time, investment-focused social media platforms are giving individuals a forum to disseminate their opinions and analysis to a vast audience. These changes have the potential to dramatically reshape how investors obtain company-specific research in the future. Our study focuses on one specific effect of the work of these social media analysts (i.e., how investors react to sell-side analyst forecasts), and we look forward to more work in this area.

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APPENDIX A
Variable Definitions

Variable	Definition
News	Sell-side analyst forecast news, measured as the EPS forecast of the individual analyst minus the outstanding analyst consensus forecast *(consensus calculated from the IBES detail file)* prior to the analyst's individual forecast, scaled by prior period stock price.
Rev	Sell-side analyst forecast revision, measured as the EPS forecast of the individual analyst minus the most recent previous EPS forecast of that same analyst, scaled by prior period stock price.
AbVol [x, y]	The daily average of abnormal volume over day x to day y relative to the sell-side analyst forecast date, calculated as the total daily volume over the window minus the average daily trading volume over days x - 260 to x -10, divided by the standard deviation of volume over days x - 260 to x - 10.
AbRet [x,y]	Buy-and-hold abnormal returns (using portfolio returns calculated from Daniel, Grinblatt, Titman, and Wermers 1997, and if missing, the value-weighted return from CRSP) over day x to day y relative to the analyst forecast date.
IPT [0,y]	Intraperiod timeliness measure (from day 0 to day y) of the speed with which the sell-side analyst forecast is impounded into stock price.
Agree	Indicator variable equal to one if either 1) social media analyst tone in the preceding 7 days is positive or zero and the sell-side analyst forecast revision is positive or zero, or 2) social media analyst tone in the preceding 7 days is negative and the sell-side analyst forecast revision is negative, and zero otherwise.
Disagree	Indicator variable equal to one if either 1) social media analyst tone in the preceding 7 days is positive or zero and the sell-side analyst forecast revision is negative, or 2) social media analyst tone in the preceding 7 days is negative and the sell-side analyst forecast revision is positive or zero, and zero otherwise.
BizPress[x, y]	The natural logarithm of 1 + the number of Dow Jones articles written about the firm during days x to y relative to the sell-side analyst forecast date.
BizPressSentiment[x, y]	The weighted average tone of Dow Jones articles written about the firm during day x to day y relative to the sell-side analyst forecast date.
EarnSurp	For sell-side analyst forecasts issued within a five day window of the firm's earnings announcement, the earnings surprise of the contemporaneous earnings announcement, measured as the firm's actual EPS from IBES relative to the median sell-side analyst forecast consensus, scaled by stock price at the beginning of the period.
Horizon	Sell-side analyst forecast horizon, defined as the number of days between the sell-side analyst forecast and the earnings announcement, scaled by 365.
InstOwn	Institutional ownership at the beginning of the period.
Following	The natural logarithm of 1 + analyst following prior to the sell-side forecast of interest.
Size	The natural logarithm of the firm's market value at the beginning of the period.
MB	Market-to-book ratio at the beginning of the period.
Turnover	Average daily trading volume for the 90 days prior to the sell-side forecast of interest, scaled by the average number of shares outstanding.
SMA[x, y]	An indicator variable equal to one if there was at least one Seeking Alpha article published about the firm between day x and day y relative to the sell-side analyst forecast of interest, and zero otherwise.
SMATone[x, y]	Average net positive tone of Seeking Alpha articles about the firm from day x to day y relative to the sell-side analyst forecast of interest, and set to zero if the article contains no tone words.

APPENDIX B

K-Means Clustering

We use k-means clustering to sort social media analysts into groups based on biographical text. K-means clustering is an unsupervised machine-learning method that attempts to identify natural clusters across a set of "features" or variables (Hartigan 1975; Hartigan and Wong 1979). Specifically, the method divides a sample of *n* observations into *k* groups (or clusters) by minimizing the Euclidean distance between each observation and the "centroid" of its assigned group. The process iteratively shifts centroids and re-groups observations until the distance between each cluster member and its centroid is minimized. K-means clustering can be applied on virtually any type of data as long as Euclidean distance represents a meaningful measure of "closeness" or similarity.

We apply k-means clustering to words and bigrams (two-word combinations) appearing in social media analysts' self-authored biographical summaries. We extract this text from social media analysts' biographies (available at seekingalpha.com/author/…). This text is enclosed in an HTML "div" tag with attribute "data-bio." We clean the biographies by removing stop words as defined by Python's NLTK package, which we supplement with the terms and bigrams seeking, alpha, and seeking alpha, as well as website indicators (com, http, www), which occasionally get separated from full webpage addresses during parsing. We also replace well-formed HTML links (i.e., http://www...) with a "WEBSITEFLAG" token. This allows a personal website or blog to contribute to cluster identification by making references to these sites uniform (and thus impactful to the procedure). Finally, we convert text to a document-term matrix including all words and bigrams with two or more letters. We apply term-frequency/inverse-document-frequency (TF/IDF) weighting (e.g., Loughran and McDonald 2011) and retain the 1,000 most common terms, or "features," for clustering.

Similar to other unsupervised methods, k-means requires the researcher to specify the number of clusters within the data. We estimate the k-means algorithm using 2 to 30 clusters and evaluate the model's fit using silhouette scores.[26] These scores essentially capture how well each observation compares to others in its cluster relative to those in other clusters. The scores are bounded at 1, and negative scores indicate a high likelihood of misclassification. Thus, higher scores indicate a lower likelihood of classification error. We plot the values for these silhouette scores in Figure B1. As shown, model fit slowly improves until 20 clusters, after which there is a steep decline. Thus, we use 20 clusters for this analysis.

As described in the text, the purpose of this analysis is to identify authors that are more likely "professional" (analysts or former analysts, fund managers, institutions) versus those that are more likely individual investors. With this in mind, we review the top 10 words and bigrams associated with each cluster and classify accordingly. Table B1 reports these words, assignments, and the proportion of the sample in each cluster. Note that two clusters (2 and 15) reflect either missing biographies (i.e., "Sorry, no bio currently available") or biographies that have minimal information that is likely to be useful in evaluating the sophistication of the social media analyst. We categorize these clusters as uninformative.

