Quantitative Analysis and the Value of Social Media Investment Research

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Abstract

We examine the impact of introducing quantitative ratings, which strongly predict returns, on the Seeking Alpha (SA) platform. After the change, SA report recommendations become more aligned with quant ratings, particularly among reports mentioning quant-related terms and reports authored by less quantitatively savvy contributors. Furthermore, both types of reports become significantly stronger predictors of returns. Retail trading also becomes more correlated with quant ratings following the release of SA research reports. The findings suggest that broader access to quantitative analysis enhances the quality of SA contributor's investment recommendations and helps retail investors incorporate quantitative signals into their investment decisions.

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1. Introduction

Individuals increasingly rely on social media for investment research. For example, a 2021 survey by CNBC finds that among younger investors (18-34 years old), social media is the most popular source of investment research, well ahead of conversations with friends and family, TV news, newspapers, and discussions with brokers and financial advisors.[1] The recent trading frenzies in Gamestop and other meme stocks, fueled by social media platforms, further highlights the potential impact that social media can have on retail trading and financial markets.

While the popular press frequently treats social media as a homogenous information source, social media sites differ meaningfully along several dimensions including the contributor and consumer base, the length and style of research, the degree of anonymity, the level of moderation, and the platform design. Recent work suggests that these differences can have meaningful implications. For example, Cookson et al. (2023) find social media sentiment exhibits very minimal correlation across three prominent social media sites (Twitter, StockTwits, and Seeking Alpha), and Bradley et al. (2024), find that the Gamestop trading frenzy had very different implications for the informativeness of research on Wallstreetbets and Seeking Alpha. While this work suggests that differences across social media platforms are important, relatively little is known about what specific features influence the investment value of social media research.

In this paper, we explore whether improved access to quantitative research is one feature that enhances the value of social media research. Academic research shows that hundreds of different firm characteristics predict stock returns, and recent studies emphasize that this predictability is not solely due to data mining (McLean and Pontiff, 2016; Chen, 2021; Jensen, Kelly, and Pedersen, 2023). Thes findings suggest that quantitative analysis may continue to predict stock returns. Further, existing evidence finds that retail investors, who tend to be the dominant users of social media (Farrell et al.

[1] See: https://www.surveymonkey.com/curiosity/cnbc-invest-in-you-august-2021/

2022), struggle with quantitative investing. For example, McLean, Pontiff, and Reilly (2022) find that retail investors systematically trade against anomalies, and this behavior accounts for roughly 30% of the poor performance of retail trades.[2] Greater access to quantitative ratings could help investors correct these mistakes by both educating investors about the value of quantitative research, and by reducing the costs associated with acquiring quantitative signals. On the other hand, simply providing investors access to useful information need not improve financial decision making, especially when the information provided is complex (see, e.g., Hastings, Madrian, and Skimmyhorn, 2013; and Fernandes, Lynch, and Netemeyer, 2014 for a review of the financial education literature).

Our empirical analysis leverages the introduction of quantitative ratings on the Seeking Alpha (SA) platform. In June of 2019 the SA product team announced the addition of quantitative ratings which would be accessible to all premium and pro subscribers on the website. Importantly, SA also released several years of historical quantitative ratings, which allows us to explore how SA users incorporate quantitative ratings both before (2016-2018) and after (2020-2022) the ratings were made available on the platform. While the exact formula of the ratings is proprietary, SA indicates that the ratings incorporate factors that have been shown to predict stock returns including valuation ratios (Fama and French, 1992), past returns (Jegadeesh and Titman, 1993), and profitability (Novy-Marx, 2013). Consistent with this description, we show that *Quant Ratings* strongly correlate with the *Momentum, Value, Profit Growth,* and *Quality* factor clusters of Jensen, Kelly, and Pedersen (2023).

We begin by examining whether *Quant Ratings* predict returns. Our analysis uncovers a statistically and economically significant relation between *Quant Ratings* and returns. A strategy that goes long stocks with *Quant Ratings* that correspond to a *Strong Buy* recommendation (roughly the top decile) and short stocks with *Quant Ratings* that correspond to a *Strong Sell* recommendation (roughly

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[2] Similarly, Green and Jame (2024) find that retail buying frenzies are associated with cumulative returns of – 38% over the subsequent two years, of which 40% can be attributed to retail buying frenzies trending against quantitative signals.

the bottom decile) earns an equal-weighted CAPM alpha of 2.15% per month and a six-factor alpha of 1.52% per month, both of which are statistically significant at a 1% level. The corresponding estimates for value-weighted portfolios are 1.92% and 1.20%, respectively, which suggests that the return predictability of *Quant Ratings* is present even in large and liquid stocks. The return predictability is similar in both the pre-period (2016-2018) and post-period (2020-2022) indicating that *Quang Ratings* remained valuable even after they were disclosed on the platform.

The return results suggest that *Quant Ratings* contain value-relevant information, but they do not offer any insight into whether SA users incorporate this information. To investigate this question, we examine the research reports of SA contributors.[3] As a first test, we count the number of SA reports that mention words commonly associated with quantitative analysis (hereafter *Quant Reports*). In the three years prior to the introduction of the *Quant Ratings*, we find a total of 71 *Quant Reports* (0.15% of all reports), whereas this number increases to 1,583 *Quang Reports* (3.15%) in the post period.

Reports can be influenced by quantitative ratings even if they do not explicitly mention quant-related words. As a broader test of the influence of quant ratings on SA research, we examine how *Quant Ratings* correlate with the SA reports recommendations (i.e., Buy, Hold, or Sell) in the pre versus post period. We find that SA report recommendations are uncorrelated with *Quant Ratings* in the pre-period but become strongly correlated with *Quant Ratings* in the post-period. For example, among reports in the post-period that do not explicitly mention quant (*Non-Quant Reports*), we find that a one-unit increase in *Quant Ratings* (e.g., moving form a Hold to a Buy) is associated with a 5.0 percentage point increase (roughly 12%) in the probability that the SA report recommendation increases by one unit (e.g., moving from a Hold to a Buy). This estimate increases to 17.5 percentage points (or a 40% increase) for *Quant Reports*. We find no evidence that SA report recommendations were becoming

[3] One critical advantage to studying SA contributors is that they receive access to all premium tools, which ensures that they have access to quantitative ratings.

more correlated with quant recommendations over time during the pre-period, which is inconsistent with pre-trends driving the results.

To provide further evidence that quant ratings have a direct impact on research production, we also examine the introduction of quantitative ratings for exchange traded funds (ETFs). Importantly, ETF *Quant Ratings* were made available on the platform nearly two years after the introduction of quant ratings for common stocks, and they rely on an entirely different formula. Despite these differences, we continue to find that SA report recommendations become significantly more correlated with ETF quant ratings after their introduction.

One limitation of financial education programs is that the benefits may primarily accrue the most sophisticated individuals, as less sophisticated individuals may be less attentive to new information sources or find the information too complex to incorporate easily (Fernandes, Lynch, and Netemeyer 2014). We use information from contributor's biographies to gauge their quantitative sophistication. Before the introduction of quant ratings on SA, less sophisticated contributors issue reports that are significantly less aligned with SA quant ratings compared to their more sophisticated counterparts. However, this pattern reverses after the introduction of quant ratings. Our findings suggest that the introduction of quant ratings benefitted less quantitatively sophisticated investors, who were presumably less aware of quantitative analysis prior to the platform design change.

We also examine whether SA report recommendations exhibit stronger correlations with future returns (hereafter: more informative) after the introduction of *Quant Ratings*. We find no evidence that *Non-Quant Reports* issued in the post-period are more informative than reports issued in the pre-period. However, *Quant Reports* issued in the post-period are significantly more informative, relative to both pre-period reports and *Non-Quant Reports*. Specifically, a one-unit increase in report recommendations (i.e., moving from a hold to a buy) for *Quant Reports* is associated with return increases of 1.85% over a one-month horizon and 2.97% over a three-month horizon.

We decompose the abnormal return into *Quant-Style returns*, defined as the average return on stock with very similar quantitative ratings, and *Quant-Adjusted returns,* defined as the difference between the return on the stock and the *Quant-Style Return*. For the three-month horizon, roughly 60% of the outperformance (1.72% out of 2.97%) is attributable to *Quant-Style Return.* Further*,* the 1.72% estimate is highly significant, which suggests that the superior performance is at least partially attributable to reports recommending stocks with higher quantitative ratings. Similarly, report informativeness increases more for less sophisticated investors, and much of this effect is attributable to less-sophisticated investors earning higher *Quant Style Returns*. We also note that the *Quant-Adjusted* returns, while frequently insignificant, are always positive. This finding is inconsistent with the concern that quantitative analysis crowds out other value-relevant information (Dugast and Foucault, 2018).

Our final set of tests examine retail trading around SA research reports. Following the platform design change, we find that retail order imbalances become more correlated with quant ratings on days when SA reports are released. In contrast, we find no evidence that retail imbalances are more correlated with quant ratings in the days immediately prior to the report release. This suggests the reports themselves help retail investors incorporate quantitative signals into their trading decisions.

SA reports may help retail investors incorporate quantitative ratings either by encouraging them to passively follow report recommendations, which align with quant ratings, or by prompting additional research into the firm, including its quantitative metrics. To explore the significance of these two channels, we decompose retail order imbalances into predicted versus residual imbalances, where the predicted imbalance is the fitted value from a regression of retail imbalances on report recommendation and residual imbalance is the difference between retail imbalances and the predicted imbalance. We find that both components become more correlated with quant rating on report days, but the magnitudes are considerably larger for the residual component. This evidence is consistent with retail investors actively incorporating quant ratings into their investment decisions rather than merely passively following report recommendations.

Our findings contribute to the literature on the value of social media investment research. Prior work finds that investment research on Seeking Alpha, Estimize, and SumZero are informative (Chen et al., 2014; Jame, Johnston, Markov, and Wolfe, 2016; Crawford, Gray, Johnson, and Price, 2018). However, studies that examine online message boards, Twitter, and Stocktwits find no evidence of informativeness (Tumarkin and Whitelaw, 2001; Chawla, Da, Xu, and Ye, 2022; Giannini, Irvine, and Shu, 2018). These contrasting results suggest that differences across social media sites are important, but there is limited evidence on what factors contribute to these differences. One exception is Cookson et al. (2023) who show that increasing the message character limit on StockTwits is associated with StockTwit sentiment becoming more predictive of one-day ahead stock returns. We highlight another important change to platform design, the introduction of *Quant Ratings* on Seeking Alpha, and we show that this change has economically large implications for report informativeness over much longer horizons, particularly for less-sophisticated contributors.

Our findings also contribute to the ongoing debate surrounding the effectiveness of financial education. While policy makers are increasingly endorsing financial education, existing evidence on the benefits of financial education are mixed.[4] For example, prior work finds that a range of educational interventions, such as surveys and improvement in disclosure, yielded minimal benefits for investors (Choi, Laibson, and Madrian, 2010 and 2011). More broadly, an early meta-analysis conducted by Fernandes, Lynch, and Netemeyer (2014) concludes that financial education interventions have, at best, small effects on actual outcomes. However, a more recent meta-analysis by Kaiser, Lusardi, Menkhoff, and Urban (2022) highlights that many financial education interventions

[4] For example, in 2022 69 different financial-education related bills were introduced across 27 states (https://docs.google.com/document/d/1tWjd8LCMl0AJT2AmE3leIDqQ-x46z5luvQ09wImV2eQ/edit).

yield significant economic benefits. In contrast to this literature, which typically emphasizes broad measures of financial literacy, our analysis focuses on one specific, but economically important, investment mistake. In this respect, our study aligns with a recent working paper by Hackethal et al. (2024) who demonstrate that educating investors about common dividend-related mistakes can improve investment behavior.

Lastly, our study relates to the literature on market anomalies. One strand of literature examines how different market participants contribute to anomalies. Edelen, Ince, and Kadlec (2016) find that institutions typically trade on the wrong-side of anomalies, and Engelberg, Mclean, and Pontiff (2020) and Guo, Li, and Wei (2020) find that sell-side analyst research is also in the wrong direction, which suggests that both institutional investors and sell-side analysts exacerbate anomaly mispricing. A second strand of literature examines factors that help market participants better trade on anomalies, and potentially correct mispricing, including the academic publication of the anomaly (Pontiff and Mclean, 2016; and Calluzo, Moneta, and Topaluglu, 2019) and access to quantitative sell-side analysts (Birru, Gokkaya, Liu, and Markov, 2022). Our findings suggest that the introduction of *Quant Ratings* is another factor that helped a subset of market participants, SA contributors and retail investors, better incorporate quantitative research, and potentially attenuate anomaly mispricing.

2. Data and Descriptive Statistics

2.1 The Seeking Alpha Sample

Seeking Alpha (SA) is one of the largest investment-related social media websites. As of 2021, roughly 17 million different people visit Seeking Alpha each month, the site has more than 10 million registered users, and more than 16,000 individuals contribute at least one SA report.[5] Reports are intended to provide new investment research, rather than to simply break news, and each report is

[5] Additional statistics are available here:
https://static.seekingalpha.com/uploads/pdf_income/sa_media_kit_01.06.21.pdf

subject to significant editorial review. Prior work finds that these reports contain value-relevant information that predicts returns (Chen et al., 2014) and facilitates more informative retail trading (Farrell et al., 2022).

In December of 2018, Seeking Alpha acquired CressCap Investment Research and hired the founder/CEO Steven Cress as head of Quant Strategies to oversee the quantitative modeling. On June 3rd of 2019, the SA Product Team announced that they added three new measures to their platform: quant ratings and recommendations, factor grades, and detailed comparison data. In addition to providing access to quant ratings, Seeking Alpha added educational tools emphasizing the value of quantitative investing. For example, the site introduced information on the strong historical performance of quant ratings and offered frequent webinars that discussed the advantages of quantitative investing. Thus, the introduction of quantitative ratings on the SA platform both educated investors about the benefits of quantitative investing and reduced the cost associated with acquiring quantitative signals.

Appendix A provides an example of the information available for each of the quantitative metrics for TSLA. We see that TLSA has a quant rating of 3.43, which corresponds to a quant recommendation of *Hold*. More generally, quant ratings are mapped to quant recommendations using the following scale: *Strong Sell* (Quant Rating < 1.5), *Sell* (*1.5*<=Quant Rating<2.5), *Hold* (*2.5* <=Quant Rating <3.5), *Buy* (*3.5*<=Quant Rating <4.5), and *Strong Buy* (Quant Rating >=4.5). Users are also able to observe the factor grades for the five primary factors that are considered in the quantitative model: Valuation, Growth, Profitability, Momentum, and Earnings Revisions. We note that the Growth factor constructed by SA is not intended to measure the academic definition of growth stocks (e.g., high market-to-book) but rather to capture growth in profitability (e.g., revenue growth, growth in ROA, etc.). Users can also click on specific factor grades to better understand their inputs and examine how TLSA ranks on each input relative to other firms in the same Global Industry Classification

Standard (GICS) sector. For example, with respect to profitability, TSLA had a relatively low grade on Gross Profit Margin but performed well on many other metrics.

SA does not provide the exact formula used to compute the quantitative ratings. They note that the five factor grades influence the overall quant rating, but they acknowledge that factors outside of the factor grades including firm size and measures of risk also influence the quant score.[6] They also emphasize that ratings are relative to the current sector at a given point in that time. Thus, the measures are designed to identify better performing stocks within a sector but should not be used to pick better performing sectors or for market timing. All quantitative measures are updated daily.

Importantly, the quantitative measures are only available to paid subscribers (i.e., premium or pro members).[7] SA reports that roughly 270,000 of its 10 million members are premium or pro subscribers. However, SA also notes that active contributors, defined as contributors who publish at least one report in the past 60 days, receive free access to premium tools, including the quant ratings. Thus, while the casual SA member is unlikely to have access to SA's quantitative research, regular SA contributors will have the ability to incorporate quantitative research into their reports.

We collect SA quant ratings, quant recommendations, and factor grades for all stocks from January 2015 through December 2022 from Seeking Alpha.[8] We also obtain all research reports published on the Seeking Alpha website over the same window. For each report, we collect the following information: a report ID assigned by Seeking Alpha, report title, main text, date and time of the article publication, author name, the ticker (or tickers) assigned to each report, and the author's

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[6] For additional information, see: https://seekingalpha.com/article/4263303-quant-ratings-and-factor-grades-faq

[7] Seeking Alpha offers three main subscription plans to users: Basic, Premium, and Pro. The basic plan is free and includes access to news updates, email alerts, and allows users to read up to five research reports per month. The premium version is $30 per month (or $240 per year), and it includes all the benefits of the basic model plus unlimited access to research reports and additional features including access to the quant ratings. The pro-model is $300 per month (or $2400 per year) and includes all the features of the premium model, plus access to exclusive research ideas and additional VIP services.

[8] Seeking Alpha currently provides historical ratings through August of 2019. However, when we began collecting the data, we were able to collect "back-filled" quantitative ratings starting from January 2015. The ratings are backfilled in the sense that they were not provided to SA users in real-time. However, all the estimates are out-of-sample. For example, 2015 quant ratings are constructed using only pre-2015 data.

rating at publication. The author's rating at publication includes the following categories: *Strong Sell*, *Sell*, *Hold*, *Buy*, and *Strong Buy*. The *Strong Sell* and *Strong Buy* labels are infrequent, and they were not used prior to December of 2018. Accordingly, we convert the author rating into a 3-point recommendation system by combining *Strong Sell* and *Sell* (hereafter: *Sell*) and combining *Strong Buy* and *Buy* (hereafter: *Buy*).

Following Chen et al. (2014) we limit the sample to reports that are associated with one ticker. We also find that Seeking Alpha updates old reports with current tickers. For example, reports written about LinkedIn prior to the Microsoft merger are still assigned Microsoft's ticker. We therefore further limit the sample to reports that explicitly mention the company's ticker or the company's name within the text.[9] Finally, we require that the report is for a common stock (CRSP share code 10 and 11) with available data in the CRSP database.

2.2 Descriptive Statistics

Table 1 provides year-by-year descriptive statistics for the sample. Here, and throughout the paper, we limit the sample to the 2016-2022 sample period which results in a three-year period prior to the introduction of the quant ratings (2016-2018), the event year (2019), and a three-year period after the introduction of quant ratings (2020-2022). In an average year, the sample includes roughly 4,200 common stocks in the CRSP universe. Roughly 65% (2,750) of the stocks have a quant rating on the Seeking Alpha platform, and the quant rating coverage has steadily improved over time. In an average year, the sample consists of 18,716 SA reports, of which close to 85% (15,710) cover stocks with an available quantitative rating. On average, about 54% of all SA reports issue a buy recommendation, 9% of SA reports issue a sell recommendation, and the remaining 37% issue a hold recommendation.

[9] This filter eliminates roughly 7% of all observations. Since it is possible that this filter also eliminates some correct reports that may use an abbreviation for the company name, we have repeated all these tests without this filter. The results are very similar.

