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Social media analysts and sell-side analyst research

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Abstract

We examine how research posted by "social media analysts" (SMAs)—individuals posting equity research online via social media investment platforms—is related to research subsequently produced by professional sell-side equity analysts. Using data from Seeking Alpha, we find that the market reaction to sell-side analyst research is substantially reduced when the analyst research is preceded by the report of an SMA, and that this is particularly true of sell-side analysts' earnings forecasts. We further find that this effect is more pronounced when SMA reports contain more decision-useful language, are produced by SMAs with greater expertise, and relate to firms with greater retail investor ownership. We also provide evidence that the attenuated response to sell-side research is most likely explained by SMA research preempting information in sell-side research and that analysts respond to SMA preemption with bolder and more disaggregated forecasts. Collectively, our results suggest that equity research posted online by SMAs provides investors with information that is similar to but arrives earlier than sell-side equity research, and speak to the connected and evolving roles of information intermediaries in capital markets.

Keywords Social media analyst · Sell-side analyst · Information intermediaries · Equity research

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1 Introduction

We examine how company-specific research posted on social media investment platforms influences investors' response to research provided by professional sell-side analysts.[1] The literature is just beginning to examine how social media content is influencing the information environment of firms, and it is unclear how firm-specific research posted by individuals on social media (hereafter "social media analysts" or "SMAs") interrelates with information produced by professional sell-side analysts. Understanding this relationship is important because the number of SMAs has been increasing rapidly and is likely to continue to rise, while the number of sell-side analysts has been steadily falling (see Figs. 1, 2, as well as Morris 2017). These trends suggest the potential for SMAs to fill any research void left by sell-side analysts.

We predict that SMA coverage will be associated with reductions in the investor response to subsequent sell-side research. We expect this to be the case for three reasons. First, SMAs have clear incentives to produce useful information in order to attract, retain, and grow their readership. Recent research suggests that the reports of SMAs are associated with significant price movements, which indicates not only that they are viewed as credible, on average, but also that they can provide useful information to investors (Chen et al. 2014; Campbell et al. 2019; Farrell et al. 2020). Second, in contrast to the more restricted dissemination of sell-side analyst reports, SMA reports are widely available online at little to no cost, which makes them especially accessible and useful to less sophisticated investors (Farrell et al. 2020; Gomez et al. 2020). Third, SMAs 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, like their followers, SMAs often have an investment position in the stock ("skin in the game"), and the disclosure of this position increases the informativeness, and therefore presumably the quality, of their analysis (Campbell et al. 2019).

However, there are several reasons that social media equity research may have little to no bearing on the pricing of sell-side analyst reports. SMAs may provide information largely orthogonal to sell-side analysts due to their substantial differences in training, resources, and oversight. Further, research suggests that the primary consumers of SMA research are retail investors (Farrell et al. 2020; Gomez et al. 2020), whereas sell-side analyst research now caters more to institutional clients (Green et al. 2014; Brown et al. 2015; Drake et al. 2019). This difference in target audiences may yield research that is largely dissimilar. In addition, SMA research may complement or substitute that produced by professional sell-side analysts. For instance, SMA research could both complement sell-side industry and strategy assessments and substitute for sell-side trading recommendations, resulting in a net effect of zero.

[1] Given our research objective, we focus on *investment*-related social media platforms (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.

Thus, whether the reports of SMAs are associated with the response to sell-side analyst research is an open question.

We test our prediction by examining whether the posting of an SMA report in the days just prior to the issuance of sell-side analyst research reduces the market reaction to the sell-side analyst report. We obtain social media reports from the investment platform Seeking Alpha. Seeking Alpha 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 primary sample consists of approximately 600,000 sell-side analyst reports during the 2006–2017 period.[3] We find that nearly 16 percent of sell-side analyst reports are preceded by at least one posting of an SMA report on Seeking Alpha during the prior seven days, and this proportion is increasing steadily over time (see Fig. 3). We also find that SMA reports do not tend to cluster in advance of sell-side analyst research; when there is a social media report in this window, there is generally only one published report. Descriptively, we find that SMA reports tend to precede sell-side research that is of higher quality (i.e., more accurate, disaggregated, and timely) and published by sell-side analysts employed by larger brokers.

Our main tests provide consistent evidence that sell-side research that is preceded by SMA reports is associated with smaller market reactions than sell-side research that is not. Specifically, we find that the magnitudes of abnormal price and volume reactions are significantly lower (by 8–10 and 11–13 percent of sample means, respectively) when at least one SMA posts an equity research article in the week prior to the sell-side analyst report. Further, we find that the magnitude of this effect is at least as large and often greater than that observed when the sell-side analyst report is preceded by another sell-side report or business press article. We further find that the positive association between the signed market reaction and the news embedded in the quantitative outputs of sell-side analyst reports is significantly lower when the analyst reports are preceded by an SMA report, particularly for earnings forecasts. These results are robust to a broad set of factors that may determine both the presence of an SMA report and the informativeness of the research, including general firm characteristics (e.g., size, book-to-market, etc.), past market performance, and business press coverage. The results are also robust to a number of alternative design choices, such as

[2] As of May 2021, Seeking Alpha reports over 40 million monthly site visits per month spread across 15.2 million unique users (Seeking Alpha 2021).

[3] Because of the flurry of news released by various financial market participants following firms' disclosures of earnings news, we conduct our primary tests using a restricted sample of forecasts issued outside of periods when firms disclose earnings or earnings guidance, but in untabulated analyses we find generally consistent results using a full, unrestricted sample of forecasts.

using different fixed effect structures, changing the measurement windows, and dropping forecasts issued around firm-initiated press releases.

Next, we conduct a number of additional analyses to provide insights into the mechanism by which SMA reports impact the response to sell-side research. We first predict and find evidence of a greater attenuation effect when SMA research is more detailed or relevant, when it is authored by an SMA with greater expertise, and when the covered firm has a greater retail following. These tests help rule out noise-based trading as an explanation for our results. Second, we further examine this noise explanation and examine whether SMA reports are associated with greater market underreactions to sell-side analyst forecasts; we find no evidence that supports this relation. Third, we more directly examine whether SMAs *preempt* sell-side analysts by providing content that "moves up" the pricing of sell-side analyst forecasts. Our evidence suggests that when the tenor of the two reports agrees (i.e., both are positive or both are negative), more of the forecast response occurs in the week prior to the forecast's issuance. The opposite occurs when the tenor of the two reports differs. Fourth, we examine whether the presence of SMA reports is associated with changes in the information provided by sell-side analysts in their reports. We find that sell-side analysts publish bolder forecasts and reports that are more disaggregated when the forecasts and reports are preceded by SMA research. Finally, we explore whether sell-side analysts appear to cater their research more to institutions when their reports are preceded by SMA research, and find some indirect evidence that they do. Collectively, our evidence suggests that SMAs make prices more efficient by helping investors incorporate information that is typically released at a later date.

This study makes several novel contributions to the literature. We contribute to the literature on the evolving role of sell-side analysts in capital markets (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 the earnings forecasts 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 investor response to 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 the budgets and headcounts of sell-side equity research departments are likely to continue to decrease (Morris 2017). In fact, these trends have led some to argue that sell-side research is a "dying industry" (Armstrong 2018; Lee 2019; Pumfrey 2019). Our evidence suggests that SMAs may be able to help fill any research void in the equity research landscape.

We also contribute to the emerging literature on the role of social media in capital markets, particularly for investment platforms such as Seeking Alpha. These studies demonstrate that SMAs provide valuable information to the market in that their reports predict future stock returns (Chen et al. 2014); provide information that retail traders use to make informed trades (Farrell et al. 2020) and improve liquidity, particularly during earnings announcements (Gomez et al. 2020); and are associated with significant price changes, especially when the SMA holds a position in the stock (Campbell et al. 2019). Blankespoor et al. (2020; p. 6) 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." Thus, while research suggests SMA reports are useful (e.g., Chen et al. 2014), we contribute to this emerging literature by demonstrating that SMA reports provide information that is similar to, but more timely than, those of professional sell-side equity analysts, preeminent intermediaries on whom investors have long relied for company-specific analysis.

2 Prior literature and motivation

2.1 Background and prior literature

Sell-side equity analysts have played an important role in capital markets for decades. Their research helps establish the market's expectations of earnings and stock price, 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 the sell-side equity analysts' activities and impact on markets, and this

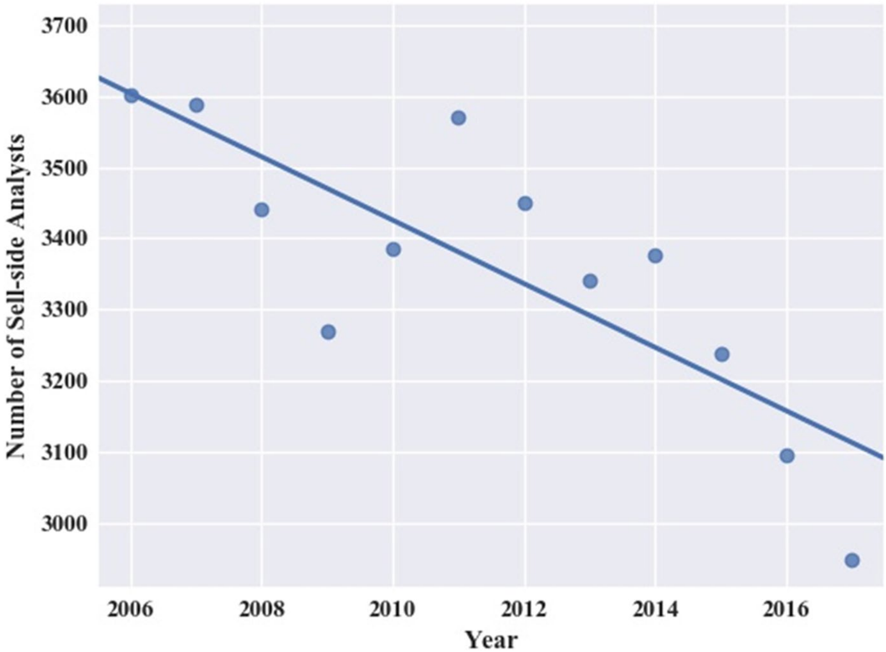

Fig. 1 Number of sell-side analysts issuing at least one earnings forecast by year