[26] We use Python's scikit-learn package to implement k-means clustering (available in sklearn.cluster). We allow up to 100 iterations for convergence, though all estimates converged well before this point.

Table B1

Cluster	Top 10 Words & Bigrams	Classification	Percent of Sample	Percent of Authors
1	investing | years | stocks | experience | time | companies | investor | value | investment | financial	Non-professional	5.8%	7.6%
2	sorry bio | currently available | bio currently | sorry | bio | available | currently | focusing | follow | young	Uninformative	2.2%	4.1%
3	websiteflag | blog | visit | blog websiteflag | financial | editor | news | site | investment | writes	Non-professional	6.5%	5.0%
4	cap | small | small cap | companies | stocks | mid cap | mid | cap stocks | micro | investor	Non-professional	1.0%	2.1%
5	university | student | finance | economics | business | school | accounting | undergraduate | college | degree	Non-professional	3.5%	7.3%
6	dividend | growth | dividend growth | stocks | income | investing | investor | portfolio | growth stocks | paying	Non-professional	4.6%	2.9%
7	term | long term | long | investor | value | investing | investment | growth | term value | stocks	Non-professional	7.1%	4.8%
8	trading | trader | options | years | market | time | markets | investor | experience | stocks	Professional	5.0%	4.6%
9	investment | manager | portfolio | years | experience | portfolio manager | financial | capital | managing | private	Professional	4.3%	5.7%
10	investor | companies | financial | years | business | technology | stocks | market | markets | individual	Non-professional	30.5%	25.6%
11	stock | market | stock market | years | stocks | investing | investor | financial | analysis | investment	Non-professional	2.8%	3.4%
12	management | investment | capital | asset | asset management | llc | firm | registered | capital management | investment management	Professional	4.5%	4.0%
13	long short | short | long | short equity | equity | fund | value | investor | hedge | investment	Professional	2.1%	1.6%
14	new york | york | new | city | university | investment | financial | years | based | firm	Professional	3.9%	2.5%
15	contributor | john | david | mark | michael | paul | james | chris | robert | mike	Uninformative	0.2%	1.6%
16	fund | hedge | hedge fund | manager | fund manager | analyst | years | portfolio | investment | capital	Professional	2.1%	2.3%
17	analyst | financial | research | research analyst | financial analyst | equity | senior | years | investment | experience	Professional	4.1%	4.5%
18	research | investment | equity | investment research | equity research | analysis | investors | firm | financial | market	Non-professional	5.2%	4.8%
19	real estate | estate | real | investment | commercial | experience | finance | years | business | financial	Non-professional	1.6%	1.5%
20	value | investor | value investor | value investing | investing | deep value | deep | companies | stocks | situations	Non-professional	3.0%	4.2%

Figure B1: Average Silhouette Score by Number of Clusters

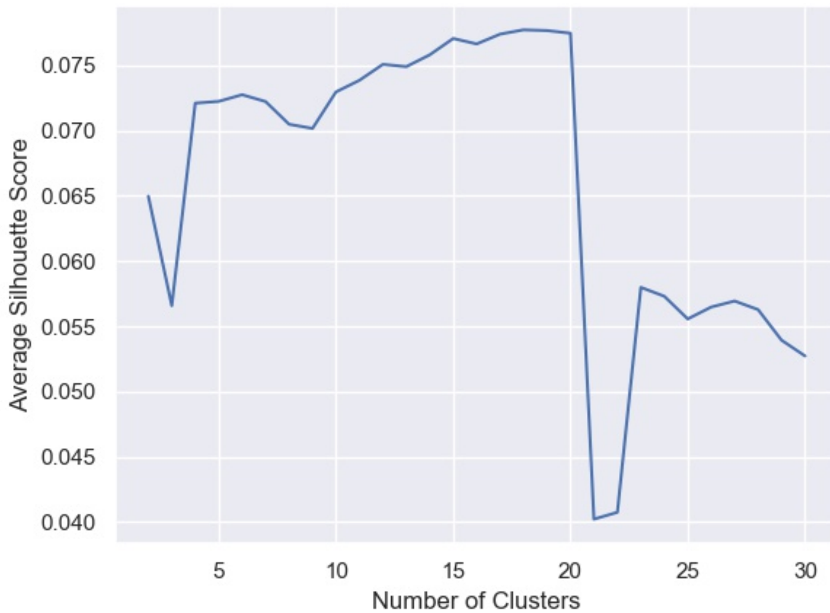

Figure 1: Number of sell-side analysts issuing at least one earnings forecast by year