Panel B of Table 1 reports the distribution of quant ratings and quant recommendations. The average quant rating is 2.95 with a standard deviation of 0.89. 64% of stocks are rated as *Hold*, while the remaining 36% of stocks are roughly evenly distributed across the other four categories (*Strong Sell*, *Sell, Buy,* and *Strong Buy*). The distribution of quant ratings and quant recommendations is stable over time, which is consistent with SA's claim that quant ratings are based on relative metrics.[10]

2.3 SA Quant Ratings Versus Academic Anomalies

In this section, we explore the extent to which *Quant Ratings* correlate with anomalies studied in the academic literature. We follow Jensen, Kelly, and Pedersen (2023) [hereafter JKP] and construct 153 firm characteristics based on various market data from CRSP and accounting data from Compustat.[11] We limit the sample to 118 firm characteristics that were significant predictors of returns in the original sample (as defined in JKP). We also group the 118 anomaly variables into 13 distinct factor clusters. We list the 118 firm characteristics used in this study, and the corresponding factor cluster, in Table IA.1 of the Internet Appendix.

To create the anomaly portfolios, each month we sort stocks into quintiles, based on NYSE breakpoints, for each anomaly characteristic. We form long-short portfolios based on the extreme quintiles where the long side is the side with the higher expected return as documented in the original publication. We compute *Net Anomaly* as the number of times the stock appears in the long leg of the anomaly portfolio less the number of times the stock appears in the short leg.

We next estimate the following panel regression:

$$Quant\ Rating_{it} = \alpha + \beta_1 NetAnomaly_{it} + FE_{it} + \varepsilon_{it.} \tag{1}$$

[10] Table IA2 of the Internet Appendix also reports transition matrices for the quant recommendations at daily, monthly, and annual horizon. We find that ratings for a given firm are highly persistent over shorter horizons and moderately persistent over longer horizons. For example, 95% of firms with a strong buy retain the strong buy rating in the subsequent day, 64% retain the strong buy in the subsequent month, and 18% over the subsequent year (compared to an unconditional mean of 9%).

[11] We thank the authors for providing detailed code and documentation needed to construct the variables. Interested readers can find more information at https://github.com/bkelly-lab/ReplicationCrisis.

Quant Rating and *Net Anomaly* are the quantitative rating provided by Seeking Alpha and the net anomaly measure, as of the end of month *t*, and *FE* denotes sector × month fixed effects. We follow SA and define sectors using the GICS 11 sector classification. We standardize *Quant Rating* and *Net Anomaly* to have mean zero and unit variance, and we cluster standard errors by firm and time.

Table 2 reports the results. As expected, we find a strong positive relation between *Net Anomaly* and *Quant Rating*. The point estimate indicates that a one-standard deviation increase in *Net Anomaly* is associated with a 0.30% standard deviation increase in *Quant Rating*. The estimate is also highly statistically significant (t-stat = 30.46). We note, however, that the r-squared from the model is only 9%, indicating that the overwhelming majority of the variation in *Quant Ratings* is unexplained by the *Net Anomaly* measure.

One potential explanation for the relatively low r-squared is that *Quant Ratings* overweight certain anomalies and underweight (or even contradict) other anomalies. To explore this possibility, Specification 2 reports the results from regressing *Quant Rating* on the *Net Anomaly* score for the 13 different factor clusters. We observe significant heterogeneity in the estimates across factor clusters. *Quant Rating* is strongly related to *Momentum, Value, Profit Growth, Low Risk,* and *Quality*. The large loadings align well with the metrics that Seeking Alpha reportedly emphasizes. *Momentum, Value and Profit Growth* are explicitly mentioned in the factor grades and many of the metrics that drive the profitability factor score (e.g., return on assets) are included in the *Quality* factor cluster. At the same time, *Quant Ratings* exhibit negative correlations with a few factors, including *Size* and *Reversal*. The negative loading on *Size* (i.e., recommending larger stocks) and the positive loading on *Low Risk* is consistent with SA's claim that *Quant Ratings* also consider size and risk. The negative loading on *Reversals*, which includes one-month return reversals (Jegadeesh, 1990), is likely driven by the fact that the momentum strategies considered by SA do not follow the common academic convention of skipping the most recent one-month return.

3. Quant Ratings and the Cross-Section of Stock Returns

We next examine whether Quant Ratings contain useful information for predicting stock returns. At the end of each month, from December 2015 through November 2022, we form five portfolios by sorting stocks based on their *Quant Recommendation*. We also consider a long-short portfolio that goes long stocks with a *Strong Buy* recommendation and short stocks with a *Strong Sell* recommendation. For each portfolio, we report the average monthly return in the month following portfolios formation (i.e., January 2016 through December 2022). We report raw-returns and alphas from the following factor models: 1) the market model (CAPM alpha), the Fama-French (1993) three-factor model (3-factor alpha), the Carhart (1997) four-factor model (4-factor alpha), the Fama-French (2015) five-factor model (5-factor alpha), and the Fama-French (2015) five-factor model augmented to include the Carhart (1997) momentum factor (6-factor alpha).

Panels A and B of Table 3 report the equal-weighted and value-weighted portfolio returns. Across all the return measures considered, we find that average portfolio returns increase with the quantitative recommendation. For example, the equal-weighted CAPM alpha increases from -1.30% for the strong sell portfolio to 0.84% for the strong buy portfolio, and the difference between the long and short portfolio of 2.15% is economically large and statistically significant. Including additional factors tends to attenuate the magnitudes. For example, the six-factor alpha falls to 1.52%, but the estimate remains highly significant. The long-short portfolio return estimates remain highly significant for the value-weighted portfolios, which suggests that the return predictability of quant ratings is present in larger and more liquid stocks. This finding is particularly important given the evidence that SA coverage exhibits a strong tilt towards larger companies (Farrell et al., 2022).[12]

[12] In Figure IA.1 of the Internet Appendix, we compute analogous return to following a quant strategy using the *Net Anomaly* measure of Jensen, Kelly and Pedersen, 2023 (as describes in Section 2.3). We find that the return patterns are qualitatively similar.

Figure 1 also reports the factor-loadings from the value-weighted six-factor model. Consistent with the estimates in Table 2, we find that the long-short portfolios load heavily on value stocks, momentum stocks, stocks with high profitability, and larger stocks. A comparison of the 6-factor alpha (1.20%) and the CAPM alpha (1.95%) suggests that passive factor loadings contributed roughly 0.75% to monthly returns.[13]

Figure 2 reports the value-weighted monthly CAPM alpha for each year in the sample. We see that the estimates are positive in six of the seven years considered. We also note that the alphas are statistically significant in both the three-year pre-event window (2016-2018) and the three-year post-event window (2020-2022). The latter finding is particularly important since it suggests that investors could potentially benefit from *Quant Ratings* even after they were made publicly available on the Seeking Alpha platform.[14]

4. Do Quant Ratings Influence SA Research?

The results from the prior section suggest that *Quant Ratings* contain useful information that can potentially enhance the informativeness of SA research reports. In this section we explore whether *Quant Ratings* influence SA research report recommendations.

4.1 The Frequency of "Quant" Reports

We begin by counting the number of SA reports that mention words commonly associated with SA's new quantitative ratings (hereafter *Quant Reports*). Specifically, we search all SA reports for any of the following expressions: 'quant', factor grade', 'value grade', 'growth grade', 'profitability grade', 'momentum grade', or 'revisions grade'.[15] Appendix B provides excerpts from a bullish and

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[13] There is considerable debate over whether the returns attributable to factor loadings are compensation for risk or mispricing. We do not take a stance on this issue. However, studies that examine the revealed preferences of retail investors using mutual fund flows conclude that investors treat returns attributable to non-market factor loadings as alpha (see, e.g., Berk and van Binsbergen, 2016, Barber, Huang, and Odean, 2016, and Clifford, Fulkerson, Jame, and Jordan, 2021).
[14] One might expect that the dissemination of quantitative ratings would attenuate anomaly mispricing. One potential explanation is that only SA premium members, a relatively small fraction of total traders, have access to the quant ratings.
[15] We also allow for minor variants of each expression such as 'grade for value' instead of 'value grade'.

bearish *Quant Report*. While anecdotal, these excerpts indicate that SA quant ratings are directly incorporated in at least some SA reports.

To provide more systematic evidence, Figure 3 plots the total number of *Quant Reports* over each year in the sample period. We see that the total number of quant reports in the three years prior to the introduction of quant ratings is small ranging from 10 reports in 2016 to 48 reports in 2018. In sum, of the 46,798 reports issued in the three-year pre period, 71 reports (0.15%) are classified as *Quant Reports*. In contrast, in the three-year post period 1,583 reports (3.15%) are classified as *Quant Reports*. Although the 3.15% estimate is not particularly large in absolute terms, it represents a more than 20-fold increase relative to the pre-period estimate. Further, the estimates have been steadily increasing over time, which points to the possibility that quant reports may become more prevalent in the future. Lastly, we note that quant ratings may influence SA contributors reports even when SA contributors do not explicitly cite Seeking Alpha's quant ratings or factor grades. We explore this possibility further in the next sections.

4.2 SA Report Recommendations and Quantitative Ratings

Our second test examines whether SA report recommendations (i.e., Buy, Hold, or Sell) become more correlated with *Quant Ratings* after they are made available on the platform. We estimate the following panel regression:

$$Report\ Rating_{it} = \alpha + \beta_1 Quant\ Rating_{it} + \beta_2 Quant\ Rating_{it} \times Post_t + FE + \varepsilon_{it.} \quad (2)$$

The dependent variable, *Report Rating*, equals one for SA reports making a buy recommendation, zero for reports making a hold recommendation, and negative one for reports making a sell recommendation. *Quant Rating* is the quantitative rating and *Post* is an indicator equal to one if the report was written in the post-period (2020-2022) and zero if the report was written in the pre-period

(2016-2018).[16] In our baseline specification FE denotes date × sector fixed effects, where sector correspond to the 11 GICS sectors. Standard errors are clustered by both firm and date.

Specifications 1 of Table 4 reports the results. We find that the coefficient on *Quant Rating* is insignificant suggesting that *Report Rating* was unrelated to *Quant Ratings* prior to the introduction of quant ratings. In contrast, the coefficient on *Quant Rating* × *Post* is positive and significant. The point estimate indicates that a one-unit increase in the quant rating is associated with a 5.50 percentage point increase in *Report Rating*. This estimate corresponds to an increase of roughly 13% relative to the mean of *Report Rating* (0.42).[17]

One potential alternative explanation for our findings is that the composition of stock with high quant ratings shifted towards firms that are generally more well-liked by SA contributors Similarly, the composition of contributors on the SA platform may have shifted over time towards contributors that naturally tend to prefer stocks with high quantitative ratings (e.g., contributors following momentum strategies). To explore these possibilities, Specifications 2 and 3 augment the baseline model by including firm fixed effects and contributor fixed effects, respectively. While the inclusion of firm or contributor fixed effects results in slightly reduced magnitudes, the estimates remain highly significant. Further, the fixed effects absorb a lot of the unexplained variation in report recommendations, resulting in more precise estimates.

Another important concern is that the increased correlation between SA report recommendation and *Quant Ratings* could reflect a shift of SA contributors towards more quantitative methods (e.g., machine learning models) that is independent of the introduction of quantitative ratings on the SA platform. If so, we might expect a gradual increase in the correlation between SA report

[16] Our main analysis excludes 2019, the year of the event. However, we include 2019 in the event-time analysis reported in Figure 4.

[17] We also repeat the analysis after replacing *Quant Rating* with indicators for the different quantitative recommendation: *Strong Buy, Buy, Sell, and Strong Sell* (where *Hold* is the omitted group). We find that the difference between the pre and post period exhibits a monotonic pattern, with the effects being particularly strong for the *Strong Sell* category (see Table IA.3 of the Internet Appendix).

recommendations and *Quant Ratings* over time. To explore this possibility, we repeat Specification 3 of Table 4 after replacing *Quant Rating* and *Quant Rating*× *Post* with *Quant Rating* interacted with indicators for each year of the sample (2016-2022). Figure 4 reports the results. We find no obvious time-series trend in the pre-period (2016-2018). In particular, the estimates on *Quant Rating* are statistically insignificant in all three years, and the estimate is largest in the first year of the sample, which is inconsistent with pre-trends driving the results. We find significant increases in each year of the post period. The largest estimate is in 2022 which also corresponds to the year with the largest increase in the number of *Quant Reports* (see Figure 3).

4.3 SA Report Recommendations and Quantitative Ratings – Quant Reports versus Non-Quant Reports

The results from the prior section suggest that after *Quant Ratings* were made available on the SA platform, SA report recommendations became more correlated with *Quant Ratings*. Intuitively, we would expect this effect to be particularly strong in reports that explicitly mention quant-related words (*Quant Reports*). However, we also conjecture that *Quant Ratings* may help align SA report recommendations with quantitative metrics even when the research report does not explicitly mention quant words (*Non-Quant Reports*). For example, a user who was planning on writing a bullish report may chose not to write the report after observing very poor quantitative ratings.

We separately examine the impact of *Quant Reports* and *Non-Quant Reports* by repeating the tests in Specifications 1-3 of Table 4 after partitioning *Quant Rating* × *Post* into *Quant Rating* × *Post* × *Non-Quant Report* and Quant *Rating* × *Post* × *Quant Report,* and we also include a *Post* × *Quant Report* indicator.[18] Specifications 4-6 of Table 4 report the results. We find that the coefficient on *Quant Rating* × *Post* × *Non-Quant Report* remains statistically significant. For example, the point estimate in Specification 4 is 4.95, which is about 90% of the baseline estimate in Specification 1 (5.50%). This

[18] We do not conduct an analogous partition for pre-period reports because the sample of pre-period *Quant Reports* is very small (see Figure 3).

finding is consistent with our prediction that *Quant Ratings* help align SA report recommendations with quantitative measures even when the report does not explicitly mention quantitative words.

The coefficient on *Quant Rating* × *Post* × *Quant Report* is highly significant, both statistically and economically. The point estimate in Specification 4 is 17.48, which represents a nearly 40% increase relative to the sample mean. The estimates remain similar when including firm and contributor fixed effects in Specifications 5 and 6. We also confirm that the estimates for *Quant Rating* × *Post* × *Quant Report* are significantly greater than the estimates for *Quant Rating* × *Post* × *Non-Quant Report* across all three specifications. Thus, as expected, reports that explicitly mention quantitative metrics issue report recommendations that are more closely aligned with quant ratings.

4.4 SA Report Recommendations and Quantitative Ratings – ETF Quant Ratings

To provide additional evidence that platform design changes can influence SA research production, in this section we examine the consequence of an alternative shock to the display of quantitative information on the SA platform: the introduction of quantitative ratings for exchange traded funds (ETFs). ETF quant ratings were introduced in March of 2021, nearly two years after the introduction of quantitative ratings for stocks. Further, the calculation of quant ratings for ETF relies on an entirely different formula. Specifically, ETF *Quant Ratings* are influenced primarily by the following five factors: Asset Flows, Risk, Dividends, Expenses, and Momentum.[19] ETF Factor grades are based on the ETFs performance on various metrics relative to other ETFs in the same asset class.[20] Although SA introduced the quant ratings in March of 2021, they provided backfilled quant ratings beginning in November of 2019. Accordingly, our sample for this analysis includes

[19] Additional details regarding the construction of ETF Quant Scores and the factors is available here: https://seekingalpha.com/article/4415372-not-all-etfs-are-created-equal-seeking-alphas-new-etf-grades-separate-the-best-from-the-worst

[20] SA assigns ETFs into one of the following ten asset classes: US Equity, Sector Equity, International Equity, Nontraditional Equity, Taxable Bond, Municipal Bond, Commodities, Allocation, Alternative, and Miscellaneous.

8,428 single-ticker ETF reports with non-missing quant ratings from November of 2019 through December 2022.

We next re-estimate Equation 2 for the ETF sample. In this analysis, we define the event-period as the [-2,2] window where month 0 is the month in which ETF quant ratings are announced (i.e., March 2021). We set *Post* equal to one for all months after the event period (i.e., June 2021-December 2022), and zero for all months prior to the event period (i.e., November 2019-December 2020). In the baseline specification, FE denotes date × asset class fixed effects. Specifications 2 and 3 augment the baseline model by adding ETF fixed effects and contributor fixed effects, respectively.

The results are reported in Table 5. Across all three specifications, we find that the coefficient on *Quant Rating ETF* is positive and significant, which indicates that SA contributors were issuing research reports that aligned with ETF *Quant Ratings* even prior to their introduction. More importantly, we find that *Quant Rating ETF × Post* is positive and significant, indicating that SA report rating become even more aligned with ETF quant ratings after the ratings were disclosed on the website. The point estimates range from 5.65 to 6.21 percentage points. These estimates are similar but slightly larger than the corresponding estimates for common stocks reported in Table 4.

Specification 4 also considers an event time analysis. We replace *Quant Rating ETF* and *Quant Rating ETF × Post* with *Quant Rating ETF* interacted with three separate pre-period indicators, an event-time indicator, and three separate post-period indicators. We find no obvious trends in the pre-period. We also observe an immediate and permanent increase in the post-period. These findings echo the patterns found for common stocks (reported in Figure 4), and they provide further evidence that quant ratings help align contributors research recommendations with quantitative signals.

4.5 SA Report Recommendations and Quantitative Ratings – The Role of Contributor Sophistication

We next examine whether the influence of quantitative ratings varies with proxies for contributors' familiarity with quantitative investing (hereafter: quantitative sophistication). We do not have strong expectations regarding the direction of this relationship. Investors with relatively low levels of quantitative sophistication may be less inclined to consider quantitative ratings once they are introduced. This could be because they are less attentive to new information sources or find the information too complex to incorporate easily. Consistent with this view, Fernandes, Lynch, and Netemeyer (2014) find that interventions to improve financial literacy were less effective among individuals with lower levels of existing sophistication. On the other hand, investors with high levels of quantitative sophistication might already be integrating quantitative analysis into their research before the introduction of quantitative ratings. In this case, the introduction of such ratings is likely to yield smaller benefits for the most sophisticated investors.

We create three measures of quantitative sophistication. The first measure, *Bio Sophistication*, involves counting words found in a contributor's self-reported bio that likely correlates with general financial acumen and experience in quantitative investing. We identify the following words as indicative of familiarity with quantitative analysis: "Quant", "Short", "Long/Short", "Analyst", "Portfolio Manager", "Mutual Fund", "Hedge Fund", "Asset Management", "Fund Manager", "Chief Investment Officer (CIO)", "Investment Bank", "Wall Street", "Sell-Side", and "Marketplace".[21] *Bio Sophistication* is set equal to one (or low) if the bio does not mention any of the above words, two (or mid) if the bio includes one word, and three (or high) if the bio contains two or more words.