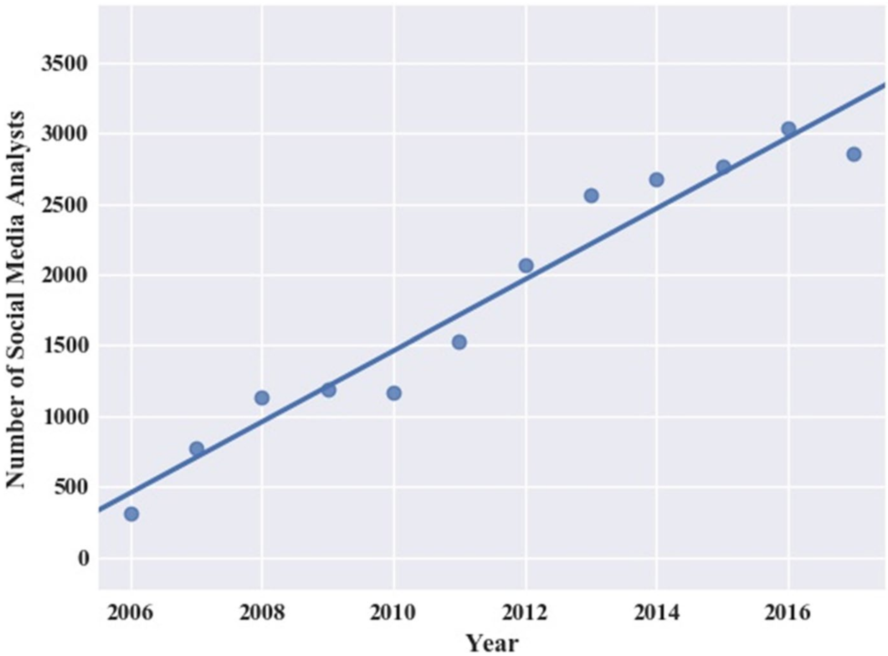

Fig. 2 Number of SMAs issuing at least one article by year

research consistently supports the idea that their reports move markets (Gleason and Lee 2003; Frankel et al. 2006; Beyer et al. 2010; Li et al. 2015).[4] This research helps us understand the various incentives that sell-side analysts have to curry favor with management, generate trading commissions, and promote investment banking transactions, and how these incentives negatively impact the objectivity of their 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. As a result, many of the most skilled analysts left the profession or moved to the buy-side (Guan et al. 2019). Sell-side analysts now focus more of their efforts on monetizing their research through trading commissions (Kadan et al. 2009; Groysberg and Healy 2013). To do this, analysts devote

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

more 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."[5] As a result of these changes, budgets and headcounts of equity research departments have fallen steadily in recent years (Groysberg and Healy 2013, Ch. 4), and Fig. 1 confirms this trend in our data.Additionally, McKinsey recently estimated that equity research budgets at the top 10 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. However, social media has opened the door for alternative sources of equity research, such as that provided by SMAs. 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). 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 by employees in reviews on Glassdoor is positively related to information in firms' future voluntary and mandatory disclosures (Hales et al. 2018).

In contrast to the trend in the number of sell-side analysts (Fig. 1), the number of SMAs posting on Seeking Alpha has grown significantly in recent years, as shown in Fig. 2. Similar to professional sell-side analysts, SMAs 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 SMAs who have "skin in the game" (i.e., have personal financial positions in the stocks they write about) as more credible than SMAs who do not. Farrell et al. (2020) find that Seeking Alpha reports facilitate informed trading by retail investors. Gomez et al. (2020) provide evidence that Seeking Alpha reduces information asymmetry and that Seeking Alpha coverage of a firm during a fiscal quarter reduces sophisticated investors' information advantage during earnings announcements. The authors' rationale is that SMA reports help to forge a consensus between less and more sophisticated investors.

[5] "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.

2.2 Hypothesis development

Several factors motivate our hypothesis that SMA reports will be associated with reduced investor reactions to sell-side equity research. First, as discussed previously, prior research finds that social media research contains value-relevant information. The production of useful information by SMAs is necessary to establish and maintain credibility with investors, increase their readership and, eventually, monetize their postings.[6] SMAs that produce poor quality reports are unlikely to generate or maintain an investor following and thus eventually are likely to stop producing research and drop off the platform. Second, the reports of SMAs are less likely to be affected by the well-documented incentives that sell-side analysts have to promote investment banking relationships and generate trading commissions. This raises the possibility that social media reports are less biased than the reports of sell-side analysts. Third, the research of SMAs 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 sell-side analysts' reports, which are less freely available.[7] These factors lead to our primary prediction, which we state in the alternative form as follows:

Hypothesis *The presence of an SMA report in the days prior to the publication of a sell-side analyst research report is associated with a reduced investor response to the sell-side report.*

There are, however, several reasons why this prediction may not hold. First, it is possible that SMAs and sell-side analysts provide orthogonal information due to important differences between the two groups. Professional sell-side analysts are trained to provide a largely standardized research report that targets a particular audience. These reports are scrutinized by the analysts' employers to ensure that they conform with industry standards and the expectations of clients. SMAs are not subject to this type of standardization and monitoring, and thus have far greater discretion over the content in their reports. Additionally, recent research suggests that social media investment research is particularly relevant to less sophisticated, retail investors (Farrell et al. 2020; Gomez et al. 2020). In contrast, sell-side analysts primarily cater their research to institutional clients (Green et al. 2014; Brown et al. 2015; Drake et al. 2019). Thus, whether due to training or target audience, SMAs may produce different types of information than sell-side analysts.

[6] 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 hosts a "marketplace" where authors can sponsor their own "paid-for" research platform, which further incentivizes SMAs to produce high-quality analysis.

[7] Seeking Alpha now puts most research behind a relatively inexpensive paywall. Users may still freely access current and recent analysis for stocks in the portfolios they maintain in their user accounts. During our sample period, the Seeking Alpha content we analyze was free to all users.

Second, SMAs may produce research that complements certain aspects of sell-side research but substitutes for others, resulting in a net effect of zero. For instance, forecasts of key financial metrics (e.g., earnings, revenues) are a key part of the typical sell-side analysis. While SMAs do not always provide forecasts, they often provide forward-looking analysis that readers could use to forecast upcoming earnings. On the other hand, SMAs could provide information that facilitates interpretation of a sell-side analyst's industry outlook. For example, SMAs commonly discuss recent firm events and their implications for the company's future, while sell-side analysts often provide detailed commentary on expected trends in an industry. It is thus possible that the information in an SMA report could make the industry analysis in a subsequent sell-side analyst report more informative to investors. Thus, whether the reports of SMAs are associated with a reduction in the response to sell-side analyst reports is an open question.

3 Data and sample

Our sample of SMA 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 long-form articles that are similar in many respects to sell-side analyst reports.[8] 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 SMA reports published by 12,971 unique SMAs.

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 referenced but not extensively discussed are denoted in the "About" ("about_stocks") field. While articles referencing multiple stocks may provide information that is relevant to investors, this signal is likely noisy. For instance, SMAs may contrast two firms, discussing one favorably and the other unfavorably, making it very difficult to identify the tenor of the article. Therefore, we limit our sample to articles focusing on a single ticker that is identified in the "Primary" stock field.This provides us with a final sample of 280,995 SMA reports, of which 118,923 precede at least one sell-side analyst report (and thus appear in our sample).[9]

Our first analysis is based on a sample of analyst reports from IBES that contain either an earnings forecast, a price target revision, a stock recommendation, or some

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

[9] One concern is that SMA reports that precede sell-side analyst reports systematically differ from those that do not. We evaluate whether this is the case in untabulated analyses. The mean (median) absolute returns for reports that precede analyst reports is 0.022 (0.013) percent, compared to 0.021 (0.013) percent for those that do not. We also find that SMA reports preceding sell-side analyst reports are slightly shorter than SMA reports not preceding them (average word count of 826 vs. 846, respectively). Thus, it is unlikely that significant differences in content contribute to our results.

combination of the three. We obtain one-quarter-ahead (i.e., FPI = 6) earnings forecast revisions and compute forecast news as the analyst's own revision (*AF*) scaled by share price.[10] We also calculate the change in the analyst's stock recommendation (*Rec*) and the percent change in the analyst's price target (*PrcTarget*). For the report to be included in our sample, we require at least one of these analyst outputs to be present in the report. This restriction increases the likelihood that the report contains value-relevant information. Note that if more than one analyst issues a report with one of these outputs on a given day, we compute the mean across analysts so that our unit of observation is at the "firm-day" level.[11] We define all variables formally in Appendix A (Table 11).

We further constrain our sample in two ways. First, we 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. Second, we restrict the sample to analyst reports that are issued *outside* of periods when significant earnings news (e.g., earnings announcements and earnings guidance issuances) is disclosed by the covered firm. Stock prices and trading volume are generally more active during earnings event windows, and financial intermediaries of all types often issue reports following these announcements. This heightened period of activity makes it more difficult for our models to isolate whether, and to what extent, SMA research is related to the market reaction to sell-side analyst research. Our final sample is 632,412 sell-side analyst reports.

4 Empirical design and primary results

4.1 Research design

We first test our hypothesis by evaluating whether the overall market response to a sell-side analyst report is attenuated when that report is preceded by at least one SMA report. To do so, we estimate the following model:

$$\left|AbRet_{[0,1]}\right| \; or \; AbVol_{[0,1]} = \alpha_0 + \alpha_1 SMA_{[-7,-1]} + \Sigma\alpha Controls + e \tag{1}$$

The dependent variable in Equation [1] is either the absolute value of the two-day abnormal market return (*AbRet*) or two-day abnormal volume (*AbVol*), each beginning on the day of the sell-side analyst forecast. *AbRet* is measured using the signed buy-and-hold return minus the return for the matched size, book-to-market, and momentum portfolio, as in Daniel et al. (1997). *AbVol* is defined as average

[10] We also consider a measure of forecast news derived from the consensus forecast and find similar results.

[11] For SMA reports and sell-side forecasts issued after 4 p.m., 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.