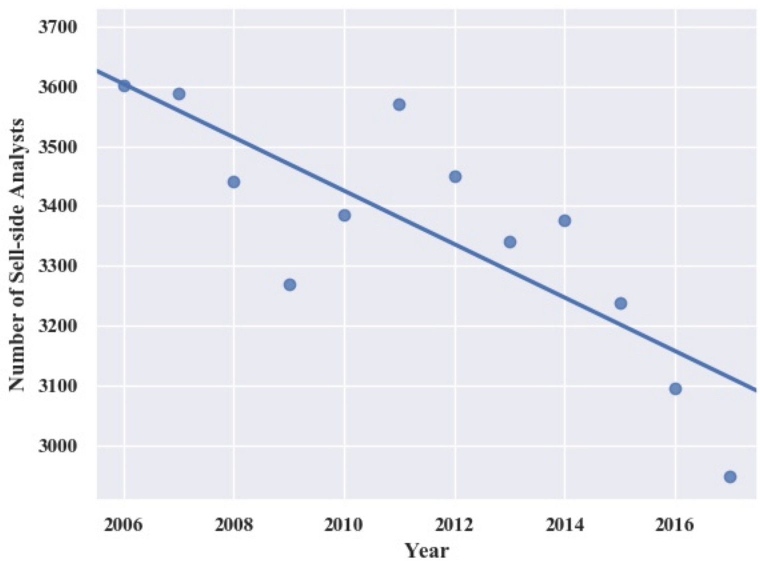

Figure 2: Number of social media analysts issuing at least one article by year

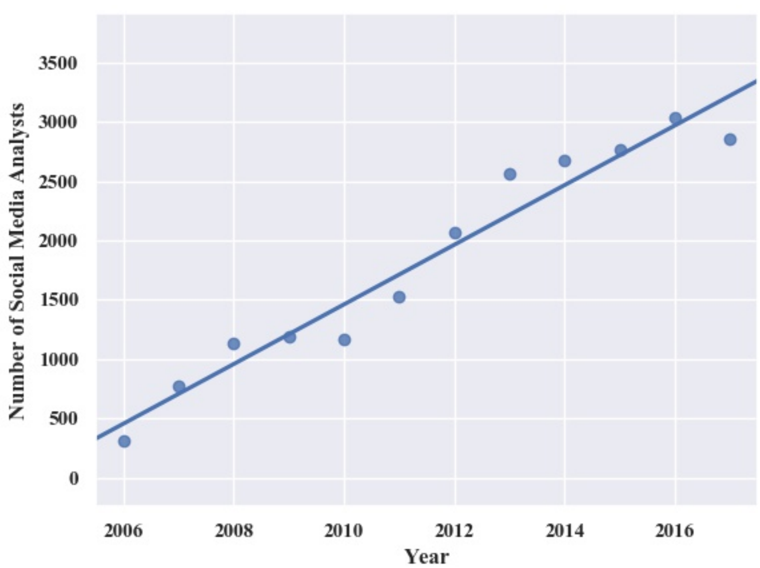

TABLE 1

Descriptive Statistics

Variable	Restricted Sample (n=368,714) Mean	Lower Quartile	Median	Upper Quartile	Std Dev	Unrestricted Sample (n=533,844) Mean	Lower Quartile	Median	Upper Quartile	Std Dev
AbRet [0,1]	-0.106	-1.531	-0.066	1.374	3.698	-0.105	-1.812	-0.070	1.645	4.600
AbVol [0, 1]	1.127	0.346	0.806	1.489	1.284	1.397	0.431	0.978	1.842	1.520
News	-0.198	-0.165	-0.018	0.056	1.394	-0.204	-0.175	-0.021	0.055	1.397
Rev	-0.219	-0.175	-0.030	0.056	1.342	-0.229	-0.187	-0.032	0.058	1.352
SMA [-7,-1]	0.172	0.000	0.000	0.000	0.377	0.165	0.000	0.000	0.000	0.371
*Size**	16,196	1,148	3,775	13,920	34,994	14,168	897	3,050	11,527	32,518
MB	2.907	1.241	2.017	3.404	4.613	2.993	1.269	2.070	3.521	4.713
SMA[0,1]	0.048	0.000	0.000	0.000	0.213	0.061	0.000	0.000	0.000	0.239
InstOwn	0.682	0.589	0.740	0.853	0.249	0.680	0.580	0.737	0.854	0.251
Turnover	0.135	0.066	0.104	0.168	0.105	0.128	0.063	0.099	0.160	0.102
*Following**	14.133	8.000	13.000	19.000	7.994	12.960	7.000	12.000	18.000	7.936
Horizon	0.119	0.049	0.101	0.184	0.079	0.152	0.063	0.153	0.244	0.093
AbRet [-5,-1]	-0.222	-2.541	-0.154	2.163	5.368	-0.160	-2.620	-0.112	2.354	5.571
*BizPress [-14, -8]**	4.413	0.000	1.000	5.000	8.268	3.764	0.000	1.000	4.000	7.597
*BizPress [-7, -1]**	5.674	0.000	2.000	7.000	9.695	6.642	0.000	3.000	9.000	9.745
*BizPress [0, +1]**	1.701	0.000	0.000	1.000	4.009	2.335	0.000	0.000	2.000	4.877
Earnsurp						-0.086	0.000	0.000	0.000	0.723

Variables denoted with * are log-transformed in regressions. However, we present underlying values here.