The word list is admittedly ad-hoc, so we also construct a 2nd biography-based measure that relies on Chat GPT's assessment of the contributors' quantitative skill (*GPT Sophistication*). Specifically, we tasked ChatGPT with rating contributor bios for quantitative skill using a scale ranging from 1 to 10. Appendix D includes two bio examples along with ChatGPT's ranking and rationale for each ranking. We set *GPT Sophistication* to one (or low) if the 1-10 bio ranking falls in the bottom quartile

[21] We include "Short" to capture short selling rather than a short investment horizon. Accordingly, we exclude "short" if it is immediately following by "term" or "horizon". We include *Marketplace* to capture investors who sell their research on Seeking Alpha's marketplace (see, e.g., https://seekingalpha.com/article/4267212-seeking-alphas-first-millionaire).

of the distribution, two (or mid) if the bio ranks in the middle 50% of the distribution, and three (or high) if the bio ranks in the top 25% of the distribution.

We expect that contributors with greater financial sophistication and quantitative abilities will garner more attention and discussion, as measured by the average number of comments on their last ten reports (*Comment Sophistication)*. We set *Comment Sophistication* to one (or low) if the average number of comments falls within the bottom quartile of the distribution, two (or mid) if the comments fall within the middle 50% of the distribution, and three (or high) if the average number of comments is in the top 25% of the distribution.

Finally, we consider a composite measure of sophistication, *Quant Sophistication*, defined as the sum of the *Bio Sophistication*, *GPT Sophistication*, and *Comment Sophistication.* We also partition *Quant Sophistication* into three groups: low, mid, and high, based on the 25th and 75th percentile breakpoints.

To examine how the relation between SA report recommendations and quant ratings varies with quant sophistication, we re-estimate equation (2) for contributors within each of the *Quant Sophistication* groups.[22] Specifications 1-3 of Table 6 report the results for the low, middle, and high sophistication groups, and Specification 4 tests whether the estimates for the low group are significantly different from the estimates for the high group.[23] Specifications 5 and 6 repeat Specification 4 after adding either firm fixed effects or contributor fixed effects.

We find that the coefficient on *Quant Rating* increases from -1.98% for the low sophistication group to 3.32% for the high sophistication group, and the difference between the two estimates is significant. Specifications 5 and 6 confirm this result is robust to including either firm fixed effects or contributor fixed effects. This finding is consistent with investors with higher levels of quant

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[22] We also estimate the results using each of the individual sophistication measures (*Bio Sophistication, GPT Sophistication, and Comment Sophistication*). The results, summarized in Figure IA.2 of the Internet Appendix, indicate that the estimates are qualitatively similar across all the sophistication measures.
[23] We modify equation 2 by replacing *Sector* × *Date* fixed effects with *Sector* × *Date* × *Quant Sophistication Group* fixed effects. The inclusion of *Quant Sophistication Group* fixed effects allows the estimates on the *Low -High* sample (e.g., Specification 4) to be equal to the estimate on the Low sample (Specification 1) minus the estimate on the *High Sample* (Specification 3).

sophistication issuing research report recommendations that are more aligned with quantitative ratings prior to the disclosure of quant ratings.

The coefficient on *Quant Rating* × *Post* displays a contrasting pattern. The estimates decline from 11.49% for the low sophistication group to 0.52% for the high sophistication group, and the difference between the estimates is highly significant. This suggests that the introduction of quant ratings had a more pronounced impact on the research report recommendations of contributors with lower quantitative sophistication. Further, the combined coefficient (i.e., *Quantrating* + *QuantRating* ×*Post*) is significantly greater for the lower sophistication group. Thus, in the post-event period research report recommendations for the lower sophistication group are more closely aligned with quant ratings. One potential explanation for this finding is that higher sophistication users incorporate a broader range of factors beyond quantitative ratings when making their report recommendations.

5. Quant Ratings and the Value of SA Research

In this section, we examine whether quant ratings make SA research more valuable, as measured by either the correlation between the report recommendation and future returns (Sections 5.1 – 5.4) or the extent to which they help retail investors incorporate quantitative analysis into their trading decisions (Section 5.5).

5.1 Quant Ratings and the Informativeness of SA Research – Baseline Results

Section 3 documents that quant ratings are strongly predictive of future returns, and Section 4 finds that SA report recommendations became more correlated with quant ratings after the introduction of quant ratings on SA platform. Taken together, these findings point to the possibility that SA report recommendations became more predictive of future returns (i.e., more informative) following the release of the quant ratings. On the other hand, prior work finds that SA research is also a strong predictor of future returns (Chen et al., 2014). Thus, if quant ratings serve as a substitute for fundamental analysis, then reports that incorporate quantitative information could contain less fundamental information, and potentially less total information. This prediction is in line with Dugast and Foucault (2018), who note that while low precision signals (e.g., quant ratings) can be valuable, their presence may ultimately harm informativeness because they reduce the incentive to collect more precise signals (e.g., users own information production). Thus, the relation between quant ratings and report informativeness is ultimately an empirical question.

We examine changes in report informativeness for quant and non-quant reports following the release of the quant ratings using the following regression:

$$Ret_{it+1,t+x} = \alpha + \beta_1 ReportRating \times Pre_t + \beta_2 ReportRating_{it} \times Post_t \times NonQuant_{it} + \beta_3 ReportRating_{it} \times Post_t \times Quant_{it} + \beta_4 Post_t \times Quant_{it} + FE + \varepsilon_{it.} \quad (3)$$

The dependent variable, $Ret_{it+1,t+x}$, is the market-adjusted stock return measured over the subsequent week (i.e., x = 5 trading days), the subsequent month (x=21), or the subsequent quarter (x=63). We define day [0] as the date on which an investor could have first traded on the report. For example, if a report was issued at 5 pm on Tuesday, August 1, we classify the date of the report as Wednesday, August 2, and we define the [1,5] day return as the return from Thursday, August 3 through Wednesday, August, 9. We exclude the Day [0] return to reduce the impact of potentially confounding news that could influence both the report and the Day [0] return.[24] *Report Rating* equals one for SA reports making a buy recommendation, zero for reports making a hold recommendation, and negative one for reports making a sell recommendation. *Pre* is an indicator equal to one for SA reports issued over the 2016-2018 period and zero otherwise, and *Post* is an indicator for reports issued over the 2020-2022 period and zero otherwise. *Non-Quant* and *Quant* are indicators for non-quant reports and quant reports, respectively. FE denote month fixed effects, and standard errors are clustered by firm and month.

[24] Chen et al. (2014) adopt a similar methodology, but they skip two days (i.e., days 0 and 1). We have repeated our tests using this approach, and we find very similar results.

Table 7 reports the results. We find that *Report Rating* × *Pre* is generally insignificant which suggests that SA report recommendations were not informative over the 2016-2018 sample period.[25] We also do not observe a robust relation between future returns and SA report recommendations of non-quant reports in the post-period. However, the coefficient on *Report Rating* × *Post* × *Quant* is significant across all return horizons. The point estimates indicate that for *Quant Reports* issued in the post period, a one-unit increase in SA report recommendations (i.e., moving from a hold to a buy) is associated with 0.84% higher returns over the subsequent week, 1.85% higher returns over the subsequent month, and 2.97% higher returns over the subsequent quarter. Further, the estimates on *Report Rating* × *Post* × *Quant* are significantly larger than the estimates on *Report Rating* × *Pre* and *Report Rating* × *Post* ×*Non-Quant,* indicating that *Quant Reports* are more informative than SA reports issued in the pre-period and more informative than *Non-Quant Reports* issued in the post-period.

5.2 Quant Ratings and the Informativeness of SA Research – Return Decomposition

The superior performance of *Quant Reports* could stem from two factors. First, *Quant Reports* may simply benefit from tilting their recommendations towards stocks with high quant ratings, which tend to earn higher future returns (Table 3). Second, *Quant Reports* may be able to identify better performing stocks event among stocks with very similar quant ratings.

To estimate the relative importance of these two factors, each day we sort stocks into 25 portfolios based on the quant rating (*Quant Portfolio*). The typical *Quant Portfolio* contains 100 stocks, and the median spread between the maximum and minimum quant rating within a *Quant Portfolio* is 0.06. We define *Quant-Style Return* as the average return across all stocks in the *Quant Portfolio*, and we define *Quant-Adjusted Return* as the difference between the stock return and the *Quant-Style Return.*

[25] SA report recommendations across all periods are strongly correlated with day 0 returns. Thus, it is possible that much of the value of report recommendations is immediately incorporated into prices. Our focus is primarily on cross-sectional patterns (i.e., which reports are relatively more informative), and we find that the main conclusions regarding cross-sectional differences in informativeness are very similar when including day 0 returns.

Thus, *Quant-Style Returns* capture the average returns attributable to recommending a stock with a specific *Quant Rating* while *Quant-Adjusted Return* captures stock-picking ability holding the *Quant Rating* (essentially) constant.

Specifications 1-3 and 4-6 of Table 8 repeat the analysis in Table 7 after replacing market-adjusted returns with *Quant-Style Return* and *Quant-Adjusted Returns*, respectively. We find that *Report Rating* × *Post* × *Quant* is significantly related to *Quant-Style Return* over both a one-month and one-quarter horizon. The one-quarter result suggests that *Quant Reports* tendency to recommend stocks with higher quant ratings results in 1.72% higher returns, which accounts for roughly 60% of the total return predictability documented in Table7.

We also find that *Report Rating* × *Post* × *Quant* is positively related to *Quant-Adjusted Returns*, although the estimate loses statistical significance at the one-quarter horizon. Nevertheless, the shorter horizon results are consistent with *Quant Reports* having some ability to identify better performing stocks within a quant rating. This finding is inconsistent with the conjecture that quant reports "crowd out" valuable fundamental analysis. Instead, the positive estimates point to the possibility that quantitative analysis serves as a complement to users own information production.

5.3 Quant Ratings and the Informativeness of SA Research – Robustness

In this section, we examine whether the findings from Tables 7 and 8 are robust to different research design choices. In the interest of brevity, we focus on the 63-day return horizon, and we only report the coefficients testing whether *Quant Reports* are more informative than pre-period reports (*Post* × *Quant - Pre)* and more informative than post-period *Non-Quant Reports* (*Post* × *Quant - Post* × *Non-Quant)*. For reference, Row 1 of Table 9 reports the baseline results from Tables 7 and 8.

Rows 2-5 explore whether our results are robust to the inclusion of various fixed effects. First, since quant ratings are relative to a sector, in Row 2 we replace month fixed effects with sector × month fixed effects. Rows 3 and 4 include firm fixed effects and firm × report rating fixed effects.

The inclusion of firm fixed effects (Row 3) helps address the concern that some firms have persistently higher return, while the inclusion of firm × report rating fixed effects addresses the concern that report informativeness is particularly strong for certain types of firms (e.g., the returns on smaller stocks following buy recommendations is particularly large, while the return following sell recommendations are particularly small). Rows 5 and 6 include contributor and contributor × report rating fixed effects. The inclusion of contributor × report rating fixed effects is particularly useful in controlling for differences in contributor skill. We find that the main patterns are qualitatively similar across all specifications.

The year-by-year results reported in Figures 3 and 4 suggest that quant ratings began influencing SA reports immediately in 2019. Accordingly, in Row 7, we expand the definition of *Post* to include 2019. We find the results are qualitatively unchanged. One concern is that our results are being driven by a few stocks that earned very extreme returns during the post-period (e.g., GME). To explore this possibility, we repeat the tests after winsorizing returns at the 1st and 99th percentile (Row 8). We find the post estimates are very similar (and more precisely estimated), which alleviates the concern that our results are driven by a small set of influential outliers.

5.4 Quant Ratings and the Informativeness of SA Research – Contribution Sophistication

The evidence from Section 4.5 indicates that the introduction of quantitative ratings had a more pronounced influence on less quantitatively sophisticated investors. This finding points to the possibility that the informativeness of reports authored by less quantitatively sophisticated investors increased relative to more sophisticated users. We examine whether changes in report informativeness vary with contributors' quantitative sophistication by estimating the following regression:

$$\begin{aligned} Ret_{it+1,t+x} = \; & \alpha + \beta_1 ReportRat. + \beta_2 ReportRat._{it} \times Post_t \\ & + \beta_3 ReportRat._{it} \times QuantSoph_{it} \\ & + \beta_4 ReportRat._{it} \times Post_t \times QuantSoph_{it} + \beta_5 QuantSoph_{it} \\ & + \beta_6 QuantSoph_{it} \times Post + FE + \varepsilon_{it.} \end{aligned} \tag{4}$$

The dependent variable, $Ret_{it+1,t+x}$, is the stock return measures over the subsequent month (x=21), or the subsequent quarter (x=63), where the stock return is either the market-adjusted return, the *Quant-Style* return, or the *Quant-Adjusted* return. *Report Ratings* and *Post* are defined as in equation (3), and *QuantSoph* is the composite quantitative sophistication measure, standardized to have mean 0.[26] Thus, our key estimate of interest is β_4 which measures how the change in report informativeness after the disclosure of quant ratings varies with contributors' quantitative sophistication.

Specifications 1- 3 of Table 10 report the market-adjusted, *Quant-Style*, and *Quant-Adjusted* returns for the 21-day horizons, and Specifications 4-6 report analogous results for the 63-day horizon. At the 63-day horizon, we find that a one unit decrease in *Quant Sophistication* is associated with a significant 0.82% increase in one-quarter ahead returns in the post-event period. The return decomposition indicates that 0.25% of this effect is attributable to simply being more aligned with quantitative ratings (i.e., *Quant Style Returns*), and this estimate is highly significant. The estimate on *Quant-Adjusted returns,* while larger in economic magnitude, is not reliably different from zero. In sum, quant ratings improved the informativeness of the research reports of investors with lower levels of sophistication relative to contributors with higher levels of sophistication, and this improvement is at least partially attributable to a stronger alignment between report recommendations and quant ratings.

5.5 Do SA Reports Help Retail Investors Incorporate Quant Ratings?

In our final set of tests, we explore whether the increased alignment between SA research reports and quant ratings helps retail investors better incorporate quantitative ratings into their trading decisions. Our approach for identifying retail trading relies on the methodology of Barber et al. (2023). Specifically, for all trades with TAQ exchange code "D", we sign a trade as a retail buy (retail sell) if the execution price is greater than (less than) the quoted midpoint, but we do not sign trades that

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[26] The results for the three individual sophistication measures, reported in Figure IA.3 of the Internet Appendix, are qualitatively similar.

execute between 40% and 60% of the National Best Bid or Offer.[27] We define daily retail order imbalances for stock *i* on day *t* as the difference between retail purchase volume and retail sell volume, scaled by total retail volume.

While the dissemination of quant ratings on Seeking Alpha could generally influence retail trading, we expect any effects to be stronger on days when SA research reports are released. First, while SA quant ratings are only available to premium members, SA reports can be disseminated much more broadly. In particular, all SA members have access to at least five free reports per month, and members can share reports with other investors. Furthermore, while only a small percentage of retail investors subscribe to Seeking Alpha premium, this subset of investors likely accounts for a much larger fraction of retail trading following the release of an SA research report (Farrell et al., 2022). In addition, SA reports may prompt investors to do additional research about the firm, including collecting data on quantitative ratings. Thus, we expect that after the platform design change, retail investor trading will become more aligned with quantitative ratings in the period immediately following the release of a research report.

To test this prediction, we sort all SA research reports into five groups based on the quant recommendation of the covered stock. We then report the average retail imbalance for each group on the first day in which an investor could have traded on the report in the pre-period and the post-period. Panel A of Table 11 reports the results. In the pre-period, we find that retail investors tend to trade in the oppose direction of the quant rating. Specifically, their order imbalances are 2.24% lower in stocks rated strong buy relative to stocks rated strong sell. In contrast, in the post-period retail imbalances are 0.78% higher in strong buy stocks relative to strong sell stocks, and the difference-in-

[27] Barber et al. (2023) finds that relying on quoted midpoints leads to higher accuracy rates than using the sub-penny digit approach of Boehmer et al. (2021).

difference estimate of 3.02% is highly significant. In terms of economic magnitude, this estimate is roughly 20% of the standard deviation of retail imbalances.

Prior works finds that retail imbalances are heavily influenced by attention-grabbing events, including earnings announcements, extreme returns, or extreme trading volume (Barber and Odean, 2008). To explore whether our patterns are robust to excluding reports issued on attention-grabbing firms, we repeat the analysis after excluding reports that are issued in the three days around earnings announcements (-1,1) or reports issued for firms that are in the 95th percentile of either absolute returns or trading volume relative to the firm's absolute returns or trading volume over the prior year. The results reported in Panel B of Table 11, indicate that the results are similar (and slightly stronger) after removing reports on attention-grabbing firms. In Figure IA.4 of the Internet Appendix, we also confirm that the difference-in-difference estimates are similar if we include date × industry fixed effects or date × industry and firm fixed effects.

Figure 5 reports the difference-in-difference estimates from Panel B in event-time days (-4, +4) around the release of the report. We find that the significant increase is limited to the day of the report release and the day after the release. In contrast, we find an economically small and statistically insignificant increase in the days prior to the report's release which is inconsistent with pre-trends driving our findings.[28] Our findings are consistent with SA reports helping retail investors better incorporate quantitative ratings into their trading decisions.

At least two mechanisms could contribute to retail investor imbalances becoming more aligned with quant ratings following the release of the report. First, retail traders tend to follow SA investment recommendations (Farrell et al., 2022), and these recommendations have become more aligned with quant ratings. Second, retail investors who are attentive to SA research reports may also collect

[28] In unreported tests, we also confirm that the estimate on Day 0 is significantly greater (at a 1% level) than the estimate on day -1 or the average estimate on days -1 through -4.

information on quant ratings, and these users may be more likely to follow a report recommendation when it aligns with the quant recommendation.

To distinguish these mechanisms, we decompose retail imbalances into predicted versus residual imbalances, where predicted imbalance is the fitted value from a regression of retail imbalances on report rating, and residual imbalance is the difference between retail imbalance and the predicted imbalance.[29] Consistent with Farrell et al (2022), we find that retail imbalances on report days are correlated with the report ratings ($p < 0.001$), however the correlation between the two measures is modest ($\rho = 2.54\%$). Table 12 repeats the analysis in Panel B of Table 11, after replacing retail imbalances with either the predicted imbalances (Panel A) or the residual imbalance (Panel B). We find that the difference-in-difference estimates for both imbalance measures are significant. However, the economic magnitudes are considerably stronger for the residual imbalance, which is consistent with retail investors actively incorporating quant ratings into their trading decisions.[30]

6. Conclusion

The last two decades have witnessed a sharp increase in the importance of social media as a source for investment research. While a growing literature studies the informativeness of specific social media sites, relatively little is known about how specific features of social media influence information production by contributors. This paper explores whether access to quantitative research can influence and enhance social media research. Our empirical strategy exploits the introduction of quantitative ratings on the Seeking Alpha platform as a shock that both educates investors about the value of quantitative research and increases the ease of collecting quantitative signals.

[29] We demean the predicted imbalances so that both the predicted and residual imbalances have mean 0.
[30] In Table IA.4 of the Internet Appendix, we also examine retail imbalances for portfolios double sorted on quant ratings and report ratings. Consistent with the residual imbalance results, in the post-period, we find that retail imbalances become more aligned with quant recommendations for each report rating. We also find that the effects are strongest when report rating equals "Hold".