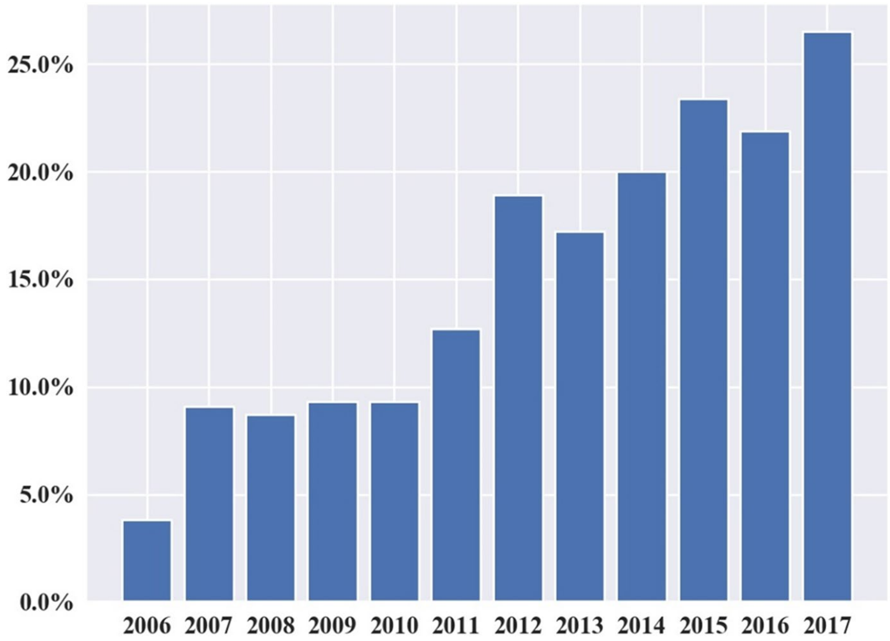

Fig. 3 Percentage of sell-side analyst reports preceded by SMAs' reports over time

abnormal trading volume over the two-day window, where abnormal volume is calculated by subtracting from daily volume the firm's average volume over days [−260, −10] and dividing by the standard deviation of volume over that same window. Our variable of interest, $SMA_{[-7,\,-1]}$, is an indicator set equal to one when the sell-side report is preceded by at least one SMA report in the prior seven days (zero otherwise). A negative α_1 would be consistent with our primary hypothesis, indicating that SMA reports in the week prior to sell-side research reports are associated with reduced market reactions to those sell-side reports.

We identify control variables that may influence both the likelihood of SMA coverage and the publication of a sell-side analyst report.[12] We include several broad measures of a firm's information environment in Equation (1), including firm size (*Size*), market-to-book (*MB*), analyst following (*Following*), and institutional ownership (*InstOwn*). These factors contribute to the demand for information from intermediaries like sell-side analysts or SMAs. We also control for news preceding the forecast, which could prompt research by SMAs as well as sell-side analysts'

[12] Despite our best efforts to control for factors that likely contribute to the SMA's decision to publish research and to the pricing of analyst research, the potential for an omitted variable remains. We evaluate parameters under which an omitted variable would alter our inferences using the method developed in Oster (2019). We implement this procedure as in Call et al. (2018). Untabulated analyses suggest that, in order to alter our inferences in Table 3, omitted correlated variables would need to be 1.1 to 5.2 times more important than the combined effect of the vector of controls we include. While omitted variables remain a limitation of our study, we believe that these diagnostics suggest that the likelihood of such a variable playing a significant role in our analyses is low.

forecasts. Specifically, we include whether the firm receives business press coverage in the two weeks preceding the forecast ($BizPress_{[-14,\,-8]}$ and $BizPress_{[-7,\,-1]}$) and whether another professional sell-side analyst issues a forecast in these same periods ($ProfAnalyst_{[-14,\,-8]}$ and $ProfAnalyst_{[-7,\,-1]}$), as well as abnormal returns or volume leading up to the forecast ($AbRet_{[-14,\,-8]}$, $AbRet_{[-7,\,-1]}$ or $AbVol_{[-14,\,-8]}$, and $AbVol_{[-7,\,-1]}$). 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 influences the investor response to sell-side research, controlling for any contemporaneous dissemination effects.[13] Finally, we estimate Equation (1) with several alternative fixed effects structures (described in the following section), and we cluster standard errors by industry and month-year to address correlation in the error term (Petersen 2009).[14]

We next test whether the reports of SMAs are associated with reductions in the informativeness of the news contained in specific sell-side analysts' estimates, specifically forecasting revisions, recommendations, and price targets (*AF*, *Rec*, and *PrcTarget*, respectively). To do so, we modify Equation (1) by examining signed market reactions and include interactions between *Est* and $SMA_{[-7,-1]}$ as well as our control variables as follows:

$$AbRet_{[0,1]} = \alpha_0 + Est(\beta_0 + \beta_1 SMA_{[-7,-1]} + \Sigma\beta Controls) + \alpha_1 SMA_{[-7,-1]} + \Sigma\alpha Controls + e \tag{2}$$

Est equals *AF*, *Rec*, or *PrcTarget* (the news contained in the analyst's forecast, recommendation, or price target, respectively). We also run a specification with all three analyst outputs included in the model together. The control variables are the same variables included in Equation (1), and they are also interacted with *Est*. Equation (2) is similar in spirit to an earnings-response-coefficient (ERC) model where the terms in parentheses (with β coefficients) capture factors that may affect the investor response to the sell-side analyst's estimate. A negative β_1 indicates that SMA reports attenuate the response to sell-side estimates.

We present descriptive statistics in Table 1. The mean values for $SMA_{[-7,-1]}$ indicate that approximately 16 percent of analyst forecasts are preempted by at least one SMA report, though this rate varies over time. We plot the average value of $SMA_{[-7,\,-1]}$ by year in Fig. 3. Consistent with the rising role of SMAs, we observe that an SMA report is published prior to a sell-side analyst forecast in 5–10 percent

[13] To the extent that SMA 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 (Whited et al. 2021). However, if we exclude them, then our results could plausibly be driven by dissemination (since business press coverage 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). In addition, we do not include a control for other analyst forecasts contemporaneous to the forecast of interest (i.e., $ProfAnalyst_{[0,1]}$), because we collapse our dataset to the firm-day level. Finally, we note that results are similar if we use the logged count of business press articles and prior analyst forecasts rather than indicator variables (untabulated).

[14] Results are robust to clustering standard errors one-dimensionally by industry-month-year instead (untabulated).

of cases in the early years of our sample period, and this increases to nearly 30 percent in 2017.

Regarding other variables, the positive mean and median values for *AbRet* (which is multiplied by 100) are consistent with the average sell-side analyst report containing positive news. With respect to the control variables, we find that the median firm has a market cap of \$3.2 billion, a market-to-book of approximately 2.1, and an analyst following of 12. We also find that 66 percent (41 percent) of forecasts in our sample have at least one business press article written about the firm in the week prior to (day of and day after) the forecast.

In Table 2, we present descriptive statistics for select variables comparing sell-side analyst reports that are preceded by at least one SMA report to sell-side analyst reports that are not. On average, we find that sell-side analyst forecasts that are preceded by social media research tend to be more accurate, less bold, more disaggregated, and more timely than those that are not. We also find that sell-side analysts that are employed by larger brokerages and sell-side analysts that cover larger firms are more likely to have their reports preceded by SMA research. We examine some of these differences in more detail in later analyses.

4.2 Primary results

Table 3 reports results from estimating Equation (1), with the coefficients of interest bolded. Note that for all regression estimations, we use Cook's Distance to identify influential observations, which we exclude from reported results. Specifically, we exclude any observation with a Cook's Distance exceeding 4/N.[15] In Table 3, we report results from estimating Equation (1). Columns 1–4 present results using $|AbRet_{[0,1]}|$, and columns 5–8 present estimates for *AbVol*. We report results without fixed effects in columns 1 and 5. In columns 2 and 6 (3 and 7), we report the results after including industry-month-year fixed effects (separate industry and month-year fixed effects). Finally, in columns 4 and 8, we report the results using firm and month-year fixed effects. These various alternative fixed effects structures allow us to examine the extent to which $SMA_{[-7,\,-1]}$ explains the usefulness of analyst research within industry, within industry time, and within firm.

Across all eight columns, we find significantly negative coefficients on $SMA_{[-7,\,-1]}$, consistent with the presence of an SMA report in the week prior to a sell-side report attenuating the market response to the analyst's research. Using $|AbRet_{[0,1]}|$, the magnitude of the result is relatively insensitive to fixed effect structures. In fact, the largest coefficient in columns 1–4 occurs when using firm fixed effects, which control for the average relevance of analysts' research for a given firm. Economically, the absolute market return is between 20 and 24 basis points lower for sell-side reports following SMA reports, or approximately 10 percent of the mean.

[15] Leone et al. (2019) note that winsorization is not an effective method for addressing significant outliers. As such, we tabulate results after applying Cook's distance. We obtain similar results if we exclude observations with studentized residuals exceeding 2 or estimate the models using robust regressions (with industry-year-month fixed effects). Consistent with winsorization not effectively addressing outliers, we find inconsistent results for the first four columns of Table 3 using winsorization alone.