TABLE 2

Correlation Matrix

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
(1)	*AbRet [0,1]*		**-0.04**	**0.07**	**0.09**	**0.01**	**0.01**	**0.01**	0.00	0.00	**-0.01**	**0.01**	**0.00**	**0.02**	**0.01**	0.00	**-0.01**
(2)	*AbVol [0, 1]*	**0.01**		**-0.03**	**-0.02**	**0.03**	**0.03**	**0.01**	**0.06**	**0.04**	**0.04**	0.00	**0.05**	**-0.06**	**0.03**	**0.10**	**0.18**
(3)	*News*	**0.11**	**-0.04**		**0.60**	**0.01**	**0.04**	**0.05**	0.00	**0.01**	**-0.09**	**0.06**	**-0.02**	**0.07**	**-0.01**	**-0.03**	**-0.03**
(4)	*Rev*	**0.14**	**-0.03**	**0.54**		**0.01**	**0.05**	**0.05**	0.00	**0.03**	**-0.09**	**0.08**	**-0.02**	**0.09**	0.00	**-0.02**	**-0.02**
(5)	*SMA [-7,-1]*	**0.00**	**0.05**	**0.01**	**0.01**		**0.40**	**0.05**	**0.28**	**-0.10**	**0.05**	**0.28**	**0.05**	**0.01**	**0.28**	**0.29**	**0.20**
(6)	*Size*	**0.03**	**0.13**	**0.09**	**0.12**	**0.34**		**0.07**	**0.31**	**-0.13**	**-0.20**	**0.35**	**-0.08**	**0.01**	**0.47**	**0.44**	**0.37**
(7)	*MB*	**0.02**	**0.04**	**0.12**	**0.12**	**0.05**	**0.24**		**0.04**	**-0.01**	**-0.03**	**0.05**	**-0.02**	**0.01**	**0.03**	**0.02**	**0.02**
(8)	*SMA[0,1]*	0.00	**0.06**	0.00	0.00	**0.28**	**0.20**	**0.04**		**-0.06**	**0.04**	**0.17**	**0.01**	**0.00**	**0.20**	**0.25**	**0.20**
(9)	*InstOwn*	0.00	**0.05**	**-0.01**	0.00	**-0.14**	**-0.06**	**0.04**	**-0.09**		**0.21**	**0.15**	**-0.04**	0.00	**-0.02**	**-0.01**	**-0.02**
(10)	*Turnover*	**-0.01**	**0.05**	**-0.06**	**-0.05**	**0.01**	**-0.14**	**-0.07**	**0.01**	**0.38**		**0.16**	**0.01**	**-0.02**	**0.05**	**0.05**	**0.04**
(11)	*Following*	**0.01**	**0.07**	**0.05**	**0.08**	**0.27**	**0.63**	**0.13**	**0.16**	**0.12**	**0.22**		**-0.16**	**0.01**	**0.21**	**0.17**	**0.16**
(12)	*Horizon*	0.00	**0.07**	**-0.04**	**-0.02**	**0.05**	**-0.14**	**-0.03**	**0.01**	**-0.01**	**0.01**	**-0.16**		**-0.01**	**0.05**	**0.15**	**-0.01**
(13)	*AbRet [-5,-1]*	**0.02**	**-0.03**	**0.10**	**0.13**	**0.01**	**0.03**	**0.02**	0.00	0.00	**-0.02**	**0.01**	**-0.01**		**0.00**	**0.00**	**0.00**
(14)	*BizPress [-14, -8]*	**0.02**	**0.04**	**0.03**	**0.04**	**0.20**	**0.31**	**0.03**	**0.12**	**0.01**	**0.05**	**0.22**	**0.07**	**0.01**		**0.59**	**0.50**
(15)	*BizPress [-7, -1]*	**0.01**	**0.14**	**0.00**	**0.01**	**0.21**	**0.24**	**0.02**	**0.16**	**0.00**	**0.03**	**0.14**	**0.22**	**0.01**	**0.40**		**0.53**
(16)	*BizPress [0, +1]*	**0.01**	**0.18**	**0.01**	**0.02**	**0.15**	**0.23**	**0.03**	**0.14**	**-0.02**	**0.03**	**0.15**	**0.04**	**0.02**	**0.32**	**0.36**	

Table 2 presents correlations using the sample for our main analyses (368,714 observations). Correlations above (below) the diagonal are Pearson (Spearman). Bolded correlations are significant at the 5% level. Variable definitions are in Appendix A.

TABLE 3

The Impact of Social Media Analyst Reports on the Price Reaction to Sell-side Analyst Forecasts

Dependent Variable: *AbRet [0,1]*

	AF = News		*AF = Rev*	
	[1]	[2]	[3]	[4]
AF	0.164***	0.278***	0.230***	0.379***
	(0.000)	(0.000)	(0.000)	(0.000)
AF × SMA $_{[-7,-1]}$	**-0.068****	**-0.111*****	**-0.079*****	**-0.132*****
	(0.026)	**(0.000)**	**(0.009)**	**(0.000)**
AF × Size	-0.003	0.013*	0.006	0.032***
	(0.650)	(0.057)	(0.447)	(0.000)
AF × MB	0.005***	0.003	0.006***	0.004*
	(0.010)	(0.129)	(0.009)	(0.062)
AF × SMA $_{[0,1]}$	-0.009	0.037	0.030	0.100**
	(0.809)	(0.320)	(0.483)	(0.015)
AF × InstOwn	0.135***	0.197***	0.202***	0.266***
	(0.000)	(0.000)	(0.000)	(0.000)
AF × Turnover	-0.242***	-0.384***	-0.327***	-0.466***
	(0.000)	(0.000)	(0.000)	(0.000)
AF × Following	-0.014	-0.042***	-0.031	-0.074***
	(0.410)	(0.004)	(0.134)	(0.000)
AF × Horizon	-0.226**	0.288***	-0.150	0.502***
	(0.030)	(0.003)	(0.179)	(0.000)
AF × AbRet $_{[-5,-1]}$	0.001	0.002**	0.002**	0.003***
	(0.116)	(0.011)	(0.033)	(0.000)
AF × BizPress $_{[-14,-8]}$	-0.041***	-0.066***	-0.051***	-0.090***
	(0.000)	(0.000)	(0.000)	(0.000)
AF × BizPress $_{[-7,-1]}$	0.010	0.013*	-0.004	0.002
	(0.206)	(0.055)	(0.689)	(0.758)
AF × BizPress $_{[0,1]}$	0.071***	0.103***	0.096***	0.138***
	(0.000)	(0.000)	(0.000)	(0.000)
AF × EarnSurp		0.014***		0.020***
		(0.000)		(0.000)
SMA $_{[-7,-1]}$	-0.024	-0.032	-0.020	-0.029
	(0.210)	(0.133)	(0.296)	(0.173)
Size	0.047***	0.013	0.042***	0.007
	(0.000)	(0.127)	(0.000)	(0.393)
MB	0.003**	0.001	0.003**	0.001
	(0.033)	(0.590)	(0.033)	(0.661)
SMA $_{[0,1]}$	-0.060**	-0.067**	-0.046	-0.049
	(0.050)	(0.046)	(0.146)	(0.142)
InstOwn	0.024	0.239***	0.028	0.232***
	(0.601)	(0.000)	(0.558)	(0.000)
Turnover	-0.005	-0.416***	-0.029	-0.437***
	(0.972)	(0.002)	(0.829)	(0.002)
Following	-0.037*	0.015	-0.039*	0.011
	(0.084)	(0.482)	(0.068)	(0.605)