We first confirm that quantitative ratings are useful. In particular, the quant ratings provided by SA are related to common academic measures of mispricing, and they strongly predict future returns. After the introduction of quant ratings, we observe a 20-fold increase in the proportion of SA reports mentioning "quant" or other quant-related words (*Quant Reports)*. In addition, SA report recommendations become more correlated with quant ratings, particularly among *Quant Reports* and reports authored by less quantitatively sophisticated contributors, who presumably had more limited exposure to quantitative analysis prior to the platform design change.

The increased alignment of SA report recommendations and quantitative ratings enhances the value of SA research reports. In particular, *Quant Report* recommendations are significantly more informative than pre-period reports and post-period *Non-Quant Reports*. A performance decomposition indicates that the superior performance of *Quant Reports* is at least partially attributable to the fact *Quant Reports* systematically recommend stocks with high quant ratings, which exhibit higher average returns. In addition, SA reports help retail investors better incorporate quantitative ratings into their trading decisions.

Our findings have meaningful implications for policy makers, and for contributors, consumers, and designers of social media sites. For policy makers, our findings suggest that modifications in platform design on social media sites could serve as a potentially significant means of improving financial literacy, even for less sophisticated investors. For contributors, we note that the percentage of *Quant Reports*, while rapidly growing, is still a relatively small fraction of total reports. Thus, our evidence suggests that contributors would benefit from more regularly incorporating quantitative research into their analysis. Similarly, consumers of SA research should, all else equal, gravitate towards reports that include some quantitative analysis, and other social media platforms may potentially benefit by providing their own versions of quantitative ratings.[31] Even SA may be able to further enhance the informativeness of their site by making platform design changes that increase the salience of quant ratings. For example, SA could offer prompts for contributors to review quantitative ratings before submitting research reports or issue warning notifications to contributors when they submit a research report with a recommendation that is inconsistent with the quant rating.

[31] Starting in September of 2021, TipRanks introduced "Smart Score Stocks", their own version of a proprietary quantitative scoring system: (https://www.tipranks.com/screener/top-smart-score-stocks).

References

Barber, B., and Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21, 785-818.

Barber, B., Huang, X., Odean, T., 2016. Which factors matter to investors? Evidence from mutual fund flows. *Review of Financial Studies* 29, 2600-2642.

Barber, B.M., Huang, X., Jorion, P., Odean, T. and Schwarz, C., 2023. A (Sub)penny For Your Thoughts: Tracking Retail Investor Activity in TAQ *Journal of Finance*, forthcoming.

Berk, J., and van Binsbergen, J., 2016. Assessing asset pricing models using revealed preferences. *Journal of Financial Economics* 119, 1-23.

Birru, J., Gokkaya, S., Liu, X., and Markov, S., 2022. Quants and market anomalies. *Journal of Accounting and Economics*, forthcoming.

Bradley, D., Hanousek Jr, J., Jame, R. and Xiao, Z., 2024. Place Your Bets? The Value of Investment Research on Reddit's Wallstreetbets. *Review of Financial Studies*, 37, 1409-1459.

Boehmer, E., Jones, C.M., Zhang, X. and Zhang, X., 2021. Tracking Retail Investor Activity. *Journal of Finance*, 76, 2249-2305.

Calluzo, P., Moneta, F., and Topaloglu, S., 2019. When anomalies are publicized broadly, do institutions trade accordingly? *Management Science* 65, 4555-4574.

Carhart, M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.

Chawla, N., Da, Z., Xu, J., and Ye, M., 2022. Information diffusion on social media: Does it affect trading, returns and liquidity? Working paper.

Chen, A., 2021. The limits of p-Hacking: Some thought experiments. *Journal of Finance* 76, 2447-2480.

Chen, H., De, P., Hu, J., and Hwang, B.H., 2014. Wisdom of the crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies* 27, 1367-1403.

Clifford, C., Fulkerson, J., Jame, R., and Jordan, B., 2021. Salience and mutual fund investor demand for idiosyncratic volatility. *Management Science* 67, 5234-5254.

Choi, J., Laibson, D., and Madrian, C., 2010. Why does the low of one price fail? An experiment on index mutual funds? *Review of Financial Studies* 23, 1405-1432.

Choi, J., Laibson, D., and Madrian, C., 2011. $100 Bills on the sidewalk: Suboptimal investment in 401(k) plans. *Review of Economics and Statistics* 33, 748-763.

Cookson, J.A., Lu, R., Mullins, W., and Niessner, M., 2023. The social signal. *Journal of Financial Economics*, forthcoming.

Crawford, S., Gray, W., Johnson, B., and Price, R., 2018. What motivates buy-side analysts to share recommendations online? *Management Science* 64, 2473-2972.

Dugast, J., and Foucault, T., 2018. Data abundance and asset price informativeness. *Journal of Financial Economics* 130, 367-391.

Edelen, R., Ince, O., and Kadlec, G., 2016. Institutional investors and stock return anomalies. *Journal of Financial Economics* 119, 472-488.

Engelberg, J., McClean, D., and Pontiff, J., 2020. Analysts and anomalies. *Journal of Accounting and Economics* 69*,* 1-13.

Fama, E., and French, K., 1992. The Cross-Section of Expected Stock Returns. *Journal of Finance* 47, 427-465

Fama, E., and French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.

Fama, E., and French, K., 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116, 1-22.

Farrell, M., Green, T.C., Jame, R. and Markov, S., 2022. The democratization of investment research and the informativeness of retail investor trading. *Journal of Financial Economics* 145, 614-641.

Fernandes, D., Lynch Jr., J., Netemeyer R., 2014. Financial literacy, financial education, and downstream financial behaviors. *Management Science* 60, 1861-1883.

Giannini, R., Irvine, P., and Shu, T., 2018. Nonlocal disadvantage. An examination of social media sentiment. *Review of Asset Pricing Studies* 8(2), 293-336.

Green, T.C., and Jame, R. 2024. Retail Trading Frenzies and Real Investment. Working paper.

Guo, L., Li, F.W., and Wei, K.C., 2020. Security analysts and capital market anomalies. *Journal of Financial Economics* 137, 204-230.

Hackenthal, A., Hanspal, T., Hartzmark, S, and Brauer, K., 2024. Educating investors about dividends. Working paper.

Hastings, J., Madrian, B., and Skimmyhorn, W., 2013. Financial literacy, financial education, and financial outcomes. *Annual Review of Economics* 5, 347-373.

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

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *Journal of Finance* 45, 881-898.

Jegadeesh, N., and Titman, S., 1993. Returns to buying winners and selling losers: Implications for market efficiency. *Journal of Finance* 48, 65-91.

Jensen, T., Kelly, B., and Pedersen, L, 2023. Is there a replication crisis in finance? *Journal of Finance* 78, 2465-2518.

Kaiser, T., Lusardi, A., Menkhoff, L., and Urban, C., 202. Financial education affects financial knowledge and downstream behaviors. *Journal of Financial Economics* 145, 255-272.

McClean, D., and Pontiff, J., 2016. Does academic research destroy stock return predictability? *Journal of Finance* 71, 5-31.

McClean, D., Pontiff, J., and Reilly, C., 2022. Taking sides on return predictability. Working paper.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics* 108, 1-28.

Tumarkin, R. and Whitelaw, R.F., 2001. News or noise? Internet postings and stock price, *Financial Analyst Journal* 57, 41-51.

Appendix A: Example of Quant Ratings, Factor Grades, and Sector Comparison Data

Quant Rating

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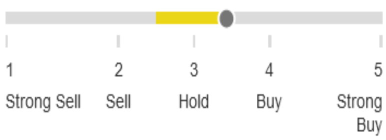

The overall quant rating is not an average of the factor grades listed. Instead, it gives greater weight to the metrics with the strongest predictive value.

Factor Grades

	Now	3M ago	6M ago
Valuation	F	D-	D-
Growth	A-	B+	B+
Profitability	A+	A+	A+
Momentum	A-	D+	D-
Revisions	C	C-	D

Profitability Grade and Underlying Metrics

TSLA Profitability Grade A+

	Sector Relative Grade	TSLA	Sector Median	% Diff. to Sector
Gross Profit Margin (TTM)	D	**21.49%**	35.30%	-39.13%
EBIT Margin (TTM)	B+	**13.46%**	7.33%	83.63%
EBITDA Margin (TTM)	A-	**17.86%**	10.65%	67.70%
Net Income Margin (TTM)	A	**12.97%**	4.28%	203.29%
Levered FCF Margin (TTM)	C+	**3.22%**	4.27%	-24.50%
Return on Common Equity (TTM)	A-	**27.96%**	10.49%	166.64%
Return on Total Capital (TTM)	A	**15.46%**	5.96%	159.27%

Appendix B: Examples of Quant Reports:

Bullish Article Example: Assertio Holdings: Acquiring Good Products Is The Key To Success

Assertio has grown through its cost-saving ability and above all through targeted and strategic acquisitions of products on the market. The last two acquisitions made in 2021 and 2022 are called OTREXUP and Sympazan and represent new assets that have rightfully entered Assertio's technological sales funnel. There seems to be no shortage of results and with strong growth in turnover (exceeding expectations) and an EBIT Margin of 29.9%, we can state that the corporate strategies have worked well at the moment…Last but not least the share price evaluation seems to be particularly advantageous, and my rating is buy…

To compare ASRT with similar companies in terms of market capitalization in the Pharmaceuticals industry I have defined the following peers:

- Xeris Biopharma Holdings, Inc. (XERS)
- ProPhase Labs, Inc. (PRPH)
- CorMedix Inc. (CRMD)
- Citius Pharmaceuticals, Inc. (CTXR)

Using Seeking Alpha's Quant Ratings we have a 'Strong Buy' verdict related to the 'Hold' or 'Strong Buy' rating of the others company.

Ratings

	ASRT	XERS	PRPH	CRMD	CTXR
Quant Rating	Strong Buy	Hold	Hold	Strong Buy	Hold

Quant Factor Grades

	ASRT	XERS	PRPH	CRMD	CTXR
Valuation	A+	B-	A+	C-	C-
Growth	A+	A-	A-	A	C-
Profitability	A+	C	A+	B-	C+
Momentum	A+	C-	A-	A-	B
EPS Revisions	A	C	D-	A-	C

Under the Quant Factor Grades point of view, we can see how Assertio is really outstanding in every area from Valuation to Growth, Profitability, and Momentum. Only in EPS Revision the grade is not outstanding but is a respectable 'A'. This comparison allows us to understand how at this moment Assertio is experiencing an astral alignment of all the positive ratios in his favor and that his peers are unable to reach this rating.

Bearish Article Example: "Nordstrom: Department Store Retail Is A Tough Business":

I shorted **Nordstrom** (NYSE:JWN) again this week after posting my momentum sort results on struggling Midcap S&P 400 picks. After mentioning the stock in a bearish article in early May, Nordstrom has continued to slide in price and underlying value…

To illustrate just how rotten business has been for Nordstrom, and the difficult investment headwinds for the stock, I have pictured some *Seeking Alpha* data points to consider below. The *Quant*, computer-driven score for the company is one of the worst in the SA database during 2020. The current 1.48 score is rated as *Very Bearish*. The company holds the last place position for underlying business strength in the *Department Store* group and ranks 405 out of 441 in the *Retail* universe followed. It lands in the bottom 10% of all 3932 stocks sorted by SA. The SA Quant rating system includes the company's financial results, the stock's trading history, and sell-side analyst estimates of future revenue and earnings, among other data.

Quant Ranking

Sector	Consumer Discretionary
Industry	Department Stores
Ranked in Industry	6 out of 6
Ranked in Sector	405 out of 441
Ranked Overall	3562 out of 3932

Ratings Summary

SA Authors	Neutral	2.50
Wall Street	Neutral	2.95
Quant	Very Bearish	1.48

Appendix C: Variable Definitions

- *Quant Rating:* a proprietary quantitative rating constructed by Seeking Alpha. These ratings were disclosed on Seeking Alpha beginning in June of 2019. We collect backfilled quantitative ratings beginning in 2015.
- *Post*: an indicator equal to one for the three-year period following the introduction of quant ratings (2020-2022) and zero for the three-year period prior to the introduction of quant ratings (2016-2018).
- *Quant Recommendation:* quantitative recommendations constructed by Seeking Alpha. Seeking Alpha converts quantitative ratings into quantitative recommendations using the following scale: *Strong Sells* (Quant Rating < 1.5), *Sells* (*1.5* <=Quant Rating <2.5), *Hold* (*2.5* <=Quant Rating <3.5), *Buys* (*3.5* <=Quant Rating <4.5), and *Strong Buys* (Quant Rating >=4.5).
  - *Strong Buy* – an indicator equal to one the quantitative recommendation is *Strong Buy* and zero otherwise. *Buy, Hold, Sell,* and *Strong Sell* are defined analogously.
- *Report Rating:* a measure of the sentiment of the SA report. *Report Rating* equals +1 for reports making a buy recommendation, 0 for reports making a hold recommendation, and -1 for reports making a sell recommendation.
- *Net Anomaly:* the number of times the stock appears in the long leg of an anomaly portfolio less the number of times the stock appears in the short leg. This measure is computed over 118 different anomalies found to be significant predictors of returns in Jensen, Kelly, and Pedersen (2023). We list the 118 firm characteristics in Table IA.1 of the Internet Appendix.
- *Net Factor Cluster:* the number of times the stock appears in the long leg of an anomaly less the number of times the stock appears in the short leg for the subset of anomalies that belong to a specific factor cluster. We consider 13 different factor clusters studied in Jensen, Kelly, and Pedersen (2023): *Value, Profitability, Profit Growth, Momentum, Quality, Accruals, Debt Issuance, Investment, Low Leverage, Low Risk, Seasonality, Size,* and *Reversal.* The link between specific anomalies and factor clusters is provided in Table IA.1 of the Internet Appendix.
- *Quant Report*: an SA report that mentions at least one of the following words in the report: 'quant', factor grade', 'value grade', 'growth grade', 'profitability grade', 'momentum grade', or 'revisions grade' or minor variants of each expression (e.g., 'grade for value').
- *Quant Rating ETF:* a proprietary quantitative rating for exchange traded funds (ETFs) constructed by Seeking Alpha. These ratings were disclosed on Seeking Alpha beginning in March of 2021. We collect backfilled quantitative ratings beginning in November 2019.
- *Post ETF:* an indicator equal to one for June 2021-December 2022 and zero for November 2019-December 2020. Post ETF is set missing for the 5 months [-2,2] centered around the introduction of ETF ratings (March 2021).
- $Ret_{i,t+x}$: the buy and hold return starting on day $t+1$ and ending on $t+x$, where we set x equal to five days, 21 days, or 63 days, and day t is the day where an investor could first trade on the report. We consider three different return measures:
  - *Market-Adjusted Return:* the difference between the raw return and the value-weighted market return
  - *Quant-Style Return*: For each firm-day, we sort stocks into 25 portfolios based on the quant rating (*Quant Portfolios*). *Quant-Style Return* is the average return across all stocks in the same *Quant Portfolio* as the stock.
  - *Quant-Adjusted Return*: the difference between the raw return and the *Quant-Style Return*.

- *Bio Sophistication* – we count the following words within each contributor's self-reportion bio on SA: *Quant*, *Short*, *Long/Short*, *Analyst*, *Portfolio Manager*, *Mutual Fund*, *Hedge Fund*, *Asset Management*, *Fund Manager*, *Chief Investment Officer* (*CIO*), *Investment Bank*, *Wall Street*, *Sell-Side*, and *Marketplace*. We set *Bio Sophistication* to 1 (or Low) if the bio has none of the words, 2 (or Mid) if the bio contains one of the words, and 3 (or High) if the bio contains two or more of the words.
    - Appendix D provides an example of Bios with low and high *Bio Sophistication* scores.
- *GPT Sophistication* - We tasked ChatGPT 3.5 with rating contributor bios for quantitative skill using a scale ranging from 1 to 10. We set *GPT Sophistication* to 1 (or Low) if the bio is ranked in the bottom quartile of the distribution, to 2 (or Mid) if the bio is ranked in the middle 50% of the distribution, and to 3 (or High) if the bio is ranked in the top 25% of the distribution.
    - Appendix D provides an example of Bios with low and high *GPT Sophistication* scores. The Appendix also provides Chat GPT's rationale for the ranking.
- *Comment Sophistication* – we compute the average number of comments on their last ten reports. We set Comment *Sophistication* to 1 (or Low) if the average number of comments is ranked in the bottom quartile of the distribution, to 2 (or Mid) if the average comments rank in the middle 50% of the distribution, and to 3 (or High) if the average comments rank in the top 25% of the distribution.
- *Quant Sophistication (Composite) – Bio Sophistication + GPT Sophistication + Comment Sophistication*.
    - *We also split Quant Sophistication* into low, mid, and high, based on the 25th and 75th percentiles of the measure.
- *Retail Imbalance* – Retail buy volume less retail sell volume scaled by total retail volume. Retail trades are assigned as buys or sells based on the Barber et al. (2023) algorithm.
    - *Predicted Imbalance* – the fitted value from a regression of retail imbalances on report rating.
    - *Residual Imbalance* – the difference between *Retail Imbalance* and Predicted *Imbalance*.

Appendix D: Example of High versus Low Contributor Sophistication:

<u>High Quant Sophistication Bio:</u>

Portuguese independent trader and **analyst**. *I have worked for both* **sell side** *(brokerage) and* **buy side** *(fund management) institutions. I've been investing professionally for around 30 years. I have a* **Marketplace** *service here on Seeking Alpha called Idea Generator that's focused on deep value, real-time actionable ideas based on valuation and catalysts. The Idea Generator portfolio has beaten the S&P 500 by more than 74% since inception (2015).*

- Bio Sophistication Count: 4; *Bio Sophistication Score* (3-High)
- Chat GPT Quantitative Skill Rank (9/10): GTP Sophistication Score (3-High)
  - *ChatGTP Assessment:* This individual has extensive experience as a Portuguese independent trader and analyst, working for both sell-side (brokerage) and buy-side (fund management) institutions for around 30 years. Their lengthy professional investment career suggests a high level of expertise in quantitative analysis, financial modeling, and risk management. Furthermore, the mention of their "Idea Generator" service on Seeking Alpha, which is focused on deep value investing and has outperformed the S&P 500 by more than 74% since its inception in 2015, demonstrates a strong ability to use quantitative methods to identify and capitalize on investment opportunities. Overall, this individual's bio suggests a high level of quantitative skill and expertise in the field of finance and investments.
- Average Comments Count: 44, *Comment Sophistication Score* (3-High)

<u>Lower Quant Sophistication Bio:</u>

I am a graduate of Grove City College, where I majored in Economics and minored in National Security. My intensive research spans subjects such as the ramifications of a uniform global currency, the viability of African foreign aid, and analysis of the recent anti-trust lawsuit against American Airlines. Currently, I focus on the retail and consumer goods sectors.