Table 1 Full descriptive statistics

Variable	N	Mean	Lower quartile	Median	Upper quartile	Std Dev	Tables where variable is used
Dependent variables							
$\|AbRet_{[0,1]}\|$	632,412	2.418	0.643	1.488	3.041	2.845	3
$AbRet_{[0,1]}$	632,412	1.191	0.345	0.808	1.503	1.900	4–6
$AbVol_{[0,1]}$	632,412	1.191	0.345	0.808	1.503	1.900	3
Accuracy	368,714	−1.367	−0.534	−0.187	−0.065	6.935	7
Boldness	368,714	0.557	0.036	0.110	0.338	1.838	7
*Outputs**	368,714	7.01	3.00	7.00	10.00	4.19	7
$AbRet_{[-5,-1]}$	368,714	−0.222	−2.541	−0.154	2.163	5.368	8
$AbRet_{[+2,+6]}$	368,714	−0.072	−2.299	−0.092	2.115	4.779	9
$AbRet_{[+2,+20]}$	368,714	−0.169	−4.924	−0.214	4.459	9.414	9
$AbRet_{[+2,\ EA]}$	368,714	−0.415	−7.420	−0.380	6.402	15.478	9
$AIA_{[0,\ +1]}$	179,036	0.440	0.000	0.000	1.000	0.496	10
$AIAC_{[0,\ +1]}$	179,036	0.825	−0.350	0.902	1.590	0.899	10
Independent variables							
$SMA_{[-7,-1]}$	632,412	0.157	0.000	0.000	0.000	0.364	3–7, 10
AF	368,714	−0.219	−0.175	−0.030	0.056	1.342	4–6, 8–9
Rec	130,759	−0.267	−1.000	−1.000	1.000	0.963	4
PrcTarget	346,804	0.024	−0.078	0.035	0.111	0.194	4
*DaysSinceLastAF**	368,714	44.56	25.00	43.00	65.00	23.90	4–10
*DaysSinceLastRec**	130,759	240.87	161.00	240.00	240.00	141.04	4
*DaysSinceLastPrcTarget**	346,804	93.08	40.00	71.00	114.23	79.96	4
$\|AbRet_{[-14,-8]}\|$	632,412	3.899	1.132	2.583	5.146	4.091	3
$\|AbRet_{[-7,-1]}\|$	632,412	4.392	1.228	2.826	5.727	4.756	3
$AbRet_{[-14,-8]}$	632,412	−0.002	−2.623	−0.050	2.541	5.652	4–10
$AbRet_{[-7,-1]}$	632,412	−0.028	−2.875	−0.046	2.775	6.473	4–10
$AbVol_{[-14,-8]}$	632,412	1.422	0.804	1.282	1.889	0.832	3
$AbVol_{[-7,-1]}$	632,412	1.557	0.857	1.354	2.007	1.005	3
$BizPress_{[-14,\ -8]}$	632,412	0.604	0.000	1.000	1.000	0.489	3–10
$BizPress_{[-7,\ -1]}$	632,412	0.656	0.000	1.000	1.000	0.475	3–10
$BizPress_{[0,\ 1]}$	632,412	0.412	0.000	0.000	1.000	0.492	3–10
*BrokerageSize**	632,412	56.84	23.00	54.00	89.00	37.20	3–10
*Following**	632,412	13.460	7.000	12.000	19.000	8.054	3–10
InstOwn	632,412	0.676	0.574	0.735	0.853	0.254	3–10
MB	632,412	3.116	1.306	2.139	3.678	4.582	3–10
$ProfAnalyst_{[-14,\ -8]}$	632,412	0.418	0.000	0.000	1.000	0.493	3–10
$ProfAnalyst_{[-7,\ -1]}$	632,412	0.414	0.000	0.000	1.000	0.492	3–10
*Size**	632,412	14,305	972	3,232	11,962	31,935	3–10
$SMA_{[0,1]}$	632,412	0.043	0.000	0.000	0.000	0.203	3–10
*Horizon**	368,714	43.44	18.00	37.00	67.00	28.94	4–9

Table 1 (continued)

Variable	N	Mean	Lower quartile	Median	Upper quartile	Std Dev	Tables where variable is used
Agree	368,714	0.089	0.000	0.000	0.000	0.280	8–9
Disagree	368,714	0.082	0.000	0.000	0.000	0.269	8–9
$SMA_{[-90,\,-1]}$	368,714	0.514	0.000	1.000	1.000	0.499	9

All continuous variables are winsorized at the 1st and 99th percentiles

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

This effect exceeds that of business press coverage (between 2 and 7 basis points) and other sell-side analysts (up to 2 basis points).[16] We observe similar effects in columns 5–8 using abnormal trading volume. Control variables generally exhibit expected associations. For example, controls that are likely to capture the dissemination of analyst research ($SMA_{[0,1]}$ and $BizPress_{[0,1]}$) load positively. The average response also declines with firm size and, to a lesser degree, institutional ownership.

We conduct a battery of untabulated tests to assess the robustness of these primary results. First, in addition to those presented in the Table 3, we estimate Equation (1) using two additional fixed effect structures that incorporate (1) sell-side analyst and month-year fixed effects and (2) sell-side analyst-covered firm and month-year fixed effects.[17] Second, we change the SMA 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 report 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. Fourth, we use a reduced sample where we exclude sell-side reports that are preceded by more than three SMA reports. Fifth, we expand the sample to consider all analyst reports, including ones issued following earnings announcements and management earnings guidance. In all cases, our inferences are similar to those tabulated in Table 3. Finally, we also examine whether the *timing* of

[16] As an additional means of comparing the effects of these various intermediaries, in untabulated analysis we include all possible interaction terms of $SMA_{[-7,-1]}$, $ProfAnalyst_{[-7,-1]}$, and $BizPress_{[-7,-1]}$. We find that the attenuating effect of SMA reports is observed in the presence of an analyst report, a business press article, or both. In contrast, the main effects of *ProfAnalyst* and *BizPress* are not consistently significant.

[17] Note that we estimate these models at the analyst level, so there can be more than one observation per trading day. In addition, we only estimate these models using the analyst forecast sample (i.e., excluding recommendations and price targets), because IBES scrambled analyst identifiers prior to our accessing data related to price targets and recommendations. This scrambling makes analyst fixed effects impossible in tests that combine research outputs, such as those in our Table 3 analyses.

Table 2 Descriptive statistics for selected variables

Variable	Full sample						$SMA_{[-7,-1]}=1$	$SMA_{[-7,-1]}=0$	*Difference*
	N	Mean	Lower Quartile	Median	Upper Quartile	Std Dev	Mean	Mean	
Accuracy	368,714	−1.367	−0.534	−0.187	−0.065	6.935	−1.069	−1.428	0.358***
Boldness	368,714	0.557	0.036	0.110	0.338	1.838	0.468	0.575	−0.107***
*Outputs**	368,714	7.01	3.00	7.00	10.00	4.19	8.11	6.78	1.33***
*DaysSinceLastAF**	368,714	44.56	25.00	43.00	65.00	23.90	41.14	45.27	−4.13***
*DaysSinceLastRec**	130,759	240.87	161.00	240.00	240.00	141.04	246.74	239.77	6.97***
*DaysSinceLastPrcTarget**	346,804	93.08	40.00	71.00	114.23	79.96	87.21	94.27	−7.06***
*BrokerageSize**	632,412	56.84	23.00	54.00	89.00	37.21	59.49	56.31	3.18***
InstOwn	632,412	0.676	0.574	0.735	0.853	0.254	0.627	0.685	−0.058***
*Size**	632,412	14,305	972	3,232	11,962	31,935	44,055	8,744	35,311***
*Horizon**	368,714	43.44	18.00	37.00	67.00	28.94	46.800	42.750	4.05***

All continuous variables are winsorized at the 1st and 99th percentiles

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

Table 3 The impact of social media analyst reports on the absolute price and volume reaction to sell-side analyst reports

	Dependent variable = $\lvert AbRet_{[0,1]} \rvert$				Dependent variable = $AbVol_{[0,1]}$			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$SMA_{[-7,-1]}$	**− 0.196*****	**− 0.157*****	**− 0.147*****	**− 0.227*****	**− 0.156*****	**− 0.146*****	**− 0.148*****	**− 0.135*****
	(− 4.45)	**(− 5.48)**	**(− 4.95)**	**(− 6.86)**	**(− 12.14)**	**(− 12.12)**	**(− 12.65)**	**(− 10.59)**
Size	− 0.306***	− 0.317***	− 0.318***	− 0.421***	− 0.034***	− 0.037***	− 0.037***	0.002
	(− 9.69)	(− 9.48)	(− 9.80)	(− 10.85)	(− 6.36)	(− 6.36)	(− 6.65)	(0.15)
MB	0.006	0.004	0.004	0.003**	0.003**	0.001	0.001*	0.000
	(1.28)	(1.59)	(1.46)	(2.56)	(2.71)	(1.73)	(1.94)	(0.58)
$SMA_{[0,1]}$	0.237***	0.241***	0.253***	0.188***	0.159***	0.152***	0.155***	0.168***
	(5.11)	(5.76)	(6.67)	(5.38)	(7.21)	(6.81)	(6.95)	(8.25)
Following	0.040	0.034	0.041	− 0.020	0.088***	0.041***	0.034***	0.029
	(0.75)	(0.88)	(1.00)	(− 0.61)	(3.74)	(3.65)	(3.20)	(0.82)
InstOwn	0.086	− 0.231	− 0.237*	− 0.068	− 0.056***	− 0.057***	− 0.056***	− 0.061***
	(0.63)	(− 1.64)	(− 1.85)	(− 0.98)	(− 5.89)	(− 7.83)	(− 7.18)	(− 4.10)
$BizPress_{[-14,-8]}$	− 0.114***	− 0.099***	− 0.101***	− 0.092***	− 0.120***	− 0.107***	− 0.108***	− 0.095***
	(− 5.54)	(− 5.16)	(− 5.40)	(− 5.82)	(− 13.09)	(− 16.04)	(− 15.61)	(− 13.27)
$BizPress_{[-7,-1]}$	− 0.065***	− 0.037***	− 0.041***	− 0.013	− 0.018*	− 0.001	− 0.003	0.009
	(− 5.10)	(− 3.16)	(− 3.73)	(− 0.98)	(− 1.95)	(− 0.17)	(− 0.44)	(1.01)
$BizPress_{[0,+1]}$	0.454***	0.464***	0.465***	0.449***	0.291***	0.293***	0.294***	0.302***
	(9.92)	(10.83)	(11.05)	(10.69)	(14.41)	(14.52)	(14.77)	(15.84)
$ProfAnalyst_{[-14,-8]}$	0.009	− 0.014	− 0.011	− 0.039***	− 0.102***	− 0.076***	− 0.078***	− 0.074***
	(0.32)	(− 0.99)	(− 0.76)	(− 3.19)	(− 15.48)	(− 10.24)	(− 10.23)	(− 8.57)
$ProfAnalyst_{[-7,-1]}$	− 0.002	− 0.004	− 0.003	− 0.020	− 0.024***	0.001	− 0.002	− 0.001
	(− 0.08)	(− 0.38)	(− 0.28)	(− 1.74)	(− 3.93)	(0.17)	(− 0.42)	(− 0.29)
DaysSinceLast	0.014	0.020**	0.018**	0.029***	0.030***	0.024***	0.023***	0.021***
	(1.16)	(2.85)	(2.54)	(4.67)	(10.81)	(10.69)	(10.28)	(8.46)