Horizon	0.263	0.902***	0.242	0.891***
	(0.116)	(0.000)	(0.150)	(0.000)
AbRet $_{[-5,-1]}$	-0.002	-0.007***	-0.003	-0.009***
	(0.571)	(0.003)	(0.362)	(0.000)
BizPress$_{[-14, -8]}$	0.052***	0.039***	0.050***	0.035***
	(0.000)	(0.000)	(0.000)	(0.000)
BizPress$_{[-7, -1]}$	-0.024***	-0.010	-0.024***	-0.009
	(0.005)	(0.196)	(0.004)	(0.222)
BizPress$_{[0, +1]}$	-0.037**	-0.008	-0.031**	-0.000
	(0.010)	(0.509)	(0.031)	(0.978)
EarnSurp		0.334***		0.332***
		(0.000)		(0.000)
Observations	368,714	533,844	368,714	533,844
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Adjusted R-sq	0.017	0.021	0.020	0.024

Table 3 presents coefficients (p-values) for the effect of social media analyst reports on sell-side analyst forecast ERCs. In columns 1 and 2 (3 and 4), AF is defined as *News* (*Rev*). Columns 1 and 3 present results excluding sell-side analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Columns 2 and 4 present results for the unrestricted sample. *** (**, *) denotes two-tailed significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level. All variables are defined in Appendix A.

TABLE 4

The Impact of Social Media Analyst Reports on the Volume Reaction to Sell-side Analyst Forecasts

Dependent Variable: *Abvol [0, 1]*

	$\|AF\| = \|News\|$		$\|AF\| = \|Rev\|$	
	[1]	[2]	[3]	[4]
$\|AF\|$	0.021***	0.017***	0.022***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
$\|AF\| \times SMA_{[-7,-1]}$	**-0.022*** **	**-0.017*** **	**-0.027*** **	**-0.023*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
$\|AF\| \times Size$	0.000	0.002*	0.002*	0.005***
	(0.795)	(0.055)	(0.094)	(0.000)
$\|AF\| \times MB$	0.002***	0.001**	0.002***	0.001***
	(0.000)	(0.011)	(0.000)	(0.009)
$\|AF\| \times SMA_{[0,1]}$	0.017**	0.009	0.025***	0.013*
	(0.016)	(0.114)	(0.006)	(0.067)
$\|AF\| \times InstOwn$	0.008	-0.005	0.006	-0.009
	(0.229)	(0.410)	(0.355)	(0.147)
$\|AF\| \times Following$	-0.004	0.007**	-0.009**	0.004
	(0.276)	(0.018)	(0.011)	(0.200)
$\|AF\| \times Horizon$	-0.027	-0.112***	-0.020	-0.104***
	(0.198)	(0.000)	(0.324)	(0.000)
$\|AF\| \times AbRet_{[-5,-1]}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$\|AF\| \times BizPress_{[-14,-8]}$	-0.012***	-0.008***	-0.012***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
$\|AF\| \times BizPress_{[-7,-1]}$	0.004**	0.006***	0.000	0.004**
	(0.025)	(0.000)	(0.818)	(0.014)
$\|AF\| \times BizPress_{[0,1]}$	0.022***	0.006***	0.025***	0.009***
	(0.000)	(0.001)	(0.000)	(0.000)
$\|AF\| \times \|EarnSurp\|$		-0.189***		-0.221***
		(0.000)		(0.000)
$SMA_{[-7,-1]}$	-0.072***	-0.136***	-0.070***	-0.135***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.045***	-0.027***	-0.047***	-0.028***
	(0.000)	(0.000)	(0.000)	(0.000)
MB	-0.000	0.003***	-0.000	0.003***
	(0.843)	(0.000)	(0.843)	(0.000)
$SMA_{[0,1]}$	0.150***	0.260***	0.149***	0.260***
	(0.000)	(0.000)	(0.000)	(0.000)
InstOwn	0.047***	0.312***	0.049***	0.314***
	(0.000)	(0.000)	(0.000)	(0.000)
Following	-0.079***	-0.201***	-0.075***	-0.199***
	(0.000)	(0.000)	(0.000)	(0.000)
Horizon	-0.464***	1.755***	-0.474***	1.752***
	(0.000)	(0.000)	(0.000)	(0.000)
$AbRet_{[-5,-1]}$	0.006***	0.007***	0.006***	0.007***

	(0.000)	(0.000)	(0.000)	(0.000)
BizPress$_{[-14, -8]}$	-0.069***	-0.139***	-0.069***	-0.138***
	(0.000)	(0.000)	(0.000)	(0.000)
BizPress$_{[-7, -1]}$	-0.059***	-0.048***	-0.057***	-0.046***
	(0.000)	(0.000)	(0.000)	(0.000)
BizPress$_{[0, +1]}$	0.344***	0.473***	0.344***	0.472***
	(0.000)	(0.000)	(0.000)	(0.000)
|*EarnSurp*|		4.386***		4.468***
		(0.000)		(0.000)
Observations	368,714	533,844	368,714	533,844
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Adjusted R-sq	0.342	0.332	0.341	0.332

Table 4 presents coefficients (p-values) for the effect of social media analyst reports on sell-side analyst forecast abnormal volume reaction. In columns 1 and 2 (3 and 4), |AF| is defined as |*News*| (|*Rev*|). Columns 1 and 3 present results excluding sell-side analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Columns 2 and 4 present results for the unrestricted sample. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 5

The Impact of Social Media Analyst Reports on the Price Reaction to Sell-side Analyst Forecasts Conditional on Social Media Analyst Expertise