- Bio Sophistication Count: 0; *Bio Sophistication Score* (1-Low)
- Chat GPT Quantitative Skill Rank (5/10); *GPT Sophistication Score* (1-Low)
  - *ChatGPT Assessment:* His background in economics and national security may involve some quantitative aspects, but the bio does not provide specific examples of strong quantitative skills or experiences related to data analysis, statistical interpretation, or financial modeling. While he mentions intensive research on various subjects, including the ramifications of a global currency and analysis of antitrust lawsuits, it's not clear how extensively he uses quantitative methods in his research. Overall, he appears to have a foundation in economics and research but does not explicitly showcase strong quantitative skills.
- *Average Comment Count:* 2; *Comment Sophistication Score* (1-Low)

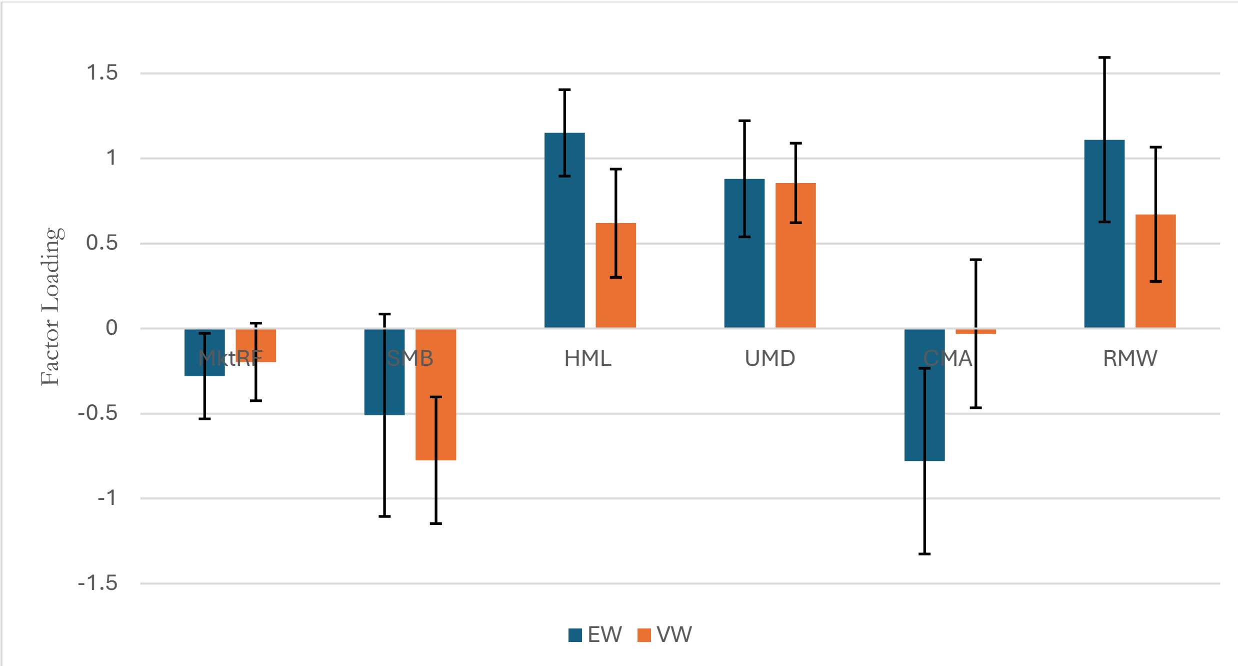

Figure 1: Factor Loading of Long-Short Portfolio Sorted on SA Quantitative Ratings
This figure plots the factor-loadings from time series regressions where the dependent variable is the monthly return on the *Strong Buy – Strong Sell* portfolio analyzed in the last column of Table 3, and the independent variables are the monthly returns on the Fama-French (2015) five factors plus the Carhart (1997) momentum factor. The blue bars report the factor loadings for equal-weighted portfolios (Panel A of Table 3), and the orange bars report the loadings for value-weighted portfolios (Panel B of Table 3). Standard errors are computed from the time-series standard deviation, and the error bars report the 95% confidence intervals.

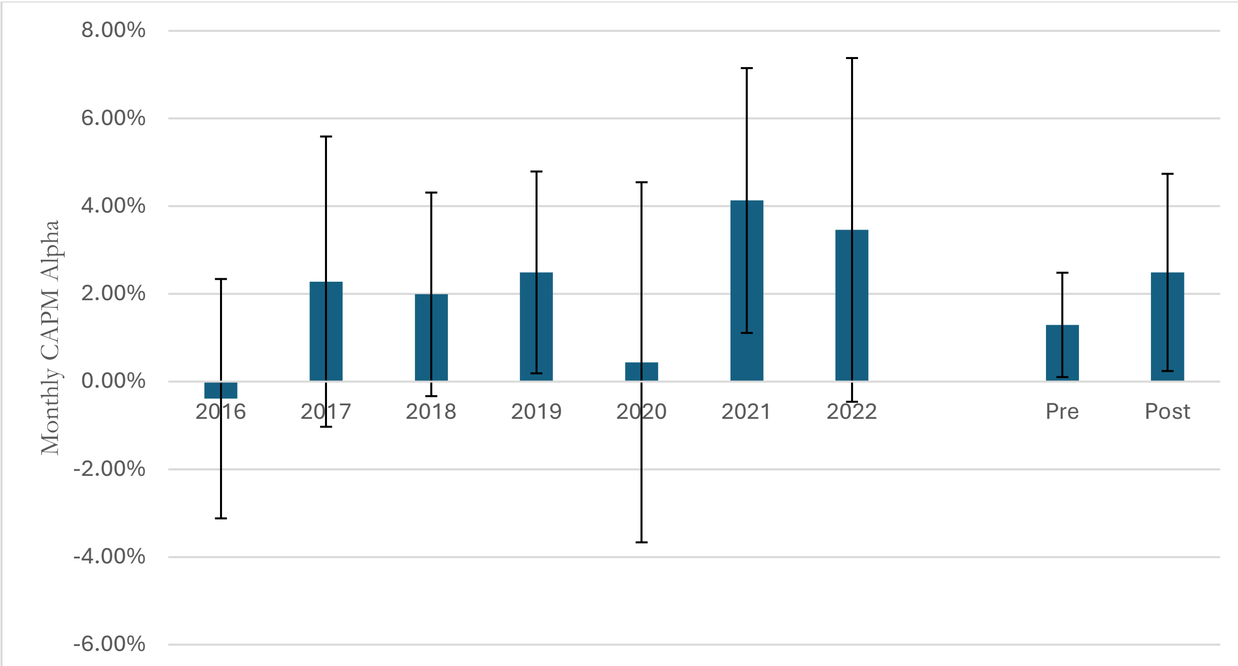

Figure 2: Returns to Long-Short Portfolios sorted on SA Quantitative Ratings by Year

This figure plots the value-weighted monthly CAPM Alpha of the *Strong Buy* – *Strong Sell* portfolio, analyzed in the last column of Table 3, year by year. We also report the estimates over a pre-period (2016-2018) and a post-period (2020-2022). Standard errors are computed from the time-series standard deviation, and the error bars report the 95% confidence intervals.

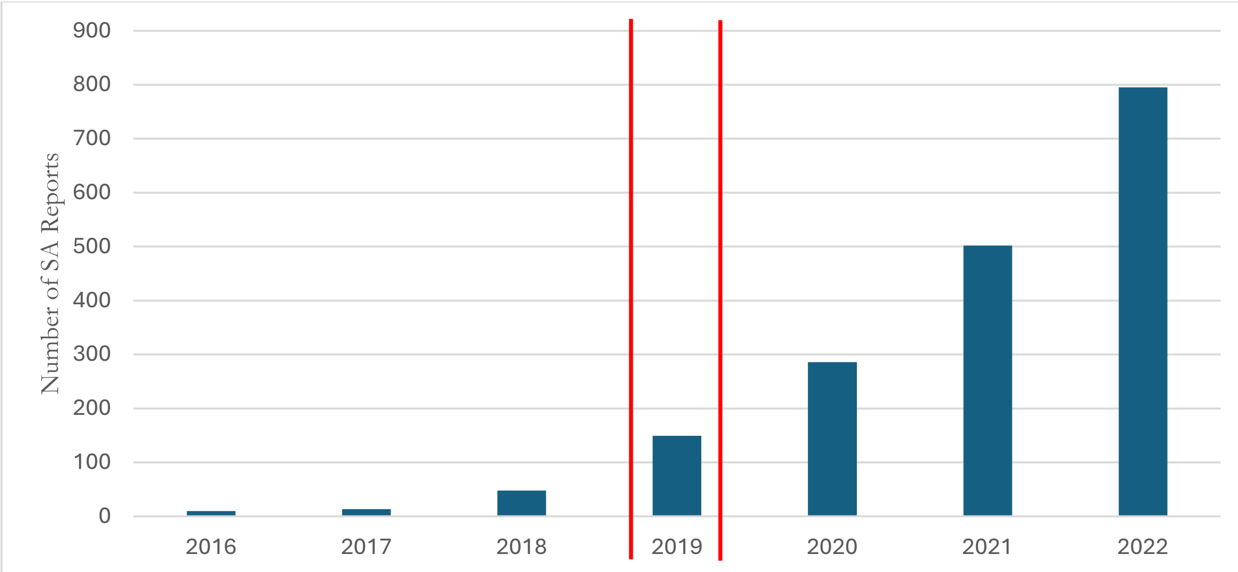

Figure 3: Frequency of *Quant Reports* by Year

This figure plots the total number of *Quant Reports* for each year in the sample. We identify a report as a *Quant Report* if the report mentions at least one of the following quant words in the report: 'quant', factor grade', 'value grade', 'growth grade', 'profitability grade', 'momentum grade', or 'revisions grade or minor variants of each expression (e.g., 'grade for value'), The red lines separate the period prior to the introduction of SA quantitative ratings (2016-2018) and the period after the introduction of the quantitative ratings (2020-2022).

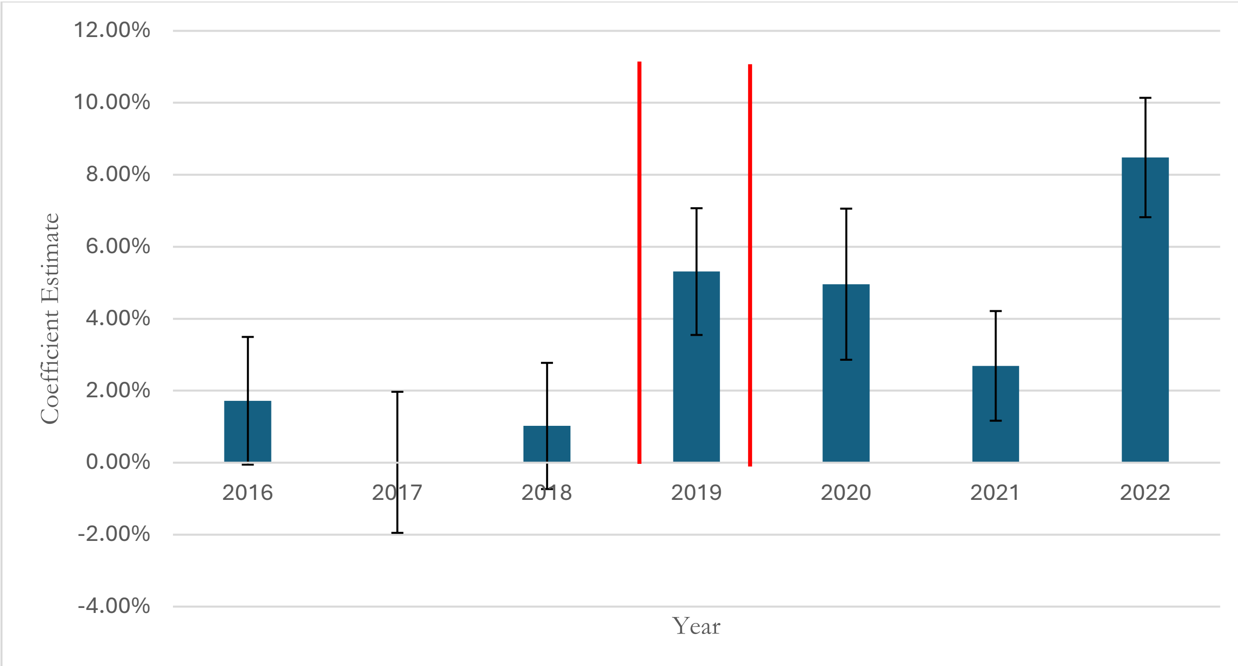

Figure 4: SA Report Recommendations and Quantitative Ratings by Year

This figure repeats the analysis in Specification 3 of Table 4 after replacing *Quant Rating* and *Quant Rating*× *Post* with *Quant Rating* interacted with indicators for each year of the sample (2016-2022). The figure plots the estimates on the *Quant Rating* interacted with each of the year indicators. Standard errors are clustered by firm and date, and the error bars report 95% confidence intervals. The red lines separate the period prior to the introduction of SA quantitative ratings (2016-2018) and the period after the introduction of the quantitative ratings (2020-2022).

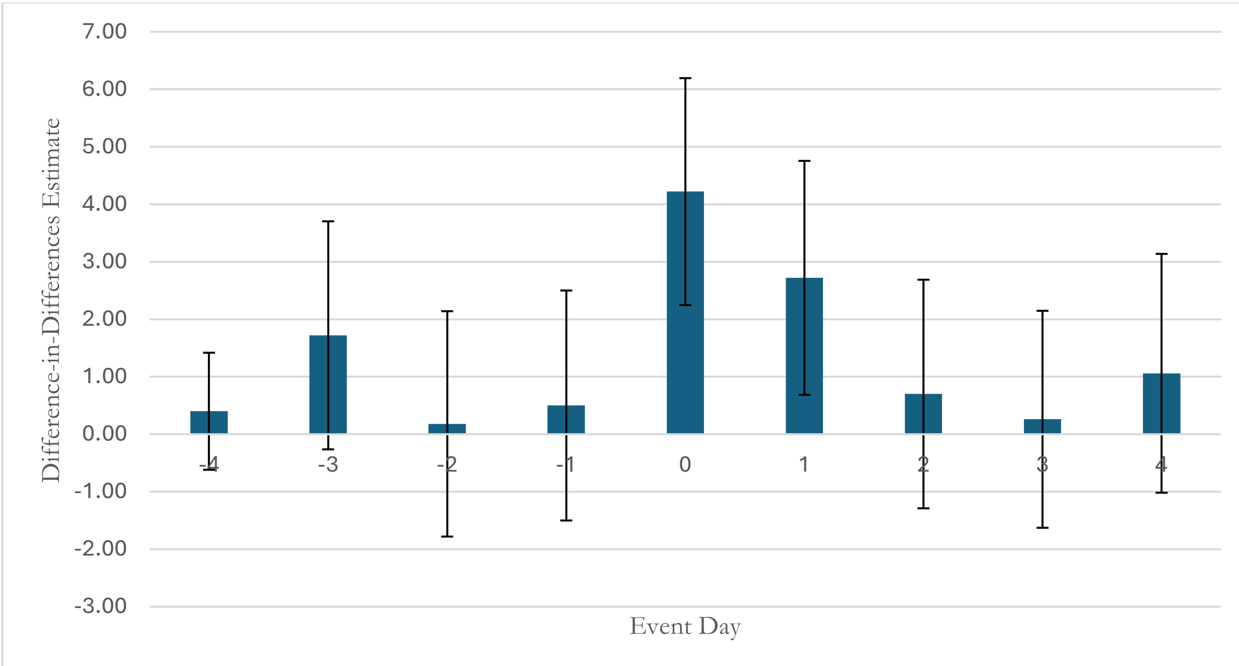

Figure 5: Retail Imbalances around SA Research Reports – Diff-in-Diff Estimates in Events Times
This table reports the difference-in-difference estimates from Panel B of Table 11 in event time around the release of SA research reports, where day 0 is defined as the first trading day in which an investor could have traded on the research report The first difference is the difference between retail order imbalances for stocks with a quant recommendation of *Strong Buy* less the imbalance for stocks with a quant recommendation of *Strong Sell*. The second difference is the difference between this measure in the post-period (2020-2022) and the pre-period. Retail imbalances are defined as retail buy volume less retail sell volume, scaled by total retail volume, where retail trading is signed using the algorithm of Barber et al. (2023). The estimates are reported as blue bars and the 95% confidence intervals as error bars.

Table 1: Descriptive Statistics

This table reports summary statistics by year. *CRSP Sample* is the number of common stocks (share codes 10 and 11) in the CRSP database, *Quant Rating Sample* is the number of stocks in the *CRSP Sample* that also have a quantitative rating on Seeking Alpha (SA). *SA Report Sample* is the number of stocks in the *CRSP Sample* with at least one Seeking Alpha research report during the calendar year. *SA Reports* is the total number of SA reports across all stocks in the *CRSP Sample,* and *Reports & Quant Rating* is the total number of SA reports across all stocks in the *Quant Rating Sample*. *Buy Reports* and *Sell Reports* report the percentage of SA reports recommending a buy and sell recommendation, respectively. We classify an SA report as a buy recommendation if the author rating is either "Buy" or Strong Buy", and we classify an SA report as a sell recommendation if the author rating is either "Sell" or "Strong Sell". Panel B reports summary statistics for the distribution of SA's quantitative rating, which range from 1 to 5. We report the mean and standard deviation of the quant ratings. We also report the fraction of all stocks that are rated as *Strong Sells* (Quant Rating < 1.5), *Sells* (*1.5* <=Quant Rating <2.5), *Hold* (*2.5* <=Quant Rating <3.5), *Buys* (*3.5* <=Quant Rating <4.5), and *Strong Buys* (Quant Rating >=4.5).