Table 3 (continued)

	Dependent variable = $\|AbRet_{[0,1]}\|$				Dependent variable = $AbVol_{[0,1]}$			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
BrokerageSize	0.016	0.029***	0.028***	0.034***	0.024***	0.023***	0.022***	0.024***
	(1.73)	(5.40)	(4.90)	(4.57)	(6.98)	(7.71)	(7.73)	(8.22)
$\|AbRet_{[-14,-8]}\|$	0.067***	0.039***	0.042***	0.021***				
	(8.22)	(8.97)	(8.82)	(7.47)				
$\|AbRet_{[-7,-1]}\|$	0.068***	0.045***	0.048***	0.030***				
	(8.45)	(9.76)	(9.41)	(8.83)				
$AbVol_{[-14,-8]}$					0.001***	0.001***	0.001***	0.001***
					(16.01)	(16.17)	(16.84)	(16.47)
$AbVol_{[-7,-1]}$					0.006***	0.005***	0.005***	0.005***
					(58.87)	(64.31)	(63.28)	(62.56)
Observations	617,094	617,094	617,094	617,094	622,926	622,926	622,926	622,926
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	None	Ind-mon-yr	Ind & mon-yr	Firm & mon-yr	None	Ind-mon-yr	Ind & mon-yr	Firm & mon-yr
Adjusted R-squared	0.147	0.188	0.182	0.213	0.326	0.350	0.345	0.352

In columns 1–4 the dependent variable is absolute abnormal returns ($|AbRet_{[0,1]}|$). In columns 5–8 the dependent variable is abnormal volume ($AbVol_{[0,1]}$). In all regressions, outliers are removed using a Cooks distance threshold of 4/N, where N = 632,412

*** (**, *) 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 SMA report matters, by including an indicator variable for each individual SMA report day in the week prior to a sell-side report. We find evidence of a significant effect on all seven indicator variables except for day −1. Thus, we do not find evidence of a clear pattern indicating that the timing of SMA reports in the period preceding sell-side analyst reports is affecting our inferences.

Moving on to our next primary analysis, in Table 4, we present the estimation results for Equation (2). Given the relative insensitivity of our Table 3 results to alternative fixed effect structures, we focus on estimations using the industry-year-month fixed effects for the remainder of our tests. When estimating Equation [2], we demean all variables not naturally centered on zero to allow us to interpret the main effect of each variable as its effect at the average levels of the other variables. We note that columns 1, 2, and 3 include only those observations with non-missing values for *AF*, *Rec*, and *PrcTarget*, respectively, yielding different sample sizes. In column 4, we include all observations and set missing values to 0.

In Table 4, column 1, we find a highly significant negative coefficient on the interaction between *AF* and $SMA_{[-7,\,-1]}$. This indicates that the market reaction to analyst forecast revisions is significantly lower when they are preceded by an SMA report. We also observe a highly significant positively coefficient on *AF*, consistent with share prices moving in the same direction as forecast news. In column 2, we find that the market also responds to changes in recommendations, as the coefficient on *Rec* is significantly positive, but this response appears unaffected by the presence of an SMA report. In column 3, we find evidence similar to that in column 1 using *PrcTarget*. Specifically, we find that the presence of an SMA report attenuates the response to analysts' price target revisions. Finally, the evidence in column 4, which combines all three types of estimates, is similar to that presented in column 1 with respect to *AF*. Interestingly, with this expanded sample we now find weak evidence that SMA reports attenuate the response to recommendation changes, and we no longer observe statistically significant attenuation of the response to price targets. Recall that missing values for each estimate are set to 0 in column 4, making it difficult to compare results across columns.

To assess the economic significance of this effect, we compare the magnitude of the interaction terms to the coefficient on the main effect for each output. For *AF,* our column 1 (4) estimates suggest that the response to analysts' forecasts is attenuated by 42 (43) percent.[18] Thus, reports by SMAs appear to have a meaningful impact on the usefulness of sell-side analysts' forecasts. The magnitude of SMA-related attenuation for *PrcTarget* (column 3) and *Rec* (column 4) is much smaller (less than 5 percent). Overall, we find some evidence that SMA reports attenuate all three analyst outputs, though evidence for both *Rec* and *PrcTarget* is more mixed and weaker in magnitude than that for sell-side forecasts. Therefore, we focus the rest of our tests on the attenuation of the response to sell-side analysts' forecasts.

We verify that results in Table 4 are robust to the same robustness tests we conducted for Equation (1) (presented in Table 3). In addition, while we include

[18] To illustrate the column 1 calculation, 0.164 divided by 0.387 equals 0.424.

an extensive array of controls to address the possibility that analyst forecast news and the reports of SMAs are non-random, it is difficult to control for the relevance of a given analyst for a specific firm or for their average forecast response coefficient (this was possible in Equation (1) using the analyst-covered-firm fixed effect because the dependent variables are unsigned). In other words, our results could be affected by "low-quality" sell-side analysts regularly issuing forecasts following analysis on Seeking Alpha. To address this issue, we estimate a simplified version of Equation (2) for each analyst-firm combination in our sample with at least 10 observations. This approach controls for the relevance of each specific analyst covering a given firm. Specifically, we focus on analyst forecasts (column 1 of Table 4) and regress *AbRet* on *AF*, *SMA*, and the interaction between *SMA* and *AF* by analyst-firm. 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 value-relevant) and compute Fama and MacBeth (1973) t-statistics for the interaction between $SMA_{[-7,\,-1]}$ and *AF*. In an untabulated analysis, we find a significantly negative average interaction across these firm-analyst-specific regressions.

5 Additional analyses

In this section, we conduct a number of additional tests to shed light on the mechanisms by which SMA reports contribute to reduced investor responses to sell-side research and to rule out alternative explanations.

5.1 Cross-sectional analyses

We first conduct several cross-sectional tests by leveraging differences in the information conveyed in SMA reports, both as signaled by the content of the report itself and by the reputation of the author. We then leverage differences in the audiences of the SMA research, as reflected in firms with high retail investor ownership and trading volume. We present these results in Table 5.

5.1.1 Variation in reports and expertise

First, we expect that SMA reports that are more detailed—that is, that provide more qualitative (number of words) or quantitative (more numbers) information—are more likely to lessen the reaction to sell-side analyst reports. To test this prediction, we re-estimate Equation (2) after replacing $SMA_{[-7,\,-1]}$ with two variables, $SMAhigh_{[-7,\,-1]}$ and $SMAlow_{[-7,\,-1]}$, which equal one if the sell-side analyst forecast is preceded by an SMA report with "high detail" or "low detail", respectively, and zero otherwise. We determine high or low detail based on above- or below-median sorts of the number of words and the number of numbers contained in the report, respectively. If SMA reports with greater detail are

Table 4 The impact of social media analyst reports on the price reaction to news in sell-side analyst reports

	Dependent variable: *AbRet* $_{[0,1]}$			
	Analyst forecasts [1]	Recommendation changes [2]	Price target changes [3]	All analyst outputs [4]
AF	0.387***			0.360***
	(12.52)			(7.60)
Rec		0.745***		1.544***
		(14.73)		(12.63)
PrcTarget			5.354***	3.635***
			(12.88)	(11.36)
$\boldsymbol{AF \times SMA_{[-7,-1]}}$	**− 0.164*** **			**− 0.155*** **
	(− 6.25)			**(− 5.50)**
$\boldsymbol{Rec \times SMA_{[-7,-1]}}$		**− 0.019**		**− 0.058***
		(− 0.43)		**(− 1.80)**
$\boldsymbol{PrcTarget \times SMA_{[-7,-1]}}$			**- 0.201** **	**− 0.062**
			(− 2.28)	**(− 0.67)**
Observations	358,682	121,925	321,003	603,284
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	0.025	0.122	0.069	0.067

Column 1 presents results for sell-side analyst forecasts (i.e., an analyst forecast ERC test), column 2 presents results for sell-side analyst recommendation changes, and column 3 presents results for sell-side analyst price target changes. Column 4 combines all analyst outputs into one regression, setting *AF*, *Rec*, and *PrcTarget* equal to zero if missing. The dependent variable is abnormal returns (*AbRet[0,1]*). In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N = 368,714, 130,759, 346,804, and 632,412 for columns 1, 2, 3, and 4, respectively

*** (**, *) 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)

associated with a greater attenuation in the response to sell-side analyst forecasts, then the coefficient on *SMAhigh* should be more negative than the coefficient on *SMAlow*.

We present the results in columns 1 and 2 of Table 5. In column 1, we use SMA report word counts, and in column 2, we use the number of numbers to proxy for the detail of the SMA report. Consistent with our expectations, in both columns we find negative coefficients on the $AF \times SMAhigh$ terms that are significantly larger in magnitude than the $AF \times SMAlow$ terms. These findings suggest that the reduction in the pricing of sell-side analysts' forecasts occurs primarily for SMA reports that provide greater detail to their readers.