Dependent Variable: *AbRet [0,1]*

	Social Media Analyst Following				*Social Media Analyst Tenure*			
	AF= News		*AF= Rev*		*AF= News*		*AF= Rev*	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
AF	0.163***	0.278***	0.230***	0.379***	0.163***	0.279***	0.230***	0.380***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AF × SMAhigh$_{[-7,-1]}$	**-0.073****	**-0.127*****	**-0.084*****	**-0.143*****	**-0.060***	**-0.131*****	**-0.088*****	**-0.173*****
	(0.023)	**(0.000)**	**(0.009)**	**(0.000)**	**(0.058)**	**(0.000)**	**(0.009)**	**(0.000)**
AF × SMAlow$_{[-7,-1]}$	**0.009**	**0.059**	**-0.040**	**-0.051**	**-0.080***	**-0.059**	**-0.061**	**-0.038**
	(0.865)	**(0.272)**	**(0.448)**	**(0.396)**	**(0.064)**	**(0.119)**	**(0.144)**	**(0.408)**
SMAhigh$_{[-7,-1]}$	-0.021	-0.018	-0.018	-0.015	-0.014	-0.001	-0.013	-0.001
	(0.287)	(0.418)	(0.378)	(0.514)	(0.529)	(0.975)	(0.561)	(0.983)
SMAlow$_{[-7,-1]}$	-0.042	-0.119*	-0.043	-0.133*	-0.039	-0.080**	-0.030	-0.072**
	(0.521)	(0.092)	(0.512)	(0.059)	(0.201)	(0.022)	(0.331)	(0.037)
Test of difference:								
AF × SMAhigh[-7,-1] vs. ***AF × SMAlow[-7,-1]***	-0.082*	-0.186***	-0.044	-0.092*	0.020	-0.072**	-0.027	-0.135***
	(0.067)	(0.001)	(0.215)	(0.068)	(0.312)	(0.038)	(0.258)	(0.002)
Observations	368,714	533,844	368,714	533,844	368,714	533,844	368,714	533,844
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.017	0.021	0.020	0.024	0.017	0.021	0.017	0.021

Table 5 presents coefficients (p-values) for cross-sectional tests based on social media analyst expertise. SMAHigh[-7,-1] (SMALow[-7,-1]) is an indicator variable equal to one if the social media analyst has high (low) expertise. Proxies for SMA expertise are as follows: Columns 1 through 4 - SMA following: SMAHigh[-7,-1] (SMALow[-7,-1]) is an indicator variable equal to one if the social media analyst has above-median (below-median) investor following, and zero otherwise. Columns 5 through 8 - SMA Tenure: SMAHigh[-7,-1] (SMALow[-7,-1]) is an indicator variable equal to one if the social media analyst's tenure (i.e., time since first contributing to SeekingAlpha) is above (below) the sample median, and zero otherwise. Columns 1, 2, 5, and 6 (3, 4, 7, and 8) present results using News (Rev) as AF. Odd-numbered columns present results excluding analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Even-numbered columns present results for the unrestricted sample. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 6

The Impact of Social Media Analyst Reports on the Price Reaction to Sell-side Analyst Forecasts Conditional on Social Media Analyst Report Detail

Dependent Variable: *AbRet [0,1]*

	Social Media Analyst Report Word Count				*Social Media Analyst Report Number of Numbers*			
	AF= News		*AF= Rev*		*AF= News*		*AF= Rev*	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
AF	0.165***	0.281***	0.232***	0.384***	0.164***	0.278***	0.231***	0.380***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
***AF* × *SMAhigh*$_{[-7,-1]}$**	**-0.081****	**-0.149*****	**-0.109*****	**-0.209*****	**-0.075****	**-0.128*****	**-0.105*****	**-0.182*****
	(0.027)	**(0.000)**	**(0.003)**	**(0.000)**	**(0.031)**	**(0.000)**	**(0.004)**	**(0.000)**
***AF* × *SMAlow*$_{[-7,-1]}$**	**-0.048**	**-0.062**	**-0.033**	**-0.022**	**-0.060***	**-0.092****	**-0.051**	**-0.074****
	(0.196)	**(0.126)**	**(0.382)**	**(0.601)**	**(0.083)**	**(0.013)**	**(0.152)**	**(0.050)**
SMAhigh$_{[-7,-1]}$	-0.036	-0.025	-0.033	-0.026	-0.000	-0.002	0.001	-0.003
	(0.168)	(0.360)	(0.207)	(0.353)	(0.999)	(0.947)	(0.967)	(0.917)
SMAlow$_{[-7,-1]}$	-0.013	-0.037	-0.007	-0.027	-0.043*	-0.055**	-0.036*	-0.047*
	(0.553)	(0.153)	(0.762)	(0.289)	(0.050)	(0.026)	(0.093)	(0.054)
Test of difference:								
AF* × *SMAhigh[-7,-1] vs. ***AF* × *SMAlow[-7,-1]***	-0.033	-0.087**	-0.076**	-0.189***	-0.015	-0.036	-0.054*	-0.108***
	(0.217)	(0.029)	(0.039)	(0.000)	(0.637)	(0.168)	(0.078)	(0.008)
Observations	368,714	533,844	368,714	533,844	368,714	533,844	368,714	533,844
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table 6 presents coefficients (p-values) for cross-sectional tests based on social media report detail. SMAHigh[-7,-1] (SMALow[-7,-1]) is an indicator variable equal to one if the social media analyst report has high (low) detail. Proxies for article detail are as follows: Columns 1 through 4 - Social Media Report Word Count: SMAHigh[-7,-1] (SMALow[-7,-1]) is an indicator variable equal to one if the social media report has above-median (below-median) number of words, and zero otherwise. Columns 5 through 8 - Social Media Report Number of Numbers: SMAHigh[-7,-1] (SMALow[-7,-1]) is an indicator variable equal to one if the social media report has above-median (below-median) number of numbers, and zero otherwise. Columns 1, 2, 5, and 6 (3, 4, 7, and 8) present results using News (Rev) as AF. Odd-numbered columns present results excluding analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Even-numbered columns present results for the unrestricted sample. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 7

The Impact of Social Media Analyst Reports on the Price Reaction to Sell-side Analyst Forecasts Conditional on Institutional Ownership