Panel A: Sample Size and SA Report Tone

Year	*CRSP Sample*	*Quant Rating Sample*	*SA Report Sample*	*SA Reports*	*Reports & Quant Rating*	*Buy Reports*	*Sell Reports*
2016	4,020	2,099	2,267	21,117	16,178	41%	7%
2017	3,943	2,244	2,144	20,878	16,851	41%	5%
2018	3,950	2,461	2,172	17,268	13,769	50%	5%
2019	3,952	2,968	2,206	15,587	12,947	61%	15%
2020	4,083	2,872	2,515	16,629	15,036	58%	12%
2021	4,774	3,061	3,011	17,362	14,362	64%	8%
2022	4,742	3,543	3,078	22,172	20,824	59%	9%
Average	4,209	2,750	2,646	18,716	15,710	54%	9%

Panel B: Distribution of Quantitative Ratings and Recommendations

Year	*Average Quant Rating*	*Std Dev. Quant Rating*	*Pct. Strong Sell*	*Pct. Sell*	*Pct. Hold*	*Pct. Buy*	*Pct. Strong Buy*
2016	2.95	0.88	8%	8%	65%	10%	9%
2017	2.92	0.88	7%	8%	64%	11%	10%
2018	2.93	0.88	8%	7%	65%	10%	10%
2019	2.92	0.89	7%	8%	63%	11%	10%
2020	2.96	0.87	7%	8%	65%	10%	9%
2021	2.99	0.91	9%	10%	62%	10%	9 %
2022	2.96	0.92	9%	10%	61%	10%	10%
Average	2.95	0.89	8%	8%	64%	10%	9%

Table 2: Determinants of SA Quantitative Ratings

This table reports estimates from the following regression:

$$Quant\ Rating_{it} = \alpha + \beta_1 NetAnomaly_{it} + FE_{it} + \varepsilon_{it}.$$

Quant Rating is the quantitative rating provided by Seeking Alpha, measured at the end of month *t*. In Specification 1, *Net Anomaly* is the number of times the stock is in the long leg of the anomaly portfolio less the number of times the stock is in the short leg, computed across 118 different anomalies that were found to be significant predictors of returns in Jensen, Kelly, and Pedersen (2023). Specification 2 decomposes *Net Anomaly* into an analogous *Net Anomaly* measure for 13 different factor clusters. The list of the 118 anomalies and how each anomaly maps into a factor cluster is available in Table IA.1 of the Internet Appendix. FE denotes sector × month fixed effects, where sectors are constructed using the GICS classification. All variables are standardized to have mean zero and unit variance. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	[1]	[2]
Net (All Anomalies)	0.30	
	(30.46)	
Net Momentum		0.50
		(75.69)
Net Value		0.14
		(14.48)
Net Profit Growth		0.06
		(14.14)
Net Low Risk		0.05
		(7.21)
Net Quality		0.05
		(5.33)
Net Debt Issuance		0.03
		(5.84)
Net Investment		-0.01
		(-2.37)
Net Profitability		0.01
		(0.86)
Net Low Leverage		-0.03
		(-5.31)
Net Accruals		-0.03
		(-6.21)
Net Seasonality		-0.02
		(-4.54)
Net Size		-0.08
		(-9.34)
Net Reversal		-0.20
		(-37.14)
Fixed Effects	Month × Sector	Month × Sector
Observations	212,365	212,365
Within R-squared	9.12%	37.66%

Table 3: Returns for Stocks sorted on SA Quantitative Ratings

At the end of each month, from December 2015 through November 2022, we form five portfolios by sorting stocks based on their SA quantitative recommendation. This table reports the average monthly return to each portfolio in the month following portfolio formation (i.e., January 2016 through December 2022). Panels A and B report the equal-weighted and value-weighted average portfolio returns, respectively. We report the raw returns and alphas from the market model (CAPM Alpha), the Fama-French 1993 three-factor model (3-Factor Alpha), the Carhart (1997) four-factor model (4-Factor Alpha), and the alpha from a model that includes the five Fama-French factors (2015) and the Carhart (1997) momentum factor (6-Factor Alpha). The last column reports the returns to a strategy that goes long stocks that in *Strong Buy* portfolio and short stocks in the *Strong Sell* portfolio. Standard errors are computed from the time-series standard deviation, and t-statistics are reported in parentheses.

Panel A: Equal-Weighted Portfolio Returns

	Strong Buy	*Buy*	*Hold*	*Sell*	*Strong Sell*	*Strong Buy - Strong Sell*
Raw Return	1.95%	1.03%	0.99%	0.80%	0.25%	1.70%
	(2.90)	(1.54)	(1.41)	(0.98)	(0.23)	(2.29)
CAPM Alpha	0.84%	-0.07%	-0.20%	-0.54%	-1.30%	2.15%
	(2.51)	(-0.18)	(-0.64)	(-1.48)	(-1.95)	(3.12)
3-Factor Alpha	0.96%	0.11%	-0.02%	-0.36%	-0.94%	1.90%
	(4.39)	(0.71)	(-0.15)	(-1.98)	(-1.91)	(3.25)
4-Factor Alpha	0.84%	0.11%	-0.01%	-0.24%	-0.81%	1.65%
	(4.34)	(0.62)	(-0.04)	(-1.53)	(-1.71)	(3.09)
6-Factor Alpha	0.90%	0.15%	0.06%	-0.16%	-0.62%	1.52%
	(4.50)	(1.06)	(0.50)	(-1.19)	(-1.65)	(3.50)

Panel B: Value-Weighted Portfolio Returns

	Strong Buy	*Buy*	*Hold*	*Sell*	*Strong Sell*	*Strong Buy - Strong Sell*
Raw Return	1.57%	0.98%	0.98%	0.55%	0.16%	1.41%
	(2.71)	(1.79)	(1.85)	(0.75)	(0.16)	(2.00)
CAPM Alpha	0.55%	0.02%	-0.02%	-0.71%	-1.40%	1.95%
	(2.55)	(0.09)	(-0.55)	(-2.39)	(-2.79)	(3.25)
3-Factor Alpha	0.52%	0.03%	-0.02%	-0.61%	-1.16%	1.68%
	(2.35)	(0.21)	(-0.57)	(2.54)	(-2.91)	(3.47)
4-Factor Alpha	0.45%	0.03%	-0.01%	-0.45%	-0.94%	1.39%
	(2.09)	(0.21)	(-0.38)	(-2.27)	(-2.53)	(3.17)
6-Factor Alpha	0.40%	-0.02%	-0.01%	-0.39%	-0.79%	1.20%
	(2.12)	(-0.14)	(-0.38)	(-1.93)	(-2.36)	(2.94)

Table 4: SA Report Sentiment and Quantitative Ratings

This table reports estimates from the following panel regression:

$$Report\ Rating_{it} = \alpha + \beta_1 QuantRating_{it} + \beta_2 QuantRating_{it} \times Post_t + FE + \varepsilon_{it}.$$

The dependent variable, *Report Rating*, equals one for SA reports making a buy recommendation, negative one for SA reports making a sell recommendation, and zero for all other reports. *Quant Rating* is Seeking Alpha's quantitative rating and *Post* is an indicator equal to one if the report was written in the post-period (2020-2022) and zero if the report was written in the pre-period (2016-2018). All regressions include date × GICS sector fixed effects. Specifications 2 and 3 augment Specification 1 by including firm and contributor fixed effects, respectively. Specifications 4-6 repeat the analysis in Specifications 1-3 after partitioning *Quant Rating* × *Post* into *Quant Rating* × *Post* × *Non-Quant Report* and Quant *Rating* × *Post* × *Quant Report,* where *Quant Report* is an indicator equal to one if the report mentions at least one of the following quant words in the report: 'quant', factor grade', 'value grade', 'growth grade', 'profitability grade', 'momentum grade', or 'revisions grade' or minor variants of each expression (e.g., 'grade for value'), and zero otherwise, and *Non- Quant Report* is an indicator equal to one for reports not classified as *Quant Reports* and zero otherwise. Below the regression estimates we test whether the coefficient on *Quant Rating* × *Post* × *Quant Report* is significantly different from the coefficient on Quant *Rating* × *Post* × *No Quant Report* (*Quant Report – No-Quant Report*). Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]	[4]	[5]	[6]
Quant Rating	0.87%	-0.07%	1.05%	0.87%	0.16%	1.05%
	(0.93)	(-0.10)	(1.89)	(0.93)	(0.27)	(1.90)
Quant Rating × *Post*	5.50%	4.13%	4.91%			
	(3.85)	(3.94)	(5.27)			
Quant Rating × *Post* × *No Quant Report*				4.95%	3.31%	4.47%
				(3.40)	(3.52)	(4.71)
Quant Rating × *Post* × *Quant Report*				17.48%	13.86%	15.84%
				(9.48)	(8.14)	(9.35)
Post × *Quant Mention*				0.01%	-4.45%	-4.44%
				(0.47)	(-2.31)	(-2.36)
Quant Report - No Quant Report				12.53%	11.37%	10.55%
				(7.15)	(6.73)	(6.36)
Observations	96,129	96,129	96,129	96,129	96,129	96,129
Sector × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No	Yes	No
Contributor FE	No	No	Yes	No	No	Yes
R-squared	18.07%	26.98%	36.82%	18.12%	27.03%	36.87%
Mean Dep. Variable	42.48%	42.48%	42.48%	42.48%	42.48%	42.48%

Table 5: SA Report Sentiment and ETF Quantitative Ratings

This table reports estimates from the following panel regression:

$$Report\ Rating_{it} = \alpha + \beta_1 QuantRatingETF_{it} + \beta_2 QuantRatingETF_{it} \times Post\ ETF_t + FE + \varepsilon_{it.}$$

The dependent variable, *Report Rating*, equals one for SA reports making a buy recommendation, negative one for SA reports making a sell recommendation, and zero for all other reports; *Quant Rating ETF* is Seeking Alpha's quantitative rating for exchange traded funds (ETFs) and *Post* ETF is an indicator equal to one if the report was written in the period after which SA quant ratings for ETFs were disclosed on the platform (June 2021 – December 2022) and zero if the report was written in the pre-period (November 2019 – December 2020). All regressions include date × asset class fixed effects. Specifications 2 and 3 augment Specification 1 by including ETF and contributor fixed effects, respectively. Specifications 4 repeats the analysis in Specification 3 after replacing *Quant Rating ETF* and *Quant Rating ETF* × *Post ETF* with *Quant Rating ETF* interacted with three separate pre-period indicators, an event-time indicator, and three separate post-period indicators. For example, *Quant Rating ETF* × *[3,9]* is the ETF quant rating interacted with an indicator equal to one if the event month was 3 to 9 months after the quant ratings were disclosed on the platform (i.e., June 2021 through December 2021). Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]	[4]
Quant Rating ETF	4.08%	3.30%	4.34%	
	(2.89)	(2.12)	(3.25)	
Quant Rating ETF × *Post ETF*	6.11%	6.21%	5.65%	
	(2.96)	(3.35)	(3.03)	
Quant Rating ETF × *[-16, -13]*				4.71%
				(1.63)
Quant Rating ETF × *[-12, -8]*				4.99%
				(2.36)
Quant Rating ETF × *[-7, -3]*				3.03%
				(1.50)
Quant Rating ETF × *[-2,2]*				3.37%
				(1.41)
Quant Rating ETF × *[3,9]*				8.61%
				(4.58)
Quant Rating ETF × *[10,15]*				12.46%
				(7.44)
Quant Rating ETF × *[16,21]*				8.89%
				(5.10)
Observations	7,442	7,442	7,442	8,428
Asset Class × Date FE	Yes	Yes	Yes	Yes
ETF FE	No	Yes	No	No
Contributor FE	No	No	Yes	Yes
R-squared	56.22%	62.45%	63.79%	64.74%
Mean Dep. Variable	28.72%	28.72%	28.72%	28.72%

Table 6: SA Report Sentiment and Quantitative Ratings by Quantitative Sophistication

This table repeats the analysis in Specification 1 of Table 4 after partitioning contributing authors into three groups based on their *Quantitative Sophistication. Quantitative Sophistication* is the sum of *Bio Sophistication*, *GPT Sophistication,* and *Comment Sophistication,* where *Bio Sophistication* is based on the count of the number of keywords associated with quantitative sophistication, *GPT Sophistication* is based on Chat GPT's assessment of the quantitative sophistication of the bio, and *Comment Sophistication* is based on the average number of comments that the contributor's past 10 reports received. Additional details of each contributor sophistication measure is available in Appendix C. We partition each sophistication measure into three groups, where the lowest values receive a score of 1 and the highest values receive a score of 3. We define a contributor as having *Low Quantitative Sophistication* if the *Quantitative Sophistication* score is in the bottom quartile of the distribution, *High Quantitative Sophistication* if the score is the top quartile of the distribution, and *Mid Quantitative Sophistication* otherwise. Specifications 1-3 report the results for the Low, Mid, and High sophistication groups, Specification 4 tests whether the estimates for the Low group are significantly different from the estimates in the High group, and Specifications 5 and 6 repeat Specification 4 after adding either firm fixed effects or contributor fixed effects. Below the regression estimates, we also report formal tests of whether the sum of *Quant Rating* and *Quant Rating* × *Post* is significantly different from zero. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	Low	*Mid*	*High*	*Low - High*	*Low - High*	*Low - High*
	[1]	[2]	[3]	[4]	[5]	[6]
Quant Rating	-1.98%	0.67%	3.32%	-5.30%	-5.44%	-4.75%
	(-1.53)	(0.73)	(2.03)	(-2.74)	(-3.52)	(-3.12)
Quant Rating × *Post*	11.49%	5.62%	0.52%	10.97%	9.44%	9.04%
	(6.67)	(4.20)	(0.20)	(3.79)	(3.94)	(3.97)
Quant + *Quant* × *Post*	9.51%	6.29%	3.84%	5.67%	4.01%	4.28%
	(8.28)	(6.99)	(2.26)	(2.91)	(2.28)	(2.67)
Observations	18,189	49,052	28,888	47,077	47,077	47,077
Sector × Date × Soph. FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	No
Contributor FE	No	No	No	No	No	Yes
R-squared	47.07%	30.02%	39.55%	42.44%	49.33%	54.32%

Table 7: SA Report Informativeness and Quant Reports

This table reports estimates from the following regression:

$$Ret_{it+1,t+x} = \alpha + \beta_1 Report\ Rating_{it} \times Pre_t + \beta_2 Report\ Rating_{it} \times Post_t \times NonQuant_{it} + \beta_3 Report\ Rating_{it} \times Post_t \times Quant_{it} + Post_t \times QuantReport + FE + \varepsilon_{it.}$$

The dependent variable, $Ret_{it+1,t+x}$, is the market-adjusted stock return measured over the subsequent week (i.e., x = 5 trading days), the subsequent month (x=21), or the subsequent quarter (x=63). *Report Rating* equals one for SA reports making a buy recommendation, negative one for SA reports making a sell recommendation, and zero for all other reports. *Pre* is an indicator equal to one for SA reports issued over the 2016-2018 period and zero otherwise, and *Post* is an indicator for reports issued over the 2020-2022 period. *Quant Report* is an indicator equal to one if the report mentions quant words (as defined in Table 4), and zero otherwise, and *Non-Quant Report* is an indicator equal to one if the report does not mention quant words and zero otherwise. Below the regression estimates we also test for whether 1) Non-Quant Reports issued in the post-period are more informative than reports issued in the pre period (*Post* × *Non-Quant* − *Pre*), 2) Quant Reports issued in the post-period are more informative than reports issued in the pre period (*Post* ×*Quant* − *Pre*), and 3) Quant Reports issued in the post-period are more informative than Non-Quant reports issued in the post period (*Post* × *Quant* − *Post* × *Non-Quant*). All return measures are expressed as percentages. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Market-Adjusted Returns		
	Ret 5	Ret21	Ret63
	[1]	[2]	[3]
Report Rating × *Pre*	0.08%	0.08%	-0.07%
	(1.82)	(0.54)	(-0.30)
Report Rating × *Post* × *Non-Quant Report*	0.24%	0.12%	-0.70%
	(2.31)	(0.39)	(-1.05)
Report Rating × *Post* × *Quant Report*	0.84%	1.85%	2.97%
	(2.24)	(2.68)	(2.26)
Post × *Nom-Quant* − *Pre*	0.16%	0.04%	-0.63%
	(1.52)	(0.13)	(-0.94)
Post × *Quant* − *Pre*	0.76%	1.77%	3.04%
	(2.00)	(2.50)	(2.24)
Post × *Quant* − *Post* × *Non-Quant*	0.60%	1.73%	3.68%
	(1.58)	(2.73)	(2.51)
Observations	95,137	95,137	95,137
Month FE	Yes	Yes	Yes

Table 8: SA Report Informativeness and Quant Reports - Return Decomposition

This table repeats the analysis in Table 7 after decomposing market-adjusted returns into *Quant-Style Returns* (Specifications 1-3) and *Quant-Adjusted Returns* (Specifications 4-6). For each firm-day, we sort all stocks into 25 portfolios based on the quant rating (*Quant Portfolios*). *Quant-Style Return* is the average return across all stocks in the same *Quant Portfolio* as the stock, and *Quant-Adjusted Return* is the difference between the return on the stock and the *Quant-Style Return*. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Quant-Style Returns			Quant-Adjusted Returns		
	Ret 5	Ret21	Ret63	Ret 5	Ret21	Ret63
	[1]	[2]	[3]	[4]	[5]	[6]
Report Rating × Pre	0.01%	-0.02%	0.03%	0.08%	0.10%	-0.10%
	(1.11)	(-0.56)	(0.31)	(1.61)	(0.67)	(-0.37)
Report Rating × Post × Non-Quant Report	0.04%	0.10%	0.09%	0.21%	0.02%	-0.79%
	(1.73)	(1.63)	(0.62)	(2.10)	(0.07)	(-1.36)
Report Rating × Post × Quant Report	0.09%	0.49%	1.72%	0.75%	1.36%	1.25%
	(0.88)	(2.06)	(3.87)	(2.10)	(2.31)	(1.07)
Post × Nom-Quant − Pre	0.03%	0.12%	0.06%	0.13%	-0.08%	-0.70%
	(1.11)	(1.53)	(0.34)	(1.40)	(-0.25)	(-1.12)
Post × Quant − Pre	0.08%	0.51%	1.69%	0.67%	1.26%	1.35%
	(0.87)	(2.16)	(3.69)	(2.03)	(2.20)	(1.13)
Post × Quant − Post × Non-Quant	0.05%	0.39%	1.63%	0.55%	1.34%	2.05%
	(0.62)	(1.86)	(4.15)	(1.63)	(2.47)	(1.50)
Observations	95,137	95,137	95,137	95,137	95,137	95,137
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: SA Report Informativeness and Quant Reports – Robustness

This table examines the sensitivity of the informativeness estimates from Tables 7 and 8. This analysis is limited to the 63-day return horizon. Specifications 1 and 4 reports *Market-Adjusted Returns* (as in Table 7), Specifications 2 and 5 report *Quant-Style Returns* (as in Specifications 3 of Table 8), and Specifications 3 and 6 report *Quant-Adjusted Returns* (as in Specifications 6 of Table 8). We report estimates for whether 1) *Quant Reports* issued in the post-period are more informative than reports issued in the pre period (*Post* ×*Quant* − *Pre*), and 2) *Quant Reports* issued in the post-period are more informative than *Non-Quant Reports* issued in the post period (*Post* × *Quant* − *Post* × *Non-Quant*). For reference, the first row reports the baseline estimates (also reported in Tables 6 and 7). In Rows 2 we replace month fixed effects with sector × month fixed effects. In Row 3-7 we augment our baseline model by including the following fixed effects: firm (row 3), firm × report rating (row 4), contributor (row 5), and contributor × report rating (row 6). In Row 7, we expand the "Post" window to include all SA reports issued in 2019, and in Row 8, we report the estimates after winsorizing returns at the 99th percentile. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Post × Quant − Pre			*Post × Quant − Post × No Quant*		
	Market-Adjusted	*Quant-Style*	*Quant-Adjusted*	*Market-Adjusted*	*Quant-Style*	*Quant-Adjusted*
	[1]	[2]	[3]	[4]	[5]	[6]
1. Baseline	3.04%	1.69%	1.35%	3.68%	1.63%	2.05%
	(2.24)	(3.69)	(1.13)	(2.51)	(4.15)	(1.50)
2. Add Sector × Month FE	3.05%	1.70%	1.34%	3.66%	1.64%	2.03%
	(2.38)	(3.88)	(1.21)	(2.82)	(4.18)	(1.76)
3. Add Firm Fe	2.03%	1.74%	0.30%	2.92%	1.74%	1.17%
	(1.62)	(3.61)	(0.25)	(2.24)	(3.66)	(0.99)
4. Add Firm × Rating FE	2.61%	1.24%	1.36%	3.23%	1.36%	1.87%
	(2.14)	(3.70)	(1.16)	(2.36)	(3.94)	(1.43)
5. Add Contributor FE	3.55%	2.18%	1.38%	3.99%	2.04%	1.95%
	(2.93)	(4.10)	(1.31)	(3.22)	(4.07)	(1.82)
6. Add Contributor × Rating FE	3.28%	1.73%	1.51%	5.12%	1.77%	3.35%
	(2.18)	(4.17)	(1.11)	(3.47)	(4.64)	(2.45)
7. Include 2019 in Post	3.26%	1.66%	1.60%	3.79%	1.55%	2.24%
	(2.78)	(4.17)	(1.57)	(3.30)	(4.31)	(2.20)
8. Winsorize Returns	3.45%	1.61%	1.84%	3.19%	1.42%	1.78%
	(3.21)	(3.70)	(2.06)	(2.96)	(3.67)	(1.92)