Table 5 The impact of social media analyst reports on the price reaction to sell-side analyst forecasts, conditional on social media analyst report content and author expertise

	Dependent variable: $AbRet_{[0,1]}$							
	Word count	Number count	Fwd-looking sentences	Accounting words	Uncertain language	Following	Tenure	Industry specialization
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
AF	0.384***	0.379***	0.423***	0.423***	0.424***	0.379***	0.380***	0.380***
	(13.84)	(13.35)	(10.42)	(10.31)	(10.40)	(13.13)	(13.49)	(13.42)
$\boldsymbol{AF \times SMAhigh_{[-7,-1]}}$	**− 0.235*****	**− 0.202*****	**− 0.137*****	**− 0.089*****	**− 0.106*****	**− 0.169*****	**− 0.187*****	**− 0.198*****
	(− 7.40)	**(− 10.29)**	**(− 6.93)**	**(− 3.66)**	**(− 3.85)**	**(− 7.47)**	**(− 8.68)**	**(− 6.94)**
$\boldsymbol{AF \times SMAlow_{[-7,-1]}}$	**− 0.016**	**− 0.084*****	**− 0.098*****	**− 0.139*****	**− 0.140*****	**− 0.058**	**− 0.115*****	**− 0.106*****
	(− 0.61)	**(− 3.38)**	**(− 4.41)**	**(− 5.54)**	**(− 5.58)**	**(− 1.18)**	**(− 3.30)**	**(− 4.00)**
$SMAhigh_{[-7,-1]}$	− 0.064***	− 0.041**	− 2.726***	− 2.731***	− 2.718***	− 0.035**	− 0.038**	− 0.059***
	(− 4.33)	(− 2.40)	(− 40.05)	(− 37.58)	(− 38.53)	(− 2.68)	(− 2.62)	(− 4.62)
$SMAlow_{[-7,-1]}$	− 0.023	− 0.045***	− 2.740***	− 2.743***	− 2.771***	− 0.116*	− 0.047	− 0.030
	(− 1.51)	(− 3.36)	(− 35.69)	(− 38.83)	(− 37.57)	(− 2.09)	(− 1.38)	(− 1.76)
Test of difference								
$\boldsymbol{AF \times SMAhigh_{[-7,-1]}}$ vs. $\boldsymbol{AF \times SMAlow_{[-7,-1]}}$	− 0.219***	− 0.118***	− 0.039**	0.050*	0.034*	− 0.111**	− 0.072**	− 0.092***
(p-value)	(0.00)	(0.00)	(0.04)	(0.06)	(0.08)	(0.03)	(0.01)	(0.00)
Observations	359,193	359,199	359,118	359,092	359,130	359,221	359,214	358,202
Adjusted R-squared	0.023	0.023	0.025	0.025	0.025	0.023	0.023	0.023

Columns 1 and 2 are based on SMA article detail. In column 1, $SMAHigh_{[-7,-1]}$ ($SMALow_{[-7,-1]}$) is an indicator variable equal to one if the SMA article has an above-median (below-median) number of words, and zero otherwise. In column 2, $SMAHigh_{[-7,-1]}$ ($SMALow_{[-7,-1]}$) is an indicator variable equal to one if the SMA article has an above-median (below-median) number of numbers, and zero otherwise. Columns 3–5 are based on SMA article language. In columns 3, 4, and 5, $SMAHigh_{[-7,-1]}$ ($SMALow_{[-7,-1]}$) is an indicator variable equal to one if the SMA article has an above-median (below-median) number of forward-looking words, accounting words, and uncertainty words, respectively, and zero otherwise. Columns 6–8 are based on SMA expertise. In columns 6, 7, and 8, $SMAHigh_{[-7,-1]}$ ($SMALow_{[-7,-1]}$) is an indicator variable equal to one if the SMA has an above-median (below-median) amount of followers, tenure, and industry specialization, respectively, and zero otherwise. In all columns, standard errors are clustered by industry and month-year; industry-month-year fixed effects are included; controls are included; and outliers are removed using a Cook's distance threshold of 4/N, where N = 368,714

For tests of differences, ***, **, and * denotes one-tailed significance at the $p<0.01$, $p<0.05$, and $p<0.10$ level, respectively. All variables are defined in Appendix A (Table 11)

We next focus on three language attributes that should proxy for the relevance of the SMA report. First, we expect reports using more forward-looking language to have a greater attenuation effect since that information is likely more relevant to the information conveyed in the forthcoming sell-side forecast; we measure forward-looking language as the percentage of sentences that include forward-looking statements, as in Li et al. (2010). Second, we expect that reports using more accounting-related language produce information more pertinent to forecasts; we measure accounting-related language as the percentage of words and phrases appearing in the glossary of Weil et al. (1994). Finally, we expect that greater uncertainty in language *reduces* the degree to which the information in social media reports attenuates the information in sell-side forecasts. We measure uncertainty as the degree to which the report conveys strong sentiment with subjective terminology.[19] For each of these proxies, we again use the same two variables, *SMAlow* and *SMAhigh,* to capture relatively higher (above median) levels in the SMA reports.

Column 3 (4) [5] of Table 5 presents results using forward-looking sentences (accounting words) [uncertain language]. Consistent with our expectations, we find that the coefficient $AF \times SMAhigh$ is larger in magnitude than the coefficient on $AF \times SMAlow$ in column 3, and an F-test indicates that the difference between the two is significant at the 5 percent level. In column 4, we find results opposite our expectations for accounting language. That is, an F-test confirms that the coefficient on $AF \times SMAlow$ is significantly larger in magnitude than that on $AF \times SMAhigh$. One possibility for this result is that accounting language typically corresponds to backward looking (less value-relevant) analysis since it refers to previously reported results. Consistent with this possibility, the correlation between forward looking language and the use of accounting language in our sample of SMA reports is negative (Pearson's $\rho = -0.08$). Finally, in column 5 of Table 5, we observe a larger attenuation effect when the report contains relatively less uncertain language.

Next, there is likely substantial variation in the expertise of SMAs. This variation may, in turn, impact investors' perceptions of their reports and thus the extent to which they influence subsequent sell-side analyst research. In columns 6–8 of Table 5, we explore how the relation between SMAs and the attenuation of the response to sell-side forecasts varies based on SMA expertise. We test this prediction with three distinct proxies for SMA expertise. First, we examine whether the attenuation effect is stronger when SMAs have a larger investor following, which we assume indicates greater perceived expertise (or quality) and larger dissemination of their reports (column 6). We obtain data on investor following from the biography page that Seeking

[19] We use Python's "textblob" package to measure sentence-level sentiment. This measure of sentiment has two parts: polarity, which is analogous to tone and varies between −1 (negative) and +1 (positive), and subjectivity, which varies between 0 and 1. We consider a sentence to generate higher uncertainty if it conveys relatively strong sentiment, defined as an absolute value of polarity that is greater than 0.75, and high subjectivity, defined as greater than 0.50. Note that we also considered dictionary-based measures of uncertainty from both Loughran and McDonald (2014) and General Inquirer dictionaries and observed no significant differences.

Alpha provides for each author. Second, we use SMA experience as measured by the length of time the SMA has contributed to Seeking Alpha (Clement 1999), as evidenced by the date of their first report (column 7). Finally, we use SMA industry specialization (column 8), based on the number of two-digit SIC industries the SMA has written about in the prior year, as a proxy for industry focus and expertise (Clement 1999). We define the same two variables as used in the previous two analyses, *SMAhigh* and *SMAlow*, based on whether the SMA falls above or below the median for each proxy. We expect the coefficient on $AF \times SMAhigh$ to be more negative than the coefficient on $AF \times SMAlow$. For all three proxies, we observe interactions that are larger in magnitude for the above-median expertise SMA reports. An F-test indicates that these differences are all statistically significant. This evidence suggests that, as predicted, the attenuation effect of SMAs is concentrated in those analysts with greater expertise.

5.1.2 Variation in investor base

Next, we examine cross-sectional variation in the firm's investor base. Because the reports of SMAs are more likely to be consumed by less sophisticated, individual investors (Farrell et al. 2020), we predict that the effect of SMAs on the pricing of sell-side research will be concentrated in firms with relatively lower proportions of institutional holdings and relatively higher levels of retail trading.[20] We test this prediction by partitioning our sample at the median of each of these two proxies and re-estimating Equation (2) within each partition.[21] We report these results in Table 6. In columns 1 and 2, we present the results using institutional ownership as the partitioning variable, and in columns 3 and 4 we report them using retail trading volume, estimated using the Boehmer et al. (2020) method.[22] Odd (even) columns report results for the low (high) partition. Consistent with our expectations, we observe that the interaction between *AF* and $SMA_{[-7,\ -1]}$ is 60 percent larger in magnitude in column 1 (low institution holdings) than in column 2 (high institutional holdings). Similarly, our results are stronger in column 3 (high retail trading) than in column 4 (low retail trading). These differences are also statistically significant. These results suggest that the influence of SMAs is concentrated in firms with a relatively less sophisticated and active investor base.

[20] The correlation between institutional holdings and retail trading intensity is − 0.44, suggesting that these two proxies capture similar but not identical aspects of ownership structure.

[21] We use sample partitions (fully interacted models) for these tests since our partitioning variable is defined for all observations. For the analyses discussed in Sect. 5.1.1, the partitioning variable (e.g., expertise) is only defined when $SMA = 1$. Therefore, we use *SMAhigh* and *SMAlow* in those analyses.

[22] This method identifies retail trades using a regulatory restriction that retail orders can receive price improvements (measured in small fractions of a cent per share) but institutional orders cannot. Using TAQ data, we divide the transaction price by 1 cent (0.01). If the remainder is in the interval (0.0, 0.4], then we identify the trade as a retail sell transaction; if the remainder is in the interval [0.6, 1.0), then we identify the trade as a retail buy transaction. Trades that occur at a round penny (remainder = 0) or those with remainders that fall around the half-penny (remainders in the interval (0.4, 0.6)) are not categorized as retail for conservatism. We then aggregate retail trading volume over each trading day.

5.2 Explanations for the attenuation effect

Our evidence thus far suggests that SMAs attenuate the response to sell-side research, and this evidence varies predictably with characteristics of the SMA, their reports, and the firm's investor base. In our final set of analyses, we identify and explore three potential explanations for this pattern of results. First, SMAs could contribute to a less efficient response to sell-side research by injecting noise into the information environment. The cross-sectional results in the prior section provide indirect evidence that this is unlikely to be the case, but we conduct a more direct test in this section. Second, SMAs could preempt some of the information in the sell-side analyst reports. Third, sell-side analysts could alter the type of information they produce when their reports are preceded by SMA reports. In this section, we conduct tests to explore each of these possibilities.