Dependent Variable: *AbRet [0,1]*

	AF = News				*AF = Rev*			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Low IO	*High IO*	*Low IO*	*High IO*	*Low IO*	*High IO*	*Low IO*	*High IO*
AF	0.155***	0.211***	0.245***	0.390***	0.221***	0.292***	0.364***	0.489***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
***AF* × *SMA*$_{[-7,-1]}$**	**-0.121*** **	**0.027**	**-0.157*** **	**-0.014**	**-0.120*** **	**-0.010**	**-0.168*** **	**-0.044**
	(0.001)	**(0.545)**	**(0.000)**	**(0.767)**	**(0.000)**	**(0.844)**	**(0.000)**	**(0.401)**
SMA$_{[-7,-1]}$	-0.014	-0.032	-0.050*	-0.016	-0.010	-0.033	-0.046*	-0.017
	(0.576)	(0.294)	(0.068)	(0.629)	(0.689)	(0.281)	(0.090)	(0.606)
Test of difference (Low IO vs. High IO): ***AF* × *SMA*$_{[-7,-1]}$**	-0.148***		-0.143***		-0.110**		-0.124**	
	(0.002)		(0.001)		(0.030)		(0.019)	
Observations	182,921	185,793	266,983	266,861	182,921	185,793	266,983	266,861
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.018	0.021	0.022	0.023	0.019	0.023	0.025	0.026

Table 7 presents coefficients (p-values) for cross-sectional tests based on institutional ownership. Low IO (High IO) is an indicator variable equal to one if the firm has below (above) median institutional ownership. Columns 1 through 4 (5 through 8) present results using News (Rev) as AF. Columns 1, 2, 5, and 6 present results excluding analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Columns 3, 4, 7, and 8 present results for the full sample. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10). All variables are defined in Appendix A.

TABLE 8

The Impact of Social Media Analyst Reports on the Price Reaction to Sell-side Analyst Forecasts Conditional on Social Media Analyst Professional Experience

Dependent Variable: *AbRet [0,1]*

	AF = News		*AF = Rev*	
	[1]	[2]	[3]	[4]
AF	0.161***	0.276***	0.232***	0.383***
	(0.000)	(0.000)	(0.000)	(0.000)
***AF* × *SMAProf*$_{[-7,-1]}$**	**-0.010**	**-0.045**	**-0.043**	**-0.103*** **
	(0.761)	**(0.138)**	**(0.206)**	**(0.002)**
***AF* × *SMANonProf*$_{[-7,-1]}$**	**-0.062** **	**-0.097*** **	**-0.090*** **	**-0.132*** **
	(0.049)	**(0.002)**	**(0.007)**	**(0.000)**
SMAProf$_{[-7,-1]}$	-0.039	-0.049*	-0.040	-0.054*
	(0.158)	(0.100)	(0.143)	(0.068)
SMANonProf$_{[-7,-1]}$	-0.008	0.011	-0.008	0.011
	(0.715)	(0.660)	(0.697)	(0.650)
Test of difference:				
AF* × *SMAProf[-7,-1] vs. ***AF* × *SMANonProf[-7,-1]***	0.052	0.052	0.047	0.029
	(0.296)	(0.262)	(0.372)	(0.512)
Observations	368,714	533,844	368,714	533,844
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Controls	Yes	Yes	Yes	Yes
Adjusted R-squared	0.017	0.021	0.020	0.024

Table 8 presents coefficients (p-values) for the cross-sectional test based on social media analyst experience. SMAProf[-7,-1] (SMANonProf[-7,-1]) is an indicator variable equal to one if the social media analyst is classified as a Professional (Nonprofessional) based on Table A1, and zero otherwise. Columns 1 & 2 (3 & 4) present results using News (Rev) as AF. Odd-numbered columns present results excluding analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Even-numbered columns present results for the unrestricted sample. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 9

The Association between the Tone of Social Media Analyst Reports and Sell-side Analyst Forecasts

Dependent Variable: *AF*

Dependent Variable =	*News*		*Rev*	
	[1]	[2]	[3]	[4]
$SMATone_{[-7,-1]}$	**0.222*****	**0.183*****	**0.190*****	**0.161*****
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Size	0.039*	0.042**	0.064***	0.066***
	(0.065)	(0.017)	(0.000)	(0.000)
MB	0.003**	0.003*	0.004***	0.004***
	(0.016)	(0.051)	(0.003)	(0.003)
InstOwn	0.112	0.150	0.262*	0.287**
	(0.464)	(0.285)	(0.075)	(0.029)
Following	0.033	-0.015	0.034	-0.011
	(0.485)	(0.643)	(0.397)	(0.678)
Horizon	-0.018	0.179	0.296	0.368*
	(0.926)	(0.322)	(0.132)	(0.056)
$BizPressSentiment_{[-14,-8]}$	0.143*	0.092	0.114	0.077
	(0.099)	(0.240)	(0.202)	(0.317)
$BizPressSentiment_{[-7,-1]}$	0.303***	0.267***	0.319***	0.368***
	(0.000)	(0.000)	(0.000)	(0.000)
EarnSurp		0.302***		0.210***
		(0.000)		(0.000)
Observations	63,320	88,099	63,320	88,099
Cluster	firm & mon-yr	firm & mon-yr	firm & mon-yr	firm & mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Adjusted R-squared	0.134	0.128	0.107	0.103

Table 9 presents coefficients (p-values) for the association between social media analyst tone and sell-side forecast news. In columns 1 and 2 (3 and 4), the dependent variable, AF, is defined as *News* (*Rev*). Columns 1 and 3 present results excluding analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Columns 2 and 4 present results for the unrestricted sample. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 10

The Impact of Social Media Analyst Reports on the Extent to Which Stock Prices Reflect Upcoming Sell-side Analyst Forecasts