Table 10: SA Report Informativeness by Quantitative Sophistication

This table reports estimates from the following regression:

$$Ret_{it+1,t+x} = \alpha + \beta_1 ReportRat. + \beta_2 ReportRat._{it} \times Post_t + \beta_3 ReportRat._{it} \times QuantSoph_{it} + \beta_4 ReportRat._{it} \times Post_t \times QuantSoph_{it} + \beta_5 QuantSoph_{it} + \beta_6 QuantSoph_{it} \times Post + FE + \varepsilon_{it.}$$

The dependent variable, $Ret_{it+1,t+x}$, is the stock return measures over the subsequent month (x=21), or the subsequent quarter (x=63), where the stock return is either the market-adjusted return, the *Quant-Style* return or the *Quant-Adjusted* return (as defined in Table 8 and Appendix C). *Report Ratings* and *Post* are defined as in Table 7, and *QuantSoph* is the composite *Quantitative Sophistication* measure (as defined in Table 6), standardized to have mean 0. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Ret21			Ret63		
	Market-Adjusted	Quant Style	Quant-Adjusted	Market-Adjusted	Quant Style	Quant Adjusted
	[1]	[2]	[3]	[4]	[5]	[6]
Rating	0.08%	-0.03%	0.11%	-0.01%	0.02%	-0.03%
	(0.54)	(-0.83)	(0.72)	(-0.05)	(0.27)	(-0.12)
Rating × *Post*	0.10%	0.15%	-0.05%	-0.51%	0.13%	-0.64%
	(0.33)	(1.97)	(0.72)	(-0.80)	(0.79)	(-1.19)
Rating × *Quant Sophistication*	-0.03%	0.02%	-0.05%	-0.11%	0.05%	-0.16%
	(-0.45)	(0.95)	(-0.17)	(-0.93)	(1.54)	(-1.44)
Rating × *Post* × *Quant Sophistication*	-0.20%	-0.13%	-0.08%	-0.82%	-0.25%	-0.56%
	(-1.14)	(-3.11)	(-0.50)	(-2.04)	(-3.19)	(-1.62)
Quant Sophistication	0.01%	0.01%	0.00%	0.20%	0.03%	0.17%
	(0.13)	(0.48)	(0.01)	(1.79)	(0.94)	(1.64)
Quant Sophistication × *Post*	0.14%	0.08%	0.06%	0.29%	0.14%	0.15%
	(0.90)	(2.03)	(0.44)	(0.83)	(1.85)	(0.47)
Observations	95,137	95,137	95,137	95,137	95,137	95,137
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Retail Order Imbalance around SA Research Reports

We sort all SA research reports into five groups based on the quant recommendation of the covered stock. For each group, we compute the average retail investor order imbalance on the first day in which an investor could have traded on the report in the pre-period (2016-2018) and post-period (2020-2022). Retail order imbalances are computed as retail buy volume less retail sell volume scaled by retail trading volume, where trades are signed using the algorithm of Barber et al. (2023). Panel A reports the estimates across all SA research reports, while Panel B excludes reports on attention-grabbing stocks, defined as stocks that issued earnings in the three-days (-1,1) surrounding the release of the report, or stocks whose absolute returns or trading volume exceeds the 95th percentile relative to the firm's absolute returns or volume over the prior year. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

Panel A: Full Sample

Quant Recommendation	Pre Period	Post Period	Post - Pre
1(Strong Sell)	2.10	0.10	-2.00
	(3.99)	(0.23)	(-2.90)
2	0.87	-0.07	-0.94
	(1.42)	(-0.17)	(-1.27)
3	0.01	0.30	0.29
	(0.05)	(2.05)	(1.06)
4	-0.31	-1.22	-0.92
	(-0.47)	(-3.20)	(-1.22)
5 (Strong Buy)	-0.14	0.88	1.03
	(-0.28)	(2.98)	(1.79)
5-1	-2.24	0.78	3.02
	(-3.08)	(1.42)	(3.34)

Panel B: Sample Excluding Attention-Grabbing Stocks

Quant Recommendation	Pre Period	Post Period	Post - Pre
1	2.59	-0.28	-2.87
	(4.21)	(-0.54)	(-3.58)
2	0.96	-0.02	-0.98
	(1.36)	(-0.05)	(-1.16)
3	-0.18	0.24	0.42
	(-0.55)	(1.59)	(1.39)
4	-0.49	-1.41	-0.92
	(-0.67)	(-3.36)	(-1.12)
5	-0.59	0.77	1.37
	(-1.09)	(2.49)	(2.27)
5-1	-3.17	1.05	4.22
	(-3.89)	(1.74)	(4.19)

Table 12: Retail Trading around SA Research Reports – Predicted versus Residual Imbalances

We repeat Panel B of Table 11 after decomposing retail order imbalances into predicted imbalances and residual imbalances. Predicted imbalances are computed as the fitted value from a regression of retail imbalances on report rating, and residual imbalances are the difference between retail imbalances and predicted imbalance. All other details are identical to Panel B of Table 11. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

Panel A: Predicted Imbalances

Quant Recommendation	Pre Period	Post Period	Post - Pre
1(Strong Sell)	0.03	-0.03	-0.07
	(1.50)	(-2.41)	(-2.59)
2	0.00	-0.03	-0.03
	(-0.05)	(-2.29)	(-1.27)
3	-0.01	-0.01	0.00
	(-0.67)	(-0.93)	(0.25)
4	0.04	0.03	-0.01
	(2.60)	(3.89)	(-0.34)
5 (Strong Buy)	0.02	0.05	0.03
	(1.23)	(4.70)	(1.96)
5-1	-0.02	0.08	0.10
	(-0.64)	(4.76)	(3.23)

Panel B: Residual Imbalances

Quant Recommendation	Pre Period	Post Period	Post - Pre
1	2.58	-0.37	-2.95
	(4.21)	(-0.73)	(-3.70)
2	0.98	-0.12	-1.10
	(1.40)	(-0.27)	(-1.33)
3	-0.14	0.12	0.27
	(-0.45)	(0.79)	(0.88)
4	-0.50	-1.58	-1.08
	(-0.69)	(-3.74)	(-1.29)
5	-0.58	0.60	1.17
	(-1.08)	(1.92)	(1.95)
5-1	-3.16	0.97	4.13
	(-3.88)	(1.60)	(4.10)

Internet Appendix for:

Quantitative Analysis and the Value of Social Media Investment Research

In this appendix, we tabulate results of robustness and supplementary analyses referenced in the paper. The set of figures and table are as follows:

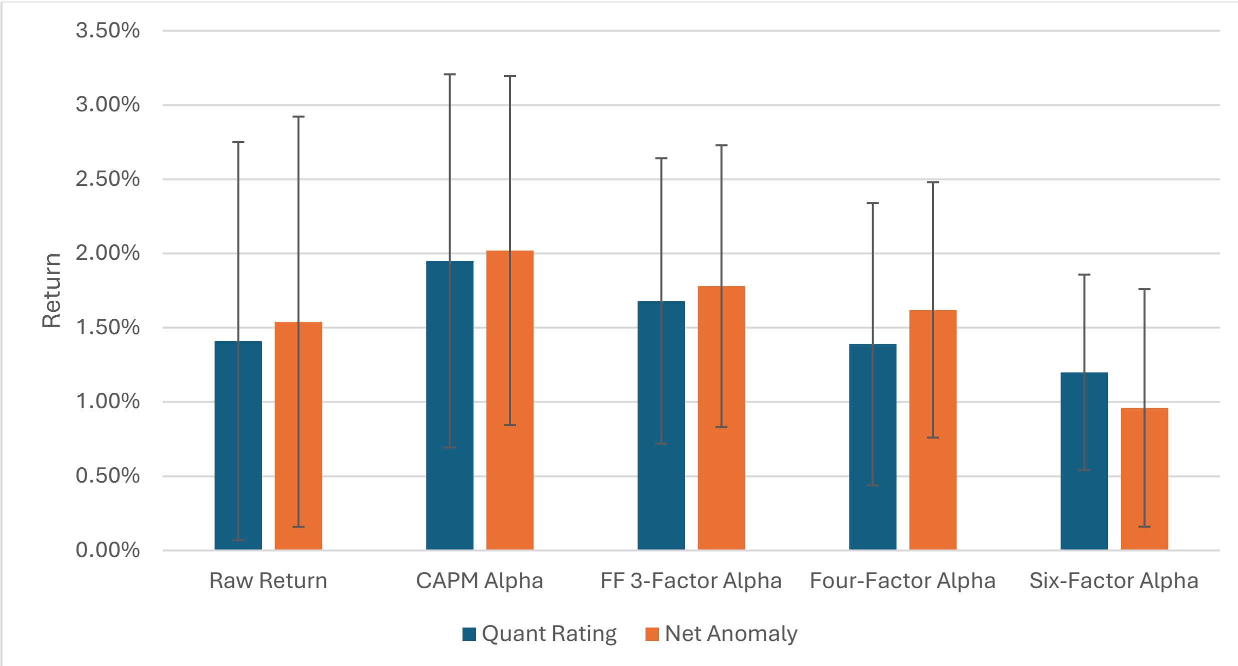

Figure IA.1: Returns Predictability of SA Quant Recommendations versus Academic Anomalies
This figure reports the value-weighted returns to a strategy that goes long stocks that in *Strong Buy* portfolio and short stocks in the *Strong Sell* portfolio. The blue bar reports the results based on sorting stocks into groups based on the Seeking Alpha quantitative recommendation. Thus, the results are identical to the final column of Table 3, Panel B. The orange bars report analogous results after sorting stocks into groups based on the *Net Anomaly Score* (as defined in Table 2), where the portfolio breakpoints are computed to include the same percentage of stocks as the SA Quant Recommendations. For example, the strong sell portfolio includes stocks in the bottom 8% of the net anomaly score. Standard errors are computed from the time-series standard deviation, and the error bars report the 95% confidence intervals.

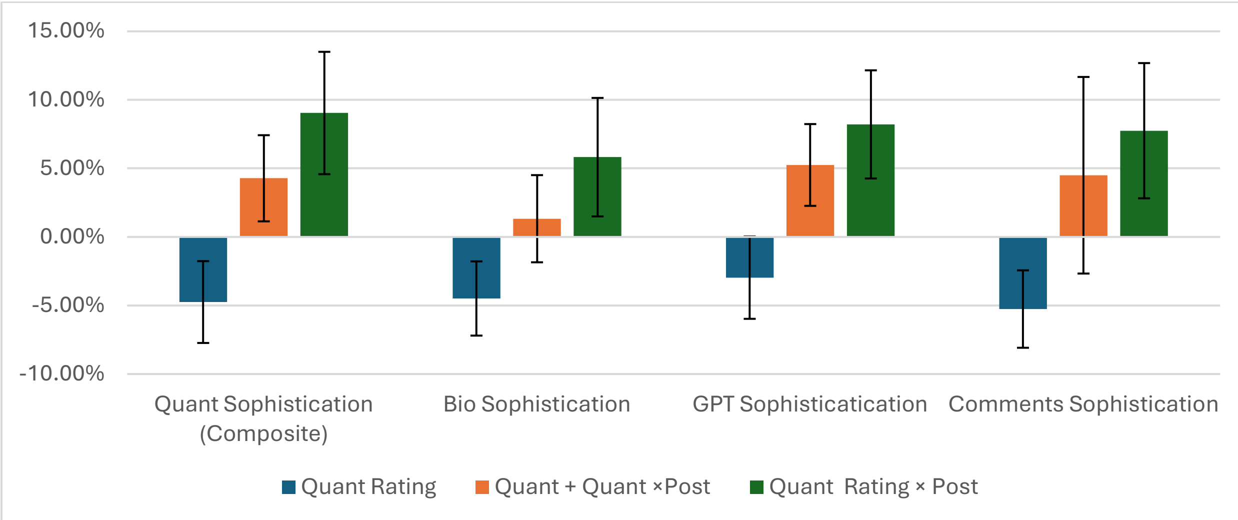

Figure IA.2: SA Report Sentiment and Quantitative Ratings by Quant Sophistication Measures
This figure reports the estimates from Specification 6 of Table 6 after replacing the composite *Quant Sophistication* measure with the three individual component measures: *Bio Sophistication, GPT Sophistication,* and *Comment Sophistication* (as defined in Table 6 and Appendix C). For reference, we also report the results for the composite measure. We report the estimates on *Quant Rating* (Blue Bars), *Quant Rating* × *Post* (Green) and the sum of the two measures (Orange). Standard errors are clustered by firm and date, and the error bars report the 95% confidence intervals.

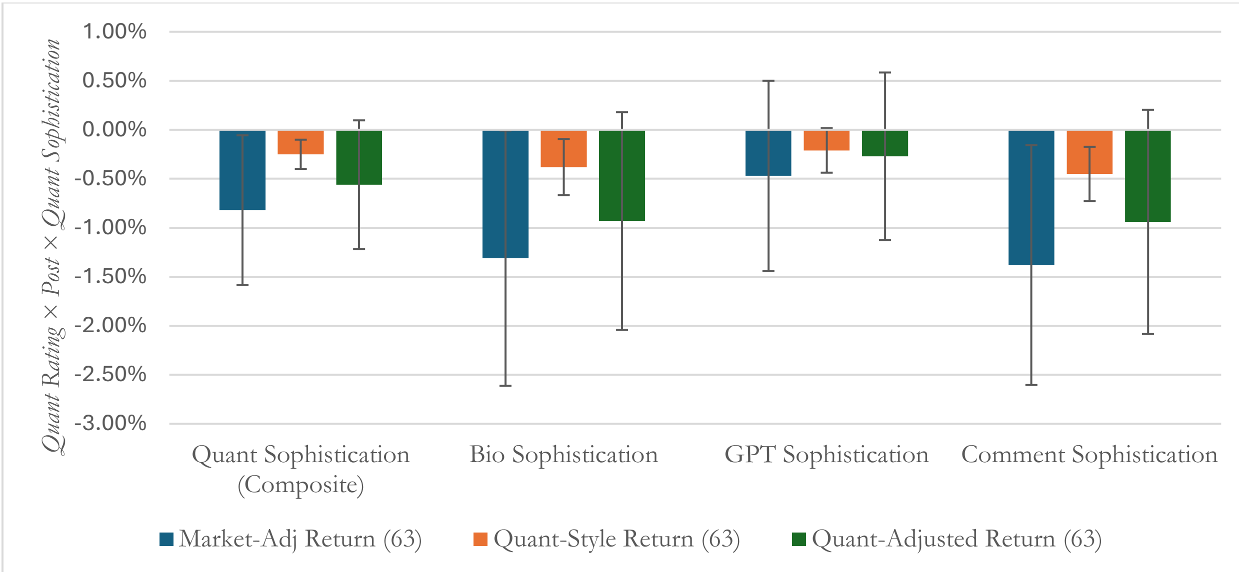

Figure IA.3: SA Report Informativeness by Quant Sophistication Measures

This figure reports the estimates on *Quant Rating* × *Post* × *Quant Sophistication* (i.e., β_4) from Specification 4-6 of Table 10 after replacing the composite *Quant Sophistication* measure with the three individual component measures: *Bio Sophistication, GPT Sophistication,* and *Comment Sophistication* (as defined in Table 6 and Appendix C). For reference, we also report the results for the composite measure. The estimates for Specification 4 (market-adjusted returns) are reported by the blue bars, Specification 5 (quant-style returns) are reported by the orange bars, and Specification 6 (quant-adjusted returns) are reported by the blue bars. Standard errors are clustered by firm and month, and the error bars report the 95% confidence intervals.

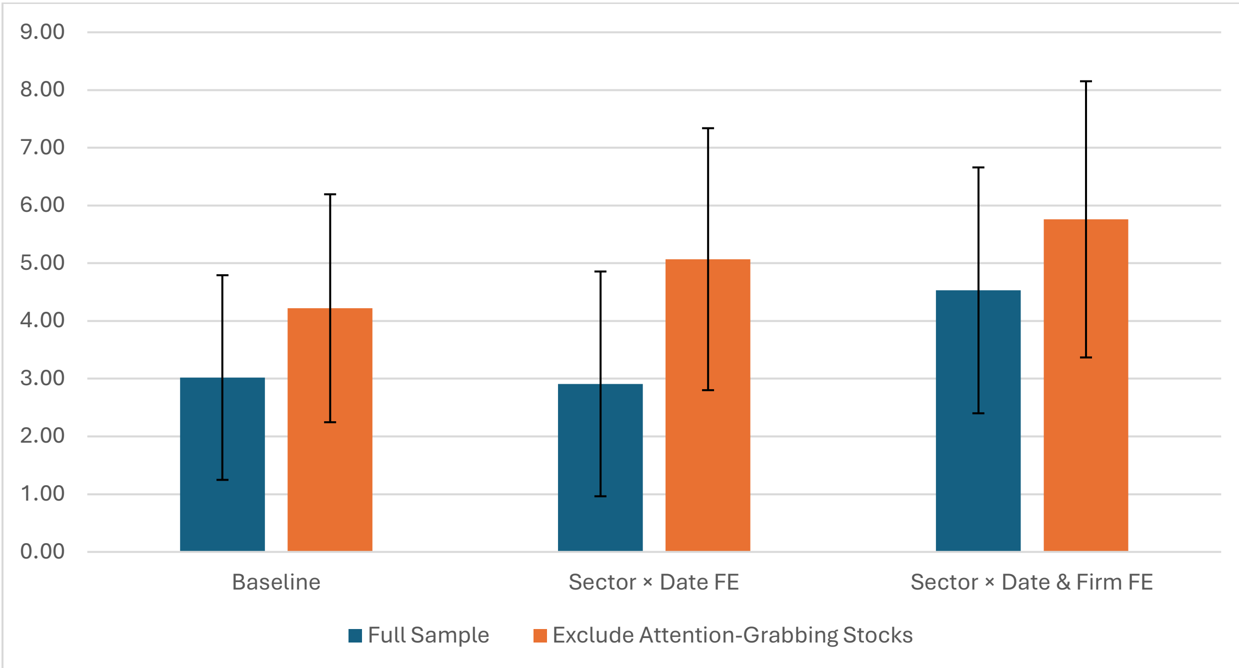

Figure IA.4: Retail Order Imbalances around SA Research Reports - Robustness
The figure repeats the analysis in Table 11 after either including no fixed effects (baseline), sector × date fixed effects, or sector × date and firm fixed effects. We report the difference-in-difference estimates for the full sample (Panel A of Table 11) and the sample excluding confounding events (Panel B of Table 11). The baseline results are identical to those reported in Table 11. Standard errors are clustered by firm and date, and the error bars report the 95% confidence intervals.