5.2.1 Underreactions to sell-side equity research

Our first set of tests examine whether the presence of an SMA report 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 trigger correlated noise trading, and we explore whether this may result in systematic underreaction to subsequently released sell-side analyst forecasts in our setting. To test this possibility, we estimate the following model:

$$AbRet_{[x,y]} = \alpha_0 + AF(\beta_0 + \beta_1 Agree + \beta_2 Disagree + \Sigma Controls) + \alpha_1 Agree + \alpha_2 Disagree + \Sigma aControls + e \tag{3}$$

In Equation (3), the dependent variables are measures of future abnormal returns over three windows starting two days after the sell-side analyst forecast: approximately one week ($AbRet_{[+2,+6]}$), approximately one month ($AbRet_{[+2,+20]}$), and until the next earnings announcement ($AbRet_{[+2,EA]}$). *Agree* is an indicator variable equal to one if the SMA article net tone, or positive words minus negative words based on the Loughran and McDonald (2014) dictionary, agrees with the sign of the forecast news (and zero otherwise).[23] We also include *Disagree* and its interaction with *AF*. *Disagree* equals one when the SMA and sell-side forecast revision are of opposite signs. The remaining variables in Equation (3) are similar to those in Equation (2).

We present the results in Table 7. Consistent with Gleason and Lee (2003), we observe positive associations between all three measures of future returns and

[23] To evaluate whether SMAs generally agree with sell-side analysts, we compare the tone of SMA reports, computed using the Loughran and McDonald (2014) sentiment dictionary, to *AF*. As expected, we observe a significantly positive association (untabulated), suggesting that the tenor of the news contained in the reports of SMAs and those of sell-side analysts generally track one another.

Table 6 The impact of social media analyst reports on the price reaction to sell-side analyst forecasts, conditional on investor base

	Dependent variable: *AbRet* $_{[0,1]}$			
	[1]	[2]	[3]	[4]
	Low IO	High IO	High retail	Low retail
AF	0.292***	0.398***	0.236***	0.254***
	(8.62)	(12.34)	(8.76)	(9.06)
$\boldsymbol{AF \times SMA_{[-7,-1]}}$	**− 0.143*** **	**− 0.089** **	**− 0.052** **	**− 0.033**
	(− 7.91)	**(− 2.92)**	**(− 2.40)**	**(− 1.44)**
$SMA_{[-7,-1]}$	− 0.029**	− 0.064**	− 0.034**	− 0.042
	(− 2.66)	(− 3.06)	(− 2.66)	(− 1.67)
Test of difference				
$\boldsymbol{AF \times SMA_{[-7,-1]}}$	− 0.054**		− 0.019*	
p-value	(0.02)		(0.08)	
Observations	173,228	177,587	176,100	174,798
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	0.021	0.025	0.020	0.023

Columns 1 and 2 present results for institutional ownership. Low IO (High IO) is an indicator variable equal to one if the firm has below- (above-) median institutional ownership. Columns 3 and 4 present results for the percentage of traders who are retail traders. High Retail (Low Retail) is an indicator variable equal to one if the firm has an above- (below-) median percentage of retail trading volume during the 90 days leading up the sell-side analyst forecast. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N = 368,714

For tests of differences, ***, **, and * denotes one-tailed significance at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ level, respectively. All variables are defined in Appendix A (Table 11)

forecast news. This suggests that the price response to analysts' forecasts is not immediate. Our interactions of interest, though, suggest that SMA reports do not negatively affect the efficiency of the price response. More specifically, the interaction coefficients for both $AF \times Agree$ and $AF \times Disagree$ are insignificant.[24]

5.2.2 Preemption of sell-side research

Another explanation for the observed effect relates to preemption. If SMA reports preempt the information in sell-side forecasts, then we expect that this is more likely to occur when the tenor of the social media report is directionally consistent with that of the sell-side analyst forecast (i.e., positive versus negative). We test this conjecture using Equation (3) but replacing the dependent

[24] In untabulated analysis, we find similar (non)results using intraperiod timeliness over the same three windows (though starting at day 0) to measure the efficiency of the price formation process (Twedt 2016).

variable with ($AbRet_{[-5,\ -1]}$). This model allows us to examine whether stock prices move in the direction of *future* analyst forecasts to a greater degree when SMAs publish analysis that agrees (in tenor) with the upcoming forecast than when they do not.

The β terms in parentheses in this version of Equation (3) 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 SMAs agree with sell-side analysts, more of the analyst forecast news (*AF*) is impounded into price in the week prior to the forecast. We predict that the coefficient on the interaction between *AF* and *Agree* will be significantly more positive than the coefficient on *AF* and *Disagree*.

We present the estimation results in Table 8. We find that the coefficient on *AF* is significantly positive, which suggests that sell-side analyst forecast news is partially impounded into price in the week leading up to the forecast announcement. Consistent with our conjecture, 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 continuous variables so that the main effects can be interpreted as the marginal effect of that variable at the average level of the interacted terms. Thus, the FERC increases by approximately 15 percent when a sell-side forecast is preceded by an SMA report. We also find that SMA reports that disagree with the forecast have the opposite effect, reducing the FERC by 20 percent. These findings indicate that SMA reports which agree with the forthcoming forecast can preempt a substantial portion of the news of subsequently released sell-side analyst forecasts. Finally, an F-test confirms that the coefficient on the interaction between *AF* and *Agree* is significantly larger than that on *AF* and *Disagree*.

5.2.3 Differences in sell-side research

Finally, we explore whether sell-side analysts' research is systematically different when preceded by an SMA report. Analysts who issue forecasts preceded by SMAs may feel compelled to alter their reports in some way to change their relevance. To explore this possibility, we consider two sets of tests. First, we examine whether analysts issue bolder or more accurate forecasts or more disaggregated reports (e.g., revenue forecasts, multiple periods of earnings forecasts, etc.) when preceded by SMA reports. We do this using the following model:

$$ResearchAttribute = \alpha_0 + \alpha_1 Agree + \alpha_2 Disagree + \Sigma\alpha Controls + e \tag{4}$$

We use *Agree* and *Disagree* as in our prior tests because the sell-side analyst's response to the presence of an SMA report may vary depending on whether the report conveys information that is similar in tenor to the sell-side analyst's research. It follows that sell-side analysts may react differently to SMA research that is directionally consistent with their own views than to SMA research that is

Table 7 The impact of social media analyst reports on price formation following sell-side analyst forecasts

Dependent variable	$AbRet_{[+2, +6]}$ [1]	$AbRet_{[+2, +20]}$ [2]	$AbRet_{[+2, EA]}$ [3]
AF	0.107***	0.216***	0.644***
	(5.65)	(4.72)	(8.04)
$AF \times Agree$	**− 0.044**	**0.000**	**0.131**
	(− 1.31)	**(0.00)**	**(1.23)**
$AF \times Disagree$	**− 0.055**	**− 0.124**	**− 0.113**
	(− 1.65)	**(− 1.76)**	**(− 0.85)**
Agree	− 0.017	− 0.157***	− 0.478***
	(− 0.56)	(− 3.27)	(− 3.79)
Disagree	− 0.040	− 0.222***	− 0.518***
	(− 1.47)	(− 3.52)	(− 3.64)
Observations	356,992	356,681	358,802
Cluster	Ind & mon-yr	Ind & mon-yr	Ind & mon-yr
Fixed Effects	Ind-mon-yr	Ind-mon-yr	Ind-mon-yr
Controls	Yes	Yes	Yes
Adjusted R-squared	0.023	0.055	0.063

In column 1 (2) [3] return drift is measured through day + 6 (+ 12) [+ 2 days after the next earnings announcement]. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N = 368,714

*** (**, *) 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)

not. *Research Attribute* represents one of three attributes of estimates appearing in the sell-side analyst's research report. For our first two attributes, we consider whether the presence of an SMA report in the week prior to a sell-side report that agrees with the forthcoming forecast news corresponds to bolder or more accurate forecasts. We define boldness as in Clement and Tse (2005) and accuracy as in Clement (1999). Our rationale for forecast boldness is that SMA activity may prompt sell-side analysts to issue forecasts that stand out from other analysts' in an attempt to gain greater visibility. For accuracy, SMAs may prompt sell-side analysts to deliver a superior work product, evidenced through higher accuracy. Our third proxy captures a key attribute of the overall research report. Specifically, we compute the natural log of one plus the number of distinct estimates corresponding to the analyst report. We anticipate that SMAs may prompt sell-side analysts to provide more information. *Controls* reflects the same set of controls as in Equation (1), except we also control for the absolute value of the news contained in the forecast ($|AF|$).

We present the Equation (4) estimation results in Panel A of Table 9. As shown in column 1, we find that sell-side forecasts are bolder when preceded by an SMA report that agrees with the forecast news. In column 2, we

Table 8 The effect of social media analyst reports on the extent to which stock prices reflect upcoming sell-side analyst forecasts

	Dependent Variable: *AbRet* $_{[-5,-1]}$
	[1]
AF	0.661***
	(10.73)
AF×*Agree*	**0.097****
	(2.39)
AF×*Disagree*	**− 0.134*****
	(− 3.31)
Agree	0.112***
	(3.16)
Disagree	0.010
	(0.27)
Test of difference	
AF×*Agree* vs. *AF*×*Disagree*	**0.231*****
p-value	0.00
Observations	356,677
Cluster	Ind & mon-yr
Fixed effects	Ind-mon-yr
Controls	Yes
Adjusted R-squared	0.034

Agree is an indicator variable equal to one if either (1) SMA tone in the preceding seven days is positive or zero and the sell-side analyst forecast revision is positive or zero, or (2) SMA tone in the preceding seven days is negative and the sell-side analyst forecast revision is negative, and zero otherwise

Disagree is an indicator variable equal to one if either (1) SMA tone in the preceding seven days is positive or zero and the sell-side analyst forecast revision is negative, or (2) SMA tone in the preceding seven days is negative and the sell-side analyst forecast revision is positive or zero, and zero otherwise. Both *Agree* and *Disagree* are set to zero if there is no social media analyst report in the 7 days preceding the sell-side analyst forecast. Outliers are removed using a Cook's distance threshold of 4/N, where N = 368,714

*** (**, *) 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)

similarly find that the number of estimates provided by the analyst is higher when preceded by an SMA report, regardless of whether the SMA report agrees or disagrees with the sell-side analyst's. However, in column 3, we do not find any evidence that forecast accuracy varies with the presence of an SMA report.