Dependent Variable: *AbRet [-5,-1]*

	AF = News		*AF = Rev*	
	[1]	[2]	[3]	[4]
AF	0.147**	0.181***	0.356***	0.394***
	(0.038)	(0.008)	(0.000)	(0.000)
AF × Agree	**0.209****	**0.212*****	**0.273*****	**0.289*****
	(0.020)	**(0.008)**	**(0.002)**	**(0.001)**
AF × Size	-0.002	-0.036	0.011	-0.016
	(0.944)	(0.177)	(0.702)	(0.603)
AF × MB	0.010	0.002	0.013	0.013
	(0.184)	(0.780)	(0.165)	(0.251)
AF × $SMA_{[0,1]}$	0.092	0.058	0.074	0.008
	(0.169)	(0.346)	(0.306)	(0.901)
AF × InstOwn	0.137	0.193	0.042	0.146
	(0.342)	(0.144)	(0.798)	(0.377)
AF × Turnover	-0.098	-0.445**	-0.194	-0.486**
	(0.583)	(0.011)	(0.370)	(0.026)
AF × Following	-0.028	0.008	-0.019	0.034
	(0.732)	(0.913)	(0.831)	(0.672)
AF × Horizon	0.481	0.259	1.226***	1.067***
	(0.218)	(0.446)	(0.005)	(0.006)
AF × $BizPress_{[-14, -8]}$	-0.098***	-0.078**	-0.187***	-0.159***
	(0.004)	(0.015)	(0.000)	(0.000)
AF × $BizPress_{[-7, -1]}$	0.076**	0.092***	0.126***	0.129***
	(0.020)	(0.002)	(0.000)	(0.000)
AF × EarnSurp		0.029***		0.043***
		(0.007)		(0.001)
Agree	0.059	0.086*	0.040	0.060
	(0.252)	(0.070)	(0.440)	(0.219)
Size	0.051	0.008	0.037	-0.009
	(0.140)	(0.788)	(0.294)	(0.771)
MB	-0.005	-0.003	-0.005	-0.003
	(0.264)	(0.435)	(0.274)	(0.429)
$SMA_{[0,1]}$	-0.084	-0.081	-0.081	-0.078
	(0.215)	(0.142)	(0.231)	(0.161)
InstOwn	0.240	0.161	0.179	0.087
	(0.272)	(0.398)	(0.405)	(0.641)
Turnover	-0.413	-0.571	-0.413	-0.542
	(0.372)	(0.161)	(0.367)	(0.178)
Following	-0.159*	-0.124*	-0.162*	-0.118
	(0.091)	(0.092)	(0.081)	(0.109)

Horizon	0.504	0.414	0.551	0.420
	(0.299)	(0.223)	(0.257)	(0.214)
BizPress$_{[-14, -8]}$	-0.006	-0.008	-0.019	-0.018
	(0.832)	(0.735)	(0.480)	(0.439)
BizPress$_{[-7, -1]}$	0.005	0.033	0.021	0.045*
	(0.863)	(0.199)	(0.496)	(0.078)
EarnSurp		0.290***		0.256***
		(0.001)		(0.002)
Observations	63,320	88,099	63,320	88,099
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Adjusted R-squared	0.047	0.042	0.052	0.047

Table 10 presents coefficients (p-values) for the effect of social media analysts on sell-side analyst forecast FERCs. In columns 1 and 2 (3 and 4), AF is defined as News (Rev). Columns 1 and 3 present results excluding analyst forecasts issued within a 5-day window of an earnings announcement or management forecast. Columns 2 and 4 present results for the unrestricted sample. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 11

The Impact of Social Media Analyst Reports on Price Formation Following Sell-Side Analyst Forecasts

Dependent Variable =	$AbRet_{[+2, +6]}$	$AbRet_{[+2, +12]}$	$IPT_{[0,+6]}$	$IPT_{[0,+12]}$
	[1]	[2]	[3]	[4]
PosAF	**-0.028**	**0.097**	**-0.080**	**0.043**
	(0.678)	**(0.347)**	**(0.390)**	**(0.787)**
PosSMA	**-0.035**	**0.035**	**-0.077**	**0.017**
	(0.523)	**(0.682)**	**(0.351)**	**(0.904)**
PosAF*PosSMA	**0.063**	**0.011**	**0.181**	**0.156**
	(0.415)	**(0.928)**	**(0.120)**	**(0.441)**
Size	0.027	0.034	-0.032	-0.071
	(0.306)	(0.450)	(0.242)	(0.159)
MB	-0.002	-0.004	-0.003	-0.009
	(0.688)	(0.578)	(0.514)	(0.221)
$SMA_{[0,1]}$	0.008	0.042	0.131	0.042
	(0.874)	(0.587)	(0.104)	(0.753)
InstOwn	0.462***	0.684**	0.189	0.040
	(0.004)	(0.016)	(0.260)	(0.901)
Turnover	-0.394	-1.277**	-0.016	0.380
	(0.295)	(0.046)	(0.959)	(0.479)
Following	0.066	-0.047	-0.223***	-0.034
	(0.397)	(0.720)	(0.006)	(0.827)
Horizon	0.706*	0.398	1.683***	1.101
	(0.088)	(0.559)	(0.000)	(0.176)
$AbRet_{[-5, -1]}$	0.000	-0.000***	-0.000	-0.000
	(0.841)	(0.001)	(0.555)	(0.232)
$BizPress_{[-14, -8]}$	0.011	-0.019	-0.046*	-0.137***
	(0.605)	(0.560)	(0.097)	(0.007)
$BizPress_{[-7, -1]}$	-0.012	-0.009	-0.060**	0.028
	(0.567)	(0.787)	(0.035)	(0.581)
$BizPress_{[0, 1]}$	-0.022	0.003	0.233***	0.251***
	(0.334)	(0.927)	(0.000)	(0.000)
Observations	63,320	63,320	63,320	63,320
Cluster	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Fixed Effects	ind-mon-yr	ind-mon-yr	ind-mon-yr	ind-mon-yr
Adjusted R-squared	0.060	0.091	0.001	0.001

Table 11 presents coefficients (p-values) for return drift following sell-side analyst forecasts (columns 1 and 2) and intraperiod timeliness (IPT) following sell-side analyst forecasts (columns 3 and 4). Column 1 (2) presents results for return drift measured from day +2 to +6 (+2 to +12). Column 3 (4) presents results from IPT measured from day +0 to +6 (+0 to +12). *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.