Table IA.1: Anomaly Descriptions

This table lists the 118 anomalies used to compute the *Net Anomaly Score*. *Description* provides a short description of the variable. More detailed variable definitions are provided in Jensen, Kelly, and Pedersen (2023) and the code to construct the variables is available here: https://github.com/bkelly-lab/ReplicationCrisis. *Citation* references the original paper creating the variable and Pubyear denotes the year in which the original paper was published. Sign equals one if the original study documented a position relation between the variable and future returns and -1 if the relation was negative. *Factor Cluster* denotes one of 13 characteristic groups as constructed and described in Jensen, Kelly, and Pedersen, (2023).

Variable	*Description*	*Citation*	*Pubyear*	*Sign*	*Factor Cluster*
age	Firm age	Jiang, Lee, and Zhang (2005)	2005	-1	Low Leverage
ami_126d	Amihud Measure	Amihud (2002)	2002	1	Size
at_gr1	Asset Growth	Cooper, Gulen, and Schill (2008)	2008	-1	Investment
be_gr1	Change in common equity	Richardson et al. (2005)	2005	-1	Investment
be_me	Book-to-market equity	Rosenberg, Reid, and Lanstein (1985)	1985	1	Value
beta_60m	Market Beta	Fama and MacBeth (1973)	1973	-1	Low Risk
betabab_1260d	Frazzini-Pedersen market beta	Frazzini and Pedersen (2014)	2014	-1	Low Risk
betadown_252d	Downside beta	Ang, Chen, and Xing (2006)	2006	-1	Low Risk
bev_mev	Book-to-market enterprise value	Penman et al. (2007)	2007	1	Value
bidaskhl_21d	The high-low bid-ask spread	Corwin and Schultz (2012)	2012	1	Low Leverage
capex_abn	Abnormal corporate investment	Titman, Wei, and Xie (2004)	2004	-1	Debt Issuance
capx_gr2	CAPEX growth (2 years)	Anderson and Garcia-Feijoo (2006)	2006	-1	Investment
capx_gr3	CAPEX growth (3 years)	Anderson and Garcia-Feijoo (2006)	2006	-1	Investment
chcsho_12m	Net stock issues	Pontiff and Woodgate (2008)	2008	-1	Value
coa_gr1a	Change in current operating assets	Richardson et al. (2005)	2005	-1	Investment
col_gr1a	Change in current operating liabilities	Richardson et al. (2005)	2005	-1	Investment
cop_atl1	Cash-based operating profits-tolagged book assets	Ball, Gerakos, Linnainmaa, and Nikolaev (2016)	2016	1	Quality
corr_1260d	Market correlation	C. Asness, Frazzini, Gormsen, and Pedersen (2020)	2020	-1	Seasonality
coskew_21d	Coskewness	Harvey and Siddique (2000)	2000	-1	Seasonality
cowc_gr1a	Change in current operating working capital	Richardson, Sloan, Soliman, and Tuna (2005)	2005	-1	Accruals
dbnetis_at	Net debt issuance	Bradshaw et al. (2006)	2006	-1	Seasonality
debt_gr3	Growth in book debt (3 years)	Lyandres, Sun, and Zhang (2008)	2008	-1	Debt Issuance
debt_me	Debt-to-market	Bhandari (1988)	1988	1	Value
div12m_me	Dividend yield	Litzenberger and Ramaswamy (1979)	1979	1	Value
dolvol_126d	Dollar trading volume	Brennan, Chordia, and Subrahmanyam (1998)	1998	-1	Profitability
dolvol_var_126d	Coefficient of variation for dollar trading volume	Chordia, Subrahmanyam, and Anshuman (2001)	2001	-1	Size
dsale_dinv	Change sales minus change Inventory	Abarbanell and Bushee (1998)	1998	1	Profit Growth
ebit_bev	Return on net operating assets	Soliman (2008)	2008	1	Profitability
ebit_sale	Profit margin	Soliman (2008)	2008	1	Profitability
ebitda_mev	Ebitda-to-market enterprise value	Loughran and Wellman (2011)	2011	1	Value
emp_gr1	Hiring rate	Belo, Lin, and Bazdresch (2014)	2014	-1	Investment
eq_dur	Equity duration	Dechow, Sloan, and Soliman (2004)	2004	-1	Value

eqnetis_at	Net equity issuance	Bradshaw, Richardson, and Sloan (2006)	2006	-1	Value
eqnpo_12m	Equity net payout	Daniel and Titman (2006)	2006	1	Value
eqnpo_me	Net payout yield	Boudoukh, Michaely, Richardson, and Roberts (2007)	2007	1	Value
eqpo_me	Payout yield	Boudoukh et al. (2007)	2007	1	Value
f_score	Pitroski F-score	Piotroski (2000)	2000	1	Profitability
fcf_me	Free cash flow-to-price	Lakonishok et al. (1994)	1994	1	Value
fnl_gr1a	Change in financial liabilities	Richardson et al. (2005)	2005	-1	Debt Issuance
gp_at	Gross profits-to-assets	Novy-Marx (2013)	2013	1	Quality
inv_gr1	Inventory growth	Belo and Lin (2012)	2012	-1	Investment
inv_gr1a	Inventory change	J. K. Thomas and Zhang (2002)	2002	-1	Investment
iskew_ff3_21d	Idio. skewness from the FF 3-factor model	Bali, Engle, and Murray (2016)	2016	-1	Reversal
ivol_capm_252d	Idio. volatility from the CAPM (252 days)	Ali, Hwang, and Trombley (2003)	2003	-1	Low Risk
ivol_ff3_21d	Idio. volatility from the FF 3-factor model	Ang, Hodrick, Xing, and Zhang (2006)	2006	-1	Low Risk
kz_index	Kaplan-Zingales index	Lamont, Polk, and SaaÂ´a-Requejo (2001)	2001	1	Seasonality
lnoa_gr1a	Change in long-term net operating assets	Fairfield, Whisenant, and Yohn (2003)	2003	-1	Investment
lti_gr1a	Change in long-term investments	Richardson et al. (2005)	2005	-1	Seasonality
market_equity	Market Equity	Banz (1981)	1981	-1	Size
mispricing_mgmt	Mispricing factor: Management	Stambaugh and Yuan (2017)	2017	1	Investment
mispricing_perf	Mispricing factor: Performance	Stambaugh and Yuan (2017)	2017	1	Quality
ncoa_gr1a	Change in noncurrent operating assets	Richardson et al. (2005)	2005	-1	Investment
netdebt_me	Net debt-to-price	Penman, Richardson, and Tuna (2007)	2007	-1	Low Leverage
netis_at	Net total issuance	Bradshaw et al. (2006)	2006	-1	Value
nfna_gr1a	Change in net financial assets	Richardson et al. (2005)	2005	1	Debt Issuance
ni_be	Return on equity	Haugen and Baker (1996)	1996	1	Profitability
ni_me	Earnings-to-price	Basu (1983)	1983	1	Value
niq_at	Quarterly return on assets	Balakrishnan, Bartov, and Faurel (2010)	2010	1	Quality
niq_be	Quarterly return on equity	Hou, Xue, and Zhang (2015)	2015	1	Profitability
niq_su	Standardized earnings surprise	Foster, Olsen, and Shevlin (1984)	1984	1	Profit Growth
nncoa_gr1a	Change in net noncurrent operating assets	Richardson et al. (2005)	2005	-1	Investment
noa_at	Net operating assets	Hirshleifer, Hou, Teoh, and Zhang (2004)	2004	-1	Debt Issuance
noa_gr1a	Change in net operating assets	Hirshleifer et al. (2004)	2004	-1	Investment
o_score	Ohlson O-score	Dichev (1998)	1998	-1	Profitability
oaccruals_at	Operating accruals	Sloan (1996)	1996	-1	Accruals
oaccruals_ni	Percent operating accruals	Hafzalla, Lundholm, and Matthew Van Winkle (2011)	2011	-1	Accruals
ocf_at	Operating cash flow to assets	Bouchaud et al. (2019)	2019	1	Profitability
ocf_at_chg1	Change in operating cash flow to assets	Bouchaud, Krueger, Landier, and Thesmar (2019)	2019	1	Profit Growth
ocf_me	Operating cash flow-to-market	Desai, Rajgopal, and Venkatachalam (2004)	2004	1	Value
ocfq_saleq_std	Cash flow volatility	Huang (2009)	2009	-1	Low Risk
op_at	Operating profits-to-book assets	Ball, Gerakos, Linnainmaa, and Nikolaev (2015)	2015	1	Quality

ope_be	Operating profits-to-book equity	Fama and French (2015)	2015	1	Profitability
opex_at	Operating leverage	Novy-Marx (2011)	2011	1	Quality
pi_nix	Taxable income-to-book income	Lev and Nissim (2004)	2004	1	Seasonality
ppeinv_gr1a	Change PPE and Inventory	Lyandres et al. (2008)	2008	-1	Investment
prc	Price per share	Miller and Scholes (1982)	1982	-1	Size
prc_hi_prc_252d	Current price to high price over last year	George and Hwang (2004)	2004	1	Momentum
qmj	Quality minus Junk: Composite	C. S. Asness et al. (2019)	2019	1	Quality
qmj_growth	Quality minus Junk: Growth	C. S. Asness et al. (2019)	2019	1	Quality
qmj_prof	Quality minus Junk: Profitability	C. S. Asness et al. (2019)	2019	1	Quality
qmj_safety	Quality minus Junk: Safety	C. S. Asness, Frazzini, and Pedersen (2019)	2019	1	Quality
rd_me	R&D-to-market	Chan et al. (2001)	2001	1	Size
resff3_12_1	Residual momentum t-12 to t-1	Blitz, Huij, and Martens (2011)	2011	1	Momentum
resff3_6_1	Residual momentum t-6 to t-1	Blitz et al. (2011)	2011	1	Momentum
ret_12_1	Price momentum t-12 to t-1	Fama and French (1996)	1996	1	Momentum
ret_12_7	Price momentum t-12 to t-7	Novy-Marx (2012)	2012	1	Profit Growth
ret_1_0	Short-term reversal	Jegadeesh (1990)	1990	-1	Reversal
ret_3_1	Price momentum t-3 to t-1	Jegadeesh and Titman (1993)	1993	1	Momentum
ret_60_12	Long-term reversal	De Bondt and Thaler (1985)	1985	-1	Investment
ret_6_1	Price momentum t-6 to t-1	Jegadeesh and Titman (1993)	1993	1	Momentum
ret_9_1	Price momentum t-9 to t-1	Jegadeesh and Titman (1993)	1993	1	Momentum
rmax1_21d	Maximum daily return	Bali, Cakici, and Whitelaw (2011)	2011	-1	Low Risk
rmax5_21d	Highest 5 days of return	Bali, Brown, and Tang (2017)	2017	-1	Low Risk
rmax5_rvol_21d	Highest 5 days of return scaled by volatility	C. Asness et al. (2020)	2020	-1	Reversal
rskew_21d	Total skewness	Bali et al. (2016)	2016	-1	Reversal
rvol_21d	Return volatility	Ang, Hodrick, et al. (2006)	2006	-1	Low Risk
sale_bev	Assets turnover	Soliman (2008)	2008	1	Quality
sale_gr1	Sales Growth (1 year)	Lakonishok, Shleifer, and Vishny (1994)	1994	-1	Investment
sale_gr3	Sales Growth (3 years)	Lakonishok et al. (1994)	1994	-1	Investment
sale_me	Sales-to-market	Barbee Jr, Mukherji, and Raines (1996)	1996	1	Value
saleq_su	Standardized Revenue surprise	Jegadeesh and Livnat (2006)	2006	1	Profit Growth
seas_11_15an	Years 11-15 lagged returns, annual	Heston and Sadka (2008)	2008	1	Seasonality
seas_16_20an	Years 16-20 lagged returns, annual	Heston and Sadka (2008)	2008	1	Seasonality
seas_16_20na	Years 16-20 lagged returns, nonannual	Heston and Sadka (2008)	2008	-1	Accruals
seas_1_1an	Year 1-lagged return, annual	Heston and Sadka (2008)	2008	1	Profit Growth
seas_1_1na	Year 1-lagged return, nonannual	Heston and Sadka (2008)	2008	1	
seas_2_5an	Years 2-5 lagged returns, annual	Heston and Sadka (2008)	2008	1	Seasonality
seas_2_5na	Years 2-5 lagged returns, nonannual	Heston and Sadka (2008)	2008	-1	
seas_6_10an	Years 6-10 lagged returns, annual	Heston and Sadka (2008)	2008	1	Seasonality
seas_6_10na	Years 6-10 lagged returns, nonannual	Heston and Sadka (2008)	2008	-1	Low Risk
taccruals_at	Total accruals	Richardson et al. (2005)	2005	-1	Accruals
taccruals_ni	Percent total accruals	Hafzalla et al. (2011)	2011	-1	Accruals

tax_gr1a	Tax expense surprise	J. Thomas and Zhang (2011)	2011	1	Profit Growth
turnover_126d	Share turnover	Datar, Naik, and Radcliffe (1998)	1998	-1	Low Risk
turnov_var_126d	Coefficient of variation for share turnover	Chordia et al. (2001)	2001	-1	Profitability
z_score	Altman Z-score	Dichev (1998)	1998	1	Low Leverage
zero_trades_126d	Number of zero trades (6 months)	Liu (2006)	2006	1	Low Risk
zero_trades_252d	Number of zero trades (12 months)	Liu (2006)	2006	1	Low Risk

Table IA.2: Transition Matrix for Quantitative Recommendations

This table reports transition probabilities for SA quant recommendation at either a daily frequency (Panel A), a monthly frequency (Panel B), or a yearly frequency (Panel C). Transition probabilities for monthly and annual measures are based on observations at the end of the calendar month and calendar year, respectively.

Panel A: Daily Transition Matrix

	Strong Buy	Buy	Hold	Sell	Strong Sell
Strong Buy	94.80%	1.82%	3.37%	0.01%	0.00%
Buy	1.86%	92.58%	5.50%	0.04%	0.01%
Hold	0.38%	0.76%	97.92%	0.70%	0.23%
Sell	0.01%	0.03%	4.26%	93.62%	2.08%
Strong Sell	0.00%	0.01%	1.72%	2.09%	96.18%

Panel B: Monthly Transition Matrix

	Strong Buy	Buy	Hold	Sell	Strong Sell
Strong Buy	63.89%	11.97%	23.66%	0.42%	0.06%
Buy	11.49%	51.49%	35.81%	0.78%	0.42%
Hold	2.60%	4.56%	85.21%	5.00%	2.63%
Sell	0.27%	0.62%	32.44%	54.84%	11.83%
Strong Sell	0.05%	0.33%	18.21%	12.45%	68.96%

Panel C: Annual Transition Matrix

	Strong Buy	Buy	Hold	Sell	Strong Sell
Strong Buy	17.79%	12.17%	57.61%	8.02%	4.41%
Buy	12.51%	16.08%	57.23%	7.52%	6.66%
Hold	7.63%	8.78%	65.29%	9.89%	8.40%
Sell	5.91%	6.17%	60.35%	18.98%	8.58%
Strong Sell	4.38%	5.47%	55.42%	9.63%	25.10%

Table IA.3: SA Report Sentiment and Quantitative Ratings

This table repeats Specifications 1 -3 of Table 4 after replacing *Quant Rating* with indicators for the different quantitative recommendations: *Strong Buy, Buy, Sell, and Strong Sell* (where *Hold* is the omitted group), and we interact each of the quant recommendations with *Post*. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]
Strong Sell	2.85%	3.15%	0.37%
	(1.40)	(1.63)	(0.21)
Sell	1.56%	2.03%	2.11%
	(0.83)	(1.29)	(1.34)
Buy	7.45%	0.79%	4.56%
	(2.48)	(0.46)	(3.04)
Strong Buy	3.83%	1.87%	3.55%
	(1.74)	(1.25)	(2.80)
Strong Sell × *Post*	-17.45%	-12.15%	-13.30%
	(-6.23)	(-4.63)	(-5.40)
Sell × *Post*	-7.37%	-6.19%	-6.73%
	(-2.94)	(-2.91)	(-3.27)
Buy × *Post*	4.65%	5.89%	6.27%
	(1.65)	(2.55)	(3.34)
Strong Buy × *Post*	6.47%	2.88%	3.20%
	(2.56)	(1.37)	(3.23)
Observations	96,129	96,129	96,129
Industry × Date FE	Yes	Yes	Yes
Contributor FE	No	No	Yes
Firm FE	No	Yes	No
R-squared	18.17%	27.08%	36.92%
Mean Dep Variable	42.48%	42.48%	42.48%

Table IA.4: Retail Trading by SA Report Rating and Quant Recommendation

This table reports the average retail investor order imbalances on the first day in which an investor could have traded on the report in the pre-period (2016-2018) and post-period (2020-2022). Retail order imbalances are computed as retail buy volume less retail sell volume scaled by retail trading volume, where trades are signed using the algorithm of Barber al. (2023). Panel A reports the results for stocks with a quant recommendation of Strong Buy, and Panel B reports the results for stocks with a quant recommendation of Strong Sell. For both groups, we report the imbalances separately based on the report recommendation (i.e., Sell, Hold, or Buy). The sample excludes reports issued on attention-grabbing stocks (as defined in Table 11). Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

Panel A: Quant Rating = Strong Buy

	Sell Reports	*Hold Reports*	*Buy Reports*
Pre	0.87	-1.39	0.23
	(0.52)	(-2.19)	(0.39)
Post	0.75	0.44	0.98
	(0.64)	(0.91)	(2.48)
Post - Pre	-0.12	1.83	0.75
	(-0.06)	(2.42)	(1.07)

Panel B: Quant Rating = Strong Sell

	Sell Repots	*Hold Reports*	*Buy Reports*
Pre	-0.67	1.97	3.59
	(-0.39)	(2.25)	(4.17)
Post	-1.65	-1.39	0.86
	(-1.10)	(-1.89)	(1.24)
Post - Pre	-0.98	-3.36	-2.73
	(-0.42)	(-2.95)	(-2.46)