While the results in Panel A suggest that sell-side analysts alter the nature of their research when it is immediately preceded by an SMA report, it is also possible that general competition from SMAs over a longer period leads to shift in the nature of sell-side research. To explore this possibility, we estimate the following empirical model:

Table 9 The impact of social media analyst reports on sell-side analyst research attributes

Dependent variable	Boldness	Ln(Outputs)	Accuracy
	[1]	[2]	[3]
Panel A: SMA articles in prior week			
Agree	**0.034****	**0.099*****	**0.015**
	(2.74)	**(12.92)**	**(0.37)**
Disagree	**0.005**	**0.115*****	**0.007**
	(0.34)	**(16.40)**	**(0.16)**
Test of difference			
Agree vs. *Disagree*	**0.029*****	**−0.016*****	**0.008**
p-value	(0.00)	(0.00)	(0.46)
Observations	362,862	358,311	365,229
Cluster	Ind & mon-yr	Ind & mon-yr	Ind & mon-yr
Fixed effects	Ind-mon-yr	Ind-mon-yr	Ind-mon-yr
Controls	Yes	Yes	Yes
Adjusted R-squared	0.181	0.158	0.332
Panel B: SMA articles in prior 90 days			
$SMA_{[-90,-1]}$	**0.074*****	**0.014****	**−0.064**
	(4.85)	**(2.83)**	**(−1.55)**
Observations	360,456	360,726	363,025
Cluster	Ind & mon-yr	Ind & mon-yr	Ind & mon-yr
Fixed effects	Ind-mon-yr	Ind-mon-yr	Ind-mon-yr
Controls	Yes	Yes	Yes
Adjusted R-squared	0.182	0.145	0.313

Panel A measures SMA activity over the 7 days prior to an analyst forecast. *Agree* is an indicator variable equal to one if either (1) SMA tone in the preceding 7 days is positive or zero and the sell-side analyst forecast revision is positive or zero, or (2) SMA tone in the preceding 7 days is negative and the sell-side analyst forecast revision is negative, and zero otherwise. *Disagree* is an indicator variable equal to one if either (1) SMA tone in the preceding 7 days is positive or zero and the sell-side analyst forecast revision is negative, or (2) SMA tone in the preceding 7 days is negative and the sell-side analyst forecast revision is positive or zero, and zero otherwise. Both *Agree* and *Disagree* are set to zero if there is no social media analyst report in the 7 days preceding the sell-side analyst forecast. **Panel B** measures SMA activity over the 90 days preceding an analyst forecast, where $SMA_{[-90,-1]}$ is an indicator variable equal to one if there was at least one SMA article published in the 90 days prior to the analyst forecast, and zero otherwise. **Panels A and B:** In column 1, the dependent variable is the boldness of the sell-side analyst forecast (*Boldness*). In column 2, the dependent variable is the natural logarithm of the number of unique outputs included in the sell-side analyst report (*Outputs*). In column 3, the dependent variable is the accuracy of the sell-side analyst forecast (*Accuracy*). In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N = 368,714

*** (**, *) 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)

$$Research\,Attribute = \alpha_0 + \alpha_1 SMA_{[-90,-1]} + \Sigma\alpha Controls + e \tag{5}$$

The dependent variable is the same set of characteristics as in Equation (4), but we replace *Agree* and *Disagree* with $SMA_{[-90,\,-1]}$, which equals one when there is at least one SMA report over the previous quarter (~90 days).[25] Since there are often multiple SMA articles over this window and because we are examining a general shift due to competition rather than the impact of a single report, we do not consider the tenor of the report as we did in Equation (4). We report these results in Panel B of Table 9. As shown, the results are similar to those reported in Panel A using a weekly SMA window. This suggests that any shifts in sell-side research content may be driven by general competition rather than the contents of single SMA reports.

In our final test, we consider another aspect of sell-side research content—whether sell-side analysts whose reports are preempted by SMAs' may cater their research more towards institutions and differentiate it from publicly available information. It is challenging to directly classify the nature of content in sell-side research or the exact readership of their reports, so we instead rely on an indirect measure—abnormal institutional investor attention—and estimate the following model:

$$AIA_{[0,1]}\,or\,AIAC_{[0,1]} = \alpha_0 + \alpha_1 SMA_{[-7,-1]} + \Sigma\alpha Controls + e \tag{6}$$

We measure abnormal institutional investor attention (*AIA* and *AIAC*) as in Ben-Rephael et al. (2017) using Bloomberg terminal data. If sell-side research preempted by SMA reports is more targeted to institutions, we expect to see higher institutional investor attention paid to the release of their reports, suggesting a positive estimate for α_1.[26] We report these results in Table 10 and, as expected, observe a significantly positive coefficient using both dichotomous and continuous versions of abnormal institutional attention. Overall, our evidence is consistent with SMAs preempting some of the information in sell-side reports and with professional analysts responding by altering the content of their reports.

6 Conclusion

This study provides novel evidence that equity research posted online by SMAs reduces the investor response to the research of professional sell-side analysts, particularly earnings forecasts. Additional analysis suggests that these results are most pronounced when social media reports have greater detail and more forward-looking and certain language, when their authors have greater expertise, and for firms with larger retail investor bases. We also find that our results are most likely explained by SMAs preempting at least some of the information

[25] We find similar inferences using the natural log of the number of SMA reports over the 90-day period instead of $SMA_{[-90,-1]}$.

[26] Note that Bloomberg data begins in 2010, resulting in a smaller sample for this test.

Table 10 The impact of social media analyst reports on institutional investor attention to sell-side analyst research

Dependent variable	$AIA_{[0, +1]}$ [1]	$AIAC_{[0, +1]}$ [2]
$SMA_{[-7,-1]}$	**0.015***** **(3.24)**	**0.055***** **(3.67)**
Observations	173,820	173,759
Cluster	Ind & mon-yr	Ind & mon-yr
Fixed effects	Ind-mon-yr	Ind-mon-yr
Controls	Yes	Yes
Adjusted R-squared	0.127	0.253

In column 1 the dependent variable is $AIA_{[0, +1]}$, an indicator variable equal to one if Bloomberg's daily maximum institutional investor attention score is 3 or 4 on the day of or following the sell-side analyst report, and zero otherwise. In column 2 the dependent variable is $AIAC_{[0, +1]}$, where we transform Bloomberg's 0, 1, 2, 3, and 4 scores to continuous values using the conditional means of truncated normal distribution. In both columns, outliers are removed using a Cook's distance threshold of 4/N, where N = 179,036

*** (**, *) denotes two-tailed significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level. All variables Appendix A (Table 11

contained in sell-side research, and by sell-side analysts altering the nature of their reports in response.

These findings increase our understanding of 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 regulations, 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. With that being said, we highlight that our study focuses on one specific effect of SMA reports (i.e., the investor response to sell-side analyst reports) and look forward to future research in this area. For instance, our research does not directly speak to the overall relevance of sell-side research; we only examine the timing of when sell-side research is priced. Future research may wish to consider whether alternative sources of information, like that produced by SMAs, is impacting the value relevance of the news provided by sell-side analysts. Additionally, we focus on quantitative outputs of sell-side analyst reports. Future research may wish to consider how qualitative aspects of sell-side research compare to the content of SMA reports.

Appendix A

Table 11 Variable definitions

Variable	Definition
Dependent variables	
$AbRet_{[x,y]}$	Buy and hold abnormal returns (using portfolio returns calculated from Daniel et al. (1997), and if missing, the value-weighted return from CRSP) over day *x* to day *y* relative to the analyst report date
$AbVol_{[x,y]}$	The daily average of abnormal volume over day x to day y relative to the analyst report date, calculated as the total daily volume over the window minus the average daily trading volume over days −260 to −10, divided by the standard deviation of volume over days −260 to −10
Accuracy	The absolute difference between the analyst earnings forecast and actual earnings, multiplied by −100, scaled by beginning-of-the-period price
Boldness	Analyst forecast boldness, measured as the absolute difference between the analyst forecast and the outstanding consensus analyst forecast immediately prior to the forecast of interest (Clement and Tse 2005)
Outputs	The number of unique outputs issued by the analyst in the report
$AIA_{[0, +1]}$	Abnormal institutional investor attention. Following Ben-Rephael et al. (2017), abnormal institutional attention is an indicator variable equal to one if Bloomberg's daily maximum institutional investor attention score is 3 or 4 on the day of or following the sell-side analyst report, and zero otherwise
$AIAC_{[0, +1]}$	Abnormal institutional investor attention (continuous measure). Following Ben-Rephael et al. (2017), we transform Bloomberg's 0, 1, 2, 3, and 4 scores to continuous values using the conditional means of truncated normal distribution. Under the normal distributional assumption, the corresponding values are − 0.350, 1.045, 1.409, 1.647, and 2.154. This variable is the average of this measure on the day of and following the sell-side analyst report
Independent variables	
$SMA_{[x, y]}$	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 report of interest; zero otherwise
AF	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
Rec	Sell-side analyst recommendation revision. Set equal to + 1 for an upgrade and set equal to −1 for a downgrade
PrcTarget	Sell-side analyst price target revision percent change: (price target new—price target old)/price target old
DaysSinceLast	The number of days since the analyst last issued an *AF*, *Rec*, or *PrcTarget*, respectively
$BizPress_{[x, y]}$	An indicator variable equal to one if there was at least one Dow Jones article written about the firm during day *x* to *y* relative to the sell-side analyst report date
BrokerageSize	The number of analysts employed by the brokerage house during the year
Following	The number of analysts following the firm prior to the sell-side report of interest
InstOwn	Institutional ownership at the beginning of the period
MB	Market-to-book ratio at the beginning of the period
$ProfAnalyst_{[x, y]}$	An indicator variable equal to one if there was at least one professional analyst report issued during day *x* to *y* relative to the sell-side analyst forecast date of interest
Size	The firm's market value 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

Table 11 (continued)

Variable	Definition
Agree	Indicator variable equal to one if either (1) SMA tone in the preceding 7 days is positive or zero and the sell-side analyst forecast revision is positive or zero, or (2) SMA 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) SMA tone in the preceding 7 days is positive or zero and the sell-side analyst forecast revision is negative, or (2) SMA tone in the preceding 7 days is negative and the sell-side analyst forecast revision is positive or zero, and zero otherwise